The Equilibrium Effects of Domestic Outsourcing

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Abstract

This paper studies the effects of domestic outsourcing on workers and labor markets. I examine these effects empirically using the National Longitudinal Survey of Youth 1979 and theoretically with a DMP-style labor search model. My main data findings are that outsourced workers earn 8.8 log points less each week and are 7.5 pp less likely to receive health insurance than workers in traditional jobs. On the other hand, a 1 pp increase in outsourcing within an occupation increases the average occupation's employment share by .085%. In my model, firms endogenously choose between hiring workers from a frictional labor market or purchasing labor from outsourcers, who themselves hire workers from the same labor market. As in the data, outsourcing has opposing effects on worker's welfare: it lowers the average job quality but increases the number of jobs available. After calibrating the model, I find the negatives outweigh the positives and eliminating outsourcing would increase total welfare by 0.39%.

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1 Introduction

Firms increasingly rely on domestic outsourcing to produce intermediate goods and services: car manufacturers Ford and GM buy components from local producers (Helper et al., 2000); tech companies Apple and Google purchase labor from other firms for tasks ranging from janitorial work to hiring employees (Irwin, 2017; Wakabayashi, 2019); and phone company AT&T contracts with other companies to install and maintain their cell towers (Weil, 2014). Firms chose between producing inputs internally or purchasing them through markets, what economists think of as the boundary of the firm (Coase, 1937; Williamson, 1979). Since the 1980's, firm boundaries have shrunk as firms focus on their "core competencies" where they have comparative advantages and rely on markets for production outside of their specialties (Prahalad, 1993). Much of this trend has been driven by globalization, where firms import to access other countries' comparative advantages (Antràs, 2003; Grossman and Helpman, 2005), but domestic outsourcing has also played an important role and has different effects on the economy. Foreign outsourcing changes who performs work; domestic outsourcing changes who employs the worker. This paper studies the consequences of domestic outsourcing in the US for workers and the labor markets they inhabit using both reduced form regressions and a structural model.

I study a type of domestic outsourcing known as contracting out, where a worker's services are provided to another firm under contract. Contracted out workers usually only work for one firm at a time and often at the client's place of business. Common contracted out jobs range from low skilled jobs such as janitors and security guards to high skilled jobs such as electricians, IT workers, and statisticians. Firms have many options when outsourcing domestically: they can purchase intermediate goods from domestic suppliers, services from individual independent contractors or freelancers, or short-term labor from temporary help firms. I focus on contracted out workers because they usually work at the client's job cite, unlike workers at domestic suppliers who usually work at their employer; they are hired by a firm, unlike independent contractors who work for themselves; and their jobs are expected to last many years, unlike temporary (temp) workers whose jobs only last a year or two at most. By focusing on contracted out jobs, I hope to isolate the effects of being employed by one firm while performing tasks for another. For the rest of this paper, I often use outsourced and contracted out interchangeably to ease understanding.

Using data on men from the National Longitudinal Survey of Youth 1979 (NLSY), I establish several empirical facts about domestic outsourcing. I find that an average of 2.2% of employed men work in contracted out jobs each week and this figure rose from about 1% of the working population in 2001 to 2.5% in 2016 (see Figure A1). These jobs are widespread and many workers have experience in them; over the entire sample, about 10% of workers are ever contracted out and 33% of occupations have at least one contracted out worker. Outsourced jobs are lower quality than traditional jobs where workers are hired directly by firms. After controlling for worker and occupation fixed effects and other observables, outsourced workers earn 8.8 log points less each week and are 7.5 pp less likely to receive health insurance. I show that worker's movement in and out of outsourced jobs is similar to that of traditional jobs; there is no evidence that outsourced workers use these jobs as stepping stones to better opportunities nor that they find these jobs at a faster rate. Despite these negatives, I also find that outsourcing increases the number of jobs available. I find a 1 pp increase in the percent of workers outsourced within the average occupation leads to a .085% increase in that occupation's employment share. The overall effect on worker welfare depends on whether the negatives or positives are stronger.

To help analyze which effect is stronger, I develop a labor search model of domestic outsourcing. The model is based on Ljungqvist and Sargent's (LS) textbook treatment of Davis (2001). I start with an otherwise standard Diamond-Mortensen-Pissarides (DMP) model where workers randomly search for jobs at heterogeneous productivity firms and bargain with their employers over wages. I then add domestic outsourcing, which allows firms to avoid hiring workers by purchasing labor from outsourcers in a Walrasian market. Outsourcers hire workers in the same labor market as firms and also bargain with their workers over wages; the model changes who pays the worker, not who does the work. The model captures the empirical trade off highlighted above: outsourcing jobs can be worse than traditional jobs, but outsourcing increases the number of jobs available. It is also consistent with several stylized facts from the literature: firms mainly use outsourcing to lower labor costs (Abraham and Taylor, 1996; Weil, 2014); more productive firms pay their outsourceable workers higher wages (Goldschmidt and Schmieder, 2017); and more productive firms are more likely to outsource (Goldschmidt and Schmieder, 2017; Drenik et al., 2020).

I analyze a simple version of the model to highlight its main mechanisms. Outsourcing allows firms to avoid bargaining with workers and avoid search frictions, both of which are more valuable to high productivity firms. Because high productivity firms are the ones who choose to outsource, workers lose access to the highest paying jobs. On the other hand, outsourcing firms' profitability increases when they outsource, so they increase their demand for labor and more overall jobs are available. To see how outsourcing effects economic efficiency, I study the Planner's problem. The Planner also wants high productivity firms to outsource because this bypasses search frictions for the most valuable (and thus most expensive) vacancies. Using taxes and subsidies on vacancy creation, the Planner can decentralize the optimal allocation of workers. The optimal tax schedule places no taxes/transfers on Outsourcing firms, as they make efficient decisions conditional on the price of outsourcing.

I then calibrate a slightly more complicated version of the model, which includes on-the-job search, to better match NLSY data and quantify the effects of outsourcing on workers. The calibration uses workers ever in high outsourcing occupations, which are occupations with more than twice the average level of outsourcing (4.35%), because they are the most likely to experience equilibrium effects. I match the model to data on the residual wage distribution, the percent of jobs that are outsourced, and the rate of worker job flows. The model matches flow data very well and wage data reasonably well. In a counterfactual without outsourcing, unemployment is 1.2% higher but the loss of jobs is outweighed by the increase in average job quality and unemployed worker's value of search increases 1.1%.

Eliminating outsourcing increases total welfare by 0.39%.

The rest of the paper is organized as follows: Section 2 overviews the literature; Section 3 provides data analysis of the NLSY and the quality of outsourced jobs; Section 4 presents the basic model and details its properties; Section 5 calibrates the model to NLSY data; and Section 6 concludes. The Appendix contains figures, tables, proofs, the more detailed calibrated model, and a guide to cleaning the data.

2 Literature Review

Domestic outsourcing has been increasing in the US and other Western countries since the 1980's.[1] From surveying manufacturing firms about outsourcing, Abraham and Taylor (1996) find that firms mainly outsource to reduce costs. Most of the literature has found that more productive firms outsource, because the cost savings of outsourcing increase with productivity (see Houseman (2001); Dube and Kaplan (2010); Goldschmidt and Schmieder (2017); Drenik et al. (2020)). More productive firms pay their outsourceable workers higher wages (Goldschmidt and Schmieder, 2017). In the US, firms can only receive tax breaks for providing health and retirement benefits if they are comparable for all full-time workers (Perun, 2010), and more productive firms use more generous benefits to attract their non-outsourceable workforce. The cost of benefits has increased over time; according to Gu (2018), between 1964 and 2004, employee benefits rose from about 14% to 25% of total compensation, with much of the rise coming in the 1980's when outsourcing became much more prominent. Weil (2014) argues that outsourcing allows firms to skirt another cost, labor laws. Because labor laws are harder to enforce at smaller firms, larger firms can outsource to smaller firms to make it harder for workers to use labor laws to extract rents. By outsourcing production, firms can turn from internal markets, where workers capture shares of rents through bargaining power or social norms, to external markets, where the forces of

[1]For evidence by country, see US: Abraham and Taylor (1996); Dey et al. (2010); Katz and Krueger (2019a); Germany: Goldschmidt and Schmieder (2017); France: Berlingieri (2015); Bilal and Lhuillier (2021); UK and Spain: Kalleberg (2000); and Australia: Wooden (1999).

supply and demand put more pressure on lowering costs (Katz, 1999). Outsourcing can also help firms cut down on hiring and recruiting costs, which make up about 2.5% of total labor costs (Villena-Roldan, 2012). The major reason firms outsource is to reduce the costs of production, and the main way outsourcing reduces costs is by making it harder for workers to access their share of production. Separating worker's from their share of surplus (along with avoiding hiring frictions) is also the reason firms outsource in my model.

The NLSY's questions on alternative jobs are taken almost verbatim from the CPS supplement Contingent Worker Survey (CWS), which ran 5 times from 1995-2005 and again in 2017. Another CWS-like survey comes from Katz and Krueger (2019a) (KK), who asked about alternative jobs as part of the RAND American Life Panel in 2015. Like my work, these surveys measure self-reported outsourcing status, so all can measure overall outsourcing and break down outsourcing by different demographic and education groups. Unlike my work, these surveys are cross-sectional, so they cannot follow workers in and out of outsourced jobs and have trouble distinguishing worker characteristics from job characteristics. My data allows me to follow workers over time and used worker fixed effect to help control for unobserved worker differences. I find similar levels of contracting out over time and fill in how outsourcing evolved over the gaps in their surveys.

I use self-reported outsourcing to measure the quality of outsourced jobs. Two papers studying outsourced job quality without a direct measure of outsourcing are Dube and Kaplan (2010) (DK) and Goldschmidt and Schmieder (2017) (GS). DK use CPS data to study janitors and security guards and impute outsourcing status using occupation and industry. GS use matched worker-firm data from Germany to study workers in food, security, cleaning, and logistic services and impute outsourcing using mass movements of workers from one firm to another.[2] The need to impute outsourcing leads these papers to focus on a few, lower skilled occupations, while my work shows that workers are outsourced across the skill

[2]One of these coauthors have a working paper Dorn et al. (2018) that uses a similar identification strategy with Longitudinal Employer-Household Dynamics (LEHD) data in the US. As of this writing, this paper is still a work in progress.

distribution. This could lead to different findings if outsourced workers are different across the ability spectrum. One example of this is the role of unions in outsourcing. DK and GS both find outsourced jobs are less likely to be unionized and conjecture that if strong unions were able to use their bargaining power to prevent firms from outsourcing, then their decline would make it easier for firms to outsource. I reach the opposite conclusion: both outsourced workers and outsourced jobs are more likely to be part of a union. By studying all workers, I am able to get a more general measure of the effects of outsourcing on workers. Despite the different types of workers studied, I find similar drops in job quality to both of these papers.

Another paper that tracks outsourced workers over time is Drenik et al. (2020). Rather than use self-reported outsourcing status, they use Argentinian administrative data that matches temp workers to both their employer and client firm. They run Abowd et al. (1999) (AKM) style models with fixed effects on both employer and client firms. They find firms who hire temp workers are larger and more productive and that temp workers receive about half of the employment rents of traditional workers. All of these facts are consistent with my analysis and model. They also find substantial sorting of temp workers; the sorting between temp workers and client firms is about three-fourths as strong as sorting between traditional workers and client firms. Because I lack firm side data, my analysis ignores any potential sorting effects.

My model shows outsourcing increases employment. If firm's demand for outsourceable services is at least partially elastic, then we should expect that the cost savings of outsourcing should increase firms' labor demand, and I show this both in the data and within the model. This finding seemingly contradicts both Berlingieri (2015) and Bloom et al. (2018), who study the Professional Business Services (PBS) industry, an industry where over 90% of production is of intermediate goods and services. Neither find any effects of increases in PBS employment on total employment. I show that only about 25% of contracted out workers are in PBS and that many PBS workers do not consider themselves contracted out, so part of the differences may be due to measuring different populations. But I also find that

PBS employment does have a positive effect on total employment, perhaps because my data comes from workers rather than establishments, as in Bloom et al. (2018), or from economy wide aggregates, as in Berlingieri (2015).

My paper also joins the literature that models firms who endogenously chose to outsource domestically. The most notable comparison is Bilal and Lhuillier (2021), who also studies how firm outsourcing affects worker outcomes in frictional labor markets. While my model is built on a DMP framework of wage bargaining and theirs is built on a Burdett-Mortensen framework of wage posting, both introduce outsourcing in similar ways. Notably, both feature outsourcers who hire workers from the same labor market as firms and sell their worker's labor in frictionless markets. As a result, both have similar implications: more productive firms hire while less productive outsource, outsourced workers earn less than they would if hired by the same firm directly, and outsourcing increases employment. They use matched worker-firm data from France to show that more productive firms are more likely to outsource and that outsourcing firms produce more. I use my NLSY data to show that outsourced workers are no quicker to find their jobs and that outsourcing within an occupation increases employment. Both papers find wage penalties for working at outsourcers. Each of these findings are consistent with both models. In this way, the papers are complementary, showing many of the conclusions are robust to model specification and are supported empirically across countries.

Another model of endogenous outsourcing is Grossman and Helpman (2002), who focus on property rights and how outsourcing helps align incentives. Their model introduces search frictions between firms and outsourcers while abstracting from labor markets; my model has frictionless outsourcing markets and frictional labor markets. With an increasing returns to scale matching function, their model can generate the coexistence of outsourcing and vertical integration even with homogeneous firms, while my model needs heterogeneous firms for hiring and outsourcing to coexist. They also model how intermediate good/service specificity effects the incentives to outsource, which my model ignores. Other models of endogenous outsourcing include Holmes and Snider (2011), Berlingieri (2015), Chan (2017), and Chan and Xu (2017). Firms in Holmes and Snider (2011) also outsource to lower worker's share of rents; their firms do so by separating production by capital and workers who can hold up capital, while my firms force workers to bargain with the outsourcer instead of themselves. Berlingieri (2015) shows that French firms who export to more countries outsource more and models the outsourcing as a way to save on management attention. My model abstracts from management and size effects. Both Chan (2017) and Chan and Xu (2017) focus on both the intensive and extensive margin between hiring and outsourcing while this paper only looks at the extensive margin.

3 Data Analysis

In this section, I discuss my data analysis of outsourced jobs, including their prevalence in the the economy, their quality compared to traditional jobs, and their effects on total employment. I focus on the NLSY but also check some aggregate results in IPUMS CPS using both monthly data and the 6 CWS surveys. The NLSY follows a nationally representative group of young adults born between 1957-1964 throughout their life.[3] NLSY data consists of biennial surveys which can be used to construct a weekly employment history. Starting in 2002, the NLSY asks workers about their alternative jobs status: whether they were contracted out, self-employed, an independent contractor, a temp worker, or an on-call worker. I use these self-reported job types and call a job traditional if it not reported as any other type. While contracted out, independent contractor, and temp workers are all outsourced jobs, I use contracted out jobs as my measurement of outsourcing.[4] As shown in Table A8, these jobs are the most comparable to traditional jobs in terms of wages, hours

[3]Special thanks to Steve McClaskie and the rest of NLS User Services for help explaining NLSY questionnaires and data and for providing needed variables.

[4]The specific question reads:

Some companies provide employees or their services to other companies under contract. A few examples of services that can be provided under contract include private security services, landscaping, or computer programming.

On this job, [did] you work for a company that [provided] your services to other companies under contract?

worked, and benefits. My timeline ranges from January 2001-October 2016, the first month is when my measure of outsourcing starts, the last month is when my weekly job data becomes scarce. I restrict my sample to men, who are both more likely to work and to be outsourced.

The employment information in this paper comes from three sources within the NLSY: On Jobs, where respondents list each job worked since the last interview and report job type; the Employer Supplement, where these listed jobs are sorted and respondents answer detailed questions about each job, such as wages and benefits; and the Employer History Roster, a retrospective data set that connects jobs across surveys and lists employment status each week. The main challenge in cleaning the data is that while there is employer identification in the Employer Supplement and Employer History Roster, there is no identification in On Jobs and no official match between these two halves of the data. Instead, I must recreate the sorting algorithm between On Jobs and the Employer Supplement to determine the outsourcing status of each job.[5] The algorithm sorts jobs in reverse order of week stopped working, starting with current employment. After running the algorithm, I fill in missing job type information across interviews, then drop any matches with conflicting start or end months or with missing or conflicting job types. Table A1 shows the step-by-step matching process from the Employer Supplement side.

My final data set is made up of 4,081 respondents and 12,360 jobs spread over 64,996 person-job-interview pairs. Overall, I am able to match 93% of Employer Supplement person-interview-job observations with a job type status. As shown in Table A2, I am also able to extract information from 89% of On Job entries with useful information.[6] While there is no guarantees any given match is correct, Table A3 shows 75% are matched on month start or end date, which is often the best an On Jobs observation can be matched given missing data

[5]I am unaware of any previous work attempting to match these two questionnaires. The NLSY 1997 asks the same job type questions after 2002, but has the same matching problems, such that NLS User Services have not made the On Jobs section available to the public. According to contact with NLS User Services, they plan on creating an official match between the two questionnaires for both the 1979 and 1997 data sets for their next public release.

[6]Although I only match 84% of outsourcing jobs, which are harder to match because outsourcing jobs have shorter tenure than traditional jobs and so are more likely to be one of many jobs that need to be matched.

constraints. A further 22% are the only jobs in their interview not matched by start/end date, most of which are the only job a worker holds in that interview. To the extent that there are errors in the matching process, they should produce noise that will only dampen any true impacts of outsourcing.

In addition to jobs data, I use data on demographics and education. Throughout, I weight results based on NLSY supplied weights which account for respondent's interview participation over time. I run summary statistics and regressions at the job level; any job present in multiple interviews uses average or modal characteristics. For more information about how the data is cleaned, including the matching algorithm and a list of all variables used, see Appendix E.

This sections analyzes the data along five different themes. First, I measure the level of outsourcing and other alternative job types in the economy overall and compare my findings to the CWS and KK. Second, I summarize the demographics of workers who are ever outsourced and workers who are ever employed in high outsourcing occupations. Third, I compare the quality of outsourced jobs to traditional jobs and compare my findings to DK and GS. Fourth, I study how outsourced workers transition between jobs compared to traditional workers. Finally, I regress percent outsourced within an occupation on the number of workers and quality of jobs in the occupation.

3.1 Levels of Outsourcing

In this section, I measure the prevalence of outsourcing and other alternative jobs in my sample and how this changes over time. Throughout, I compare to CWS and KK, but before I do, I note some underlying differences in the samples.[7] First, both of these surveys study both men and women, while my main sample studies only men, who I have found

[7]For the CWS, I often refer to the BLS reports on this supplement for 2005 `https://www.bls.gov/news.release/history/conemp.txt` and 2017 `https://www.bls.gov/news.release/pdf/conemp.pdf`. For KK, I mostly compare to their companion paper Katz and Krueger (2019b) which provides alternative weights that attempt to match the CPS sample based on percent self-employed and percent multiple job-holders. I also compare to some findings in their working paper Katz and Krueger (2016), which contains more specific details on contracted out jobs.

are more likely to be contracted out. Second, my survey follows a cohort from ages 37-44 to ages 51-59, and some results in the CWS and KK suggest that older workers are more likely to be contracted out. Third, my respondents are repeatedly interviewed over time and fill out each survey on their own behalf, while both other surveys use cross-sections of respondents and the CWS allows for proxy respondents (such as significant others). KK show that proxy respondents make up about half of all CWS responses and are about 2 pp less likely to report working in an alternative arrangement. If repeated exposure to these questions makes it easier for workers to classify their own jobs, then my results may show more contracting out. On the other hand, when the NLSY introduced the alternative job questions in 2002, they pre-assigned 90% of existing jobs as traditional and I assume these classifications are correct. For these reasons, my results are more likely to be underestimates in earlier years and more likely to be overestimates in later years.

In my sample, an average of 2.17% of employed workers are contracted out each week, and, as shown in Figure A1, this percent grew from 1% in 2001 to 3% in 2014, before dropping to 2.5% in 2016. In 2001 and 2005, the CWS showed about 1% and 1.5% of all workers were contracted out, while in 2017 this number was still about 1.5%.[8] In 2015, KK found that about 2.5% of workers were contracted out, depending on how the sample is weighted. My results are very close to CWS 2001 and KK; higher but within statistical range of CWS 2005; and would almost certainly be higher but potentially within statistical range of CWS 2017. Given the sharp drop in outsourcing from KK in 2015 to the CWS in 2017, we might be worried that KK's sample is too different from the CWS to be a useful comparison.[9] KK speculate that some of the discrepancy between their numbers in 2015 and the CWS numbers in 2017 is from the improving economy. My measure suggests that this is a plausible story and that results of both KK and the CWS 2017 are consistent with my data.

As I mentioned above, one weakness of my data is that I only see one cohort and contract-

[8] These point estimates come from Katz and Krueger (2019b) Table 1.

[9] See Katz and Krueger (2019b) for more on these discrepancies.

ing out may be increasing in age. Figure A2 shows percent of employed workers outsourced by age and gives potential reason to be concerned. The figure shows outsourcing increasing then decreasing in a pattern similar to the time trend. Figure A3 plots percent outsourced each year by birth cohort and shows that most of the dip in later years is a cohort effect, for some reason the older cohorts in my sample are less likely to be outsourced and my old age observations come only from these cohorts. To see if there is a time trend after accounting for age, I plot Figure A4, which measures percent outsourced each week only for workers age 43-47, where Figure A2 shows approximately no change in percent outsourced.[10] For workers of all ages, outsourcing starts at 1% in 2001 and significantly increases to 3% by 2012; for ages 43-47 it starts at a little over 1.5% in 2001 and increases to 5% by 2012, albeit with more noise. While age might have some effect on my data, the underlying increase in outsourcing is real.

How do my measures of other non-traditional job types compare with the CWS and KK? Table A4 shows the percent of person-job weeks worked in each job type and Figure A5 shows how these measures changed over time. In both the CWS and KK, independent contractors made up 7% of all jobs, in my data they make up only 1.5%. On the other hand, the CWS found 10% of workers were self-employed and KK re-weight their findings to try and match this percentage, while my data shows 15% of workers are self-employed.[11] One potential explanation is that CWS and KK ask about self-employment status separately from job type, while the NLSY groups these questions together. Respondents are asked if they are self-employed before they are asked if they an independent contractor, and the survey often skips later job type questions when earlier ones have been answered. If many self-employed independent contractors are only asked the first question, then they will be measured as self-employed but not an independent contractor in my data.

For temp workers and on-call jobs, my numbers are closer. KK finds 1.5% of workers

[10] I perform a similar test for ages 49-53, with similar results.

[11] This slightly understates total self-employment, as I classify all self-employed independent contractors as only independent contractors to make sure each worker has only one job type. Both the CWS and KK ask self-employment status separately from job type.

are in temp jobs and the CWS finds a little less than 1%, I find 0.6%, perhaps because my prime-aged sample is less likely to seek temp jobs. I find on-call jobs make up 1.3% percent of total employment, the CWS find 1.5% and KK 2.5%. For trends, my data shows on-call prevalence rose, while independent contracting and temp work stayed about the same. Overall, my data matches the CWS and KK on contracting out remarkably well but is less well matched to other alternative job types.

The CWS, KK, and my results each show that contracting out is widespread throughout many occupations. Table A5 shows that 33% of occupations have some workers contracted out. Because I want to study potential equilibrium effects of increases in outsourcing, I sometimes focus on workers who are ever employed in a high outsourcing (HO) occupations, defined as occupation with more that twice the average level of outsourcing ($\geq$ 4.35%). There are 58 high outsourcing occupations and 1,325 (33%) respondents ever work in these occupations. Workers ever employed in HO occupations are unsurprisingly more likely to be outsourced, but the overall trend in outsourcing is similar, as seen in Figure A6.

3.2 Demographics of Outsourced Workers

Who works in outsourced jobs or in occupations that tend to be outsourced? To find out, I divide workers based on two criteria. The first is ever outsourced versus never outsourced, where ever outsourced workers are those who report working an outsourced job in On Jobs, including those whose job was unmatched in the final data set. The second is those ever in a HO occupation, who are the most likely to experience equilibrium effects of outsourcing because they compete with more outsourced workers. In Table A6, I look at the demographic information of workers, separating by these groups. Overall, 9.88% of workers are ever outsourced in my sample and 32.46% ever work in a HO occupation.[12] Outsourced workers are significantly more likely to be Black in my sample, although the difference does not carry through to HO Occupations. These workers are slightly more likely to have a high

[12]Because I only see part of each worker's job history, these both under count the true prevalence of ever outsourced or HO occupation workers.

school diploma or associates degree and slightly less likely to have a BA degree or higher, but in general these groups have similar levels of education to the rest of the population. Outsourced workers are slightly less likely to be married and have slightly fewer children living with them (but the same total number of children), while workers in HO occupations have slightly more children.

To see how these results might generalize to the rest of the population, I turn to the CPS, as shown in Table A7. While the CPS in general does not have a measure of outsourcing, I can use my measure of HO occupations from the NLSY and see how workers in these occupations differ from the rest of the population. I make this comparison for two groups: for all men age 18-65 and for all men in the NLSY cohort (born between 1957-1964). Overall, the CPS shows fewer workers in HO occupations, about 13% of workers both overall and in the NLSY cohort.[13] Comparing within the NLSY cohort, the CPS is less Black and more Hispanic. Education levels are similar, but HO occupation workers are noticeably more likely to be high school graduates and associate degree holders and less likely to have a bachelors degree or above. The CPS sample is less likely to be single and more likely to be married. Comparing the overall CPS sample to the NLSY cohort, the groups look similar except for the differences we would expect from a younger group: more Hispanic and single and fewer married. I conclude that the NLSY cohort is a reasonable proxy for the rest of the population and that my NLSY sample captures this cohort well.

I now compare the demographics of ever contracted out workers to the demographics of currently contracted out workers in the CWS and KK. Both the 2005 and 2017 CWS show approximately the same proportion of Black workers but much more Hispanic workers, partially because they include younger cohorts. The 2005 shows about the same number of workers with less than a high school education, but the 2017 shows much fewer; only 4% of contracted out workers had less than a high school diploma compared to about 10% in

[13] This is not quite the same comparison, as the NLSY divides by ever in a HO occupation and the CPS figures observe workers for at most one year. But in any given week, about 24% of NLSY workers are in HO occupations, which is still significantly more.

my sample. On the other end of the education spectrum, both the 2005 and 2017 CWS measured about 40% of contracted out workers had a bachelor's degree or more compared to about 20% in my sample. Demographics in KK look similar to the 2017 CWS. I am not sure how to reconcile the large education differences between my results and the CWS and KK, but I feel my result are more plausible as they better match the range of occupations where outsourcing is common.

3.3 Quality of Outsourced Jobs

From the demographic comparisons above, it is clear that outsourced workers are similar to the rest of the population, but what about outsourced jobs? I now compare the quality of outsourced jobs to traditional jobs. My main analysis focuses on all male workers and compares person-jobs, so jobs with observations over multiple interview are assigned average/modal characteristics.[14] I will first compare summary statistics of contracted out jobs to other types of jobs. Then I will use worker and occupation fixed effects regressions to examine how these jobs differ after controlling for potential underlying differences. Finally, I will try to recreate DK's measure of outsourcing in my sample to see how different measures of outsourcing change my results.

Throughout this subsection, I will compare to DK and GS, but first I highlight some differences in samples. DK uses data from the CPS monthly survey, which has no direct measure of outsourcing. Instead, they follow Abraham (1990) and impute outsourcing for janitors and security guards using occupation and industry. Their definition of outsourcing purposefully excludes temp workers, so if independent contractors are rare in these occupations, then their definition of outsourced workers should mostly consist of contracted out workers and line up well with my measure of outsourcing. Like this paper, their identification strategy is selection on observables and worker fixed effects. GS use matched worker-firm data on German workers from the Integrated Employment Biographies (IEB), focusing on

[14] I get similar results if I look only at workers ever in HO occupations or separate job observations by interview. Email the author for details.

workers in on food, security, cleaning, and logistic services (FCLS) industries. They also have no direct measure of outsourcing; instead their identification strategy is to find groups of workers (say all janitors) matched at one firm one quarter and then all matched at a new firm the next (while the old firm still exists). They call these workers onsite outsourced; they are still performing the same jobs at the same location but their legal employer has changed. Onsite outsourcing is a subset of contracting out, they observe the jobs that transition between traditional and contracted out. According to my model and their data, high productivity firms are the most likely to start outsourcing, so we can think of their results as an upper bound for mine, which compares contracted out jobs to all traditional jobs.

We start with summary statistics, which are available in Table A8 for all job types. I first focus on my main comparison: outsourced jobs versus traditional jobs. In both wages and hours worked, outsourced jobs are statistically indistinguishable from traditional jobs.[15] When I broaden my measure to other measures of job quality, these jobs do not perform so well. Outsourced workers are significantly less likely to receive benefits, about 8-10 pp less likely both overall and for major benefits of interest such as health insurance and retirement plans. Outsourced jobs are considerably shorter; average tenure is 2.5 years which is less than half the average tenure of traditional jobs which is 6 years. Both DK and GS found that outsourced workers were significantly less likely to be union members and contemplated if this gap was partially responsible for lower wages. My findings suggest outsourced workers are more than twice as likely to be unionized, perhaps because I look at all occupations and not just the lower skilled FSCL occupations they study.[16]

Table A8 also makes clear why I focus on contracted out jobs as my measurement of outsourcing. While independent contractors and temp workers are also outsourced, their jobs

[15] All wages are in logs of real 2016 dollars. I drop wages of people making less than \$3.30 (Federal minimum wage in 2002 was \$5.15, which is equivalent to about \$6.60 in 2016) or more than \$400 in real hourly wages or working 0 hours or more than 80 hours per week. I classify a worker as part time if they work less than 35 hours a week.

[16] Higher rates of unionization could arise from the type of occupations outsourced workers are employed in, but restricting the sample to workers ever in a HO occupation suggests, if anything, a bigger gap in union membership. Also in Table A18 below, I show workers are more likely to be unionized in their current outsourced job than their previous or next job.

look significantly different from contracted out or traditional jobs. Independent contractors make similar wages, but work fewer hours and are more than twice as likely to be part-time. Temp workers make significantly lower hourly wages and have jobs with much shorter job tenure, averaging about a year. Both of the these job types are about 40-60 pp less likely to come with any benefits, including health insurance or retirement plans. The NLSY also asks workers to rate their job satisfaction, with 1 as the highest satisfaction and 4 as the lowest. I use this as a crude proxy for the total utility a worker derives from a job, including total compensation and satisfaction with the work environment. Despite worse observable outcomes, independent contractors are more satisfied (although not significantly) with their jobs than outsourced or traditional workers, probably due to compensating differentials such as the ability to be their own boss. Temp workers rate their jobs significantly worse. Independent contracting and temp jobs are very different from traditional jobs while contracted out jobs are reasonably similar. By using contracted out as my measure of outsourcing, I am more directly measuring the direct effects of performing tasks for one firm while being paid by another.

Outsourced jobs look, on average, worse than traditional jobs despite being held by demographically similar people. I now want to see if these effects hold up after controlling for observables. To do so, I run regressions on various measures of job quality: log real hourly and weekly wages, hours worked per week, part-time status, job satisfaction, and receiving any benefits or health insurance. Results are reported in Table A9. Equation (1) shows my main specification for outcome Y for person i in job j which is part of occupation k

$$Y_{ijk} = \beta_0 \, outsourced_{ij} + \beta_1 X_{ij} + \alpha_i + \psi_k + \epsilon_{ijk}. \tag{1}$$

My main parameter of interest is *outsourced*, which measures the effect of an outsourced job compared to a traditional one. I control for worker and occupation fixed effects using α and ψ. Other job and worker characteristics, including other job types such as independent contractor and temp worker, are captured by X.[17] All standard errors are clustered by demographic sample, which the NLSY used when creating the data set to ensure it was nationally representative.

These regressions make it clear that outsourced jobs are worse than traditional jobs. In my summary statistics, outsourced and traditional jobs paid similar wages, in my regressions, outsourced wages are significantly lower.[18] Outsourced workers make 8.8 log points per week less than traditional workers, which will be the outcome of interest in my model below. They are also about 7.5 pp less likely to receive any benefits overall or health insurance in particular. Outsourced workers work insignificantly fewer hours, have insignificantly worse job satisfaction (higher numbers are less satisfied), and are equally likely to work part-time. GS find FSCL workers in Germany make about 4-15 log points per day less and DK find outsourced security guards and janitors in the US make about 7-11 log points per hour less and are 5-15 pp less likely to receive health insurance. I find similar effects when studying outsourcing over a broader set of workers, suggesting their results are largely generalizable to the whole population.

My regressions use worker fixed effects, so my outsourcing effect is estimated by workers moving in and out of outsourced jobs. Because worker job transitions are endogenous, we might worry this biases my outcomes. In the vein of Gibbons and Katz (1992), I investigate how large these biases might be by regressing job outcomes on previous rather than current job type. In Table A10, I take all jobs for which I have current and previous job type and run the same regression as above, once using current job type and once using previous job type. My results using current job type are similar to the results in Table A9 despite the smaller sample. From job search models, I expect current job quality to effect next job quality because the worker is willing to accept lower quality future jobs (i.e. Burdett and

[17] Other controls are a quartic in age and job tenure, dummies for year job started and ended, union status, region of country, if in a MSA, marital status, total number of children, and children in household. Regressions for hourly wages and job satisfaction also contain controls for hours worked and part-time status.

[18] This suggests that outsourced workers are positively rather than negatively selected for productivity. I provide more evidence for this in Section 3.4 below.

Mortensen (1998)) or because the worker can use their current job as an outside option (i.e. Postel-Vinay and Robin (2002)). As outsourced jobs are lower quality, I should expect having an outsourced job previously should have a negative effect on job outcomes. My regressions show this is indeed the case, having a previously outsourced jobs slightly lowers current job quality, but most of the effects are small and insignificant. I conclude that while there is likely some selection bias in my regressions from the job offers workers agree to take, these biases are not enough to overturn my main finding that outsourced jobs are lower quality.

Outsourcing jobs are clearly worse than traditional jobs, but how do they compare to other jobs overall? To find out, I run my full regression for log real weekly wage, but instead of controlling for worker type (making traditional jobs the default), I add job types in batches. The results are in Table A11. The first column compares outsourced jobs to non-outsourced jobs and finds outsourced weekly wages the same as all non-outsourced jobs. If I also control for self-employment and independent contractors, to separate workers who are working for themselves, I find outsourced weekly wages are 4.8 log points lower which is still insignificant. Only when I also separate on-call and temp jobs do my result become significant. This regression also shows that other job types make 30-75 log points per week less than traditional jobs after controlling for worker and occupational effects and observables. Similar results arise when I study hourly wages, benefits, or health insurance. Contracted out jobs have lower compensation than traditional jobs, but they appear to have substantially higher compensation than other non-traditional jobs.[19] Worker's welfare will depend on which types of jobs are being replaced.

Of all the papers I compare with, the most similar is DK. Like this paper, they also study outsourcing in the US and their main identification strategy is selection on observables and worker fixed effects. The main differences are workers studied and method of identifying outsourced workers. Their data comes from the CPS Outgoing Rotation Groups (ORG) and March Supplement for the years 1983-2000. They impute outsourcing using a worker's

[19] In terms of job satisfaction, self-employed workers are significantly more satisfied than traditional workers while all other job types are statistically indistinguishable.

occupation and industry. They take janitors (occupation 453 in CPS/4220 in the NLSY) and security guards (426/3920) and consider them outsourced if they are in the services to buildings and dwellings industry (722/7690) or protective services industry (740/7680), respectively. The idea is that these industries specialize in providing services to other firms, so janitors or security guards employed in these firms must be outsourced. This measure should exclude temp workers (who should be reported in the temporary worker industry and they explicitly state they are not measuring as outsourced) who are part of their control group. If independent contracting is rare in these two occupations, my measure of outsourcing focusing on contracted out workers and their measure should capture similar populations.

To test if this is the case, I measure outsourcing in the NLSY for janitors and security guards using both my method and their method. Summary statistics for janitor and security guards are available in Table A12 and Table A13. I compare outsourcing in my data set using their measure (rows 3 and 4) to their Table 1 (pg 291) and Table 2 (pg 292). Due to the nature of my data set, I have a much smaller sample size, only have men rather than both men and women, and my workers are about 8 years older on average. For the percent of workers outsourced, I match their measure well: they find 22% and 48% of janitors and security guards were outsourced from 1998-2000; using their measure, I find 22% and 51%. My janitors make about $12 per hour in 2016 dollars whether they are outsourced or not, while security guards make about $12 per hour outsourced and $15 per hour otherwise. Their janitors make about $11 outsourced and $13 otherwise while security guards make $12 outsourced and $15 otherwise, so the wages appear close.[20] I also find similar percentages of workers receiving health insurance and similar gaps between outsourced and other workers. My education in much more concentrated in high school graduates, they have more workers with more and less schooling. Overall my sample is roughly in line with theirs, especially given the differences in underlying populations and years.

When I compare their measure of outsourcing to my measure, the most obvious differ-

[20]I could not find their reference year for real wages in their paper, so I assumed it was 2000.

ence is the number of outsourced workers. Only 4% and 16% of janitors and security guards are outsourced by my measure. Low sample sizes for janitors make comparisons of summary statistics difficult, but for security guards, the different definitions do not seem to lead to different interpretations of results, other than DK's measure suggesting Black workers are more likely to be outsourced. What is causing such a wide discrepancy in measured outsourcing? To find out, I break down jobs by self-reported job type (my measure) and occupation-industry matching (DK's measure) for both janitors and security guards in Table A14 and Table A15. For workers in the upper left intersection of self-reported contracted out and industry-occupation outsourced and the lower right corner of self-reported traditional and industry-occupation not outsourced, my measure agrees with DK. My measure of outsourced, contracted out workers, are not always considered outsourced by their measure: about 50% of contracted out janitors and 25% of contracted out security guards would not be considered outsourced. Some discrepancy comes from independent contractors, temp workers, on-call workers, and the self-employed, all of whom my measure of outsourcing explicitly leaves out.[21] But the major discrepancy comes from traditional jobs: these workers were explicitly asked if their job was an alternative job type and answered negatively each time.[22] Industry-Occupation measures classify 17% of traditional janitors and 40% of traditional security guards as outsourced. This is the main reason why outsourcing is much higher using the industry-occupation measure.

To better assess why these measures are different, I repeat this exercise with CWS data from all 6 rounds of the supplement for both men and women. As before, I separate workers by self-reported job type (where workers who don't report a job type are considered traditional) and by industry-occupation classification. Results for Janitors and Security Guards

[21]Note that in my data, the industry-occupation classification includes many temp workers that DK hoped were excluded from their measure.

[22]When introducing these alternative job types in 2002, the NLSY assumed about 90% of existing jobs were traditional. For janitors and security guards, 79 (30%) and 47 (35%) jobs were pre-assigned traditional. Of the these pre-assigned traditional jobs, 13 (16%) and 24 (51%) were outsourced according to industry-occupation measures, which make up 17% and 25% of traditional jobs classified as outsourced by this measure. Even if all of these jobs would be classified differently if asked, most of the differences would still be present.

are in Table A16 and Table A17. For the CWS, the occupation-industry measure misses about 30% of contracted out janitors and 8% of security guards while falsely reporting 16% of traditional janitors and 36% of security guards as outsourced. Overall, the industry-occupation method agrees more with the CWS sample, but there are still considerable disagreements. These results suggest that self-reported and industry-occupation classifiers are fundamentally different measures of the outsourced population.

3.4 Job Transitions

In this subsection, I study how workers transition between jobs and how this differs for outsourced versus traditional workers. To do so, I match current outsourced and traditional jobs to previous and next job worked. I use this data to study the similarities and differences between subsequent jobs and how much time it takes for workers to go between jobs.

My summary statistics of job transitions are in Table A18, which compares all outsourced and traditional workers in their previous, current, and next job. The first row measures if previous or next jobs are outsourced. There is clear persistence in outsourcing; 20% of previous and next jobs are outsourced for currently outsourced workers while only 3% of these jobs are outsourced for currently traditional workers. The next two rows compare occupations and industries; both outsourced and traditional workers stay in the same occupation and industry about 35% of the time. Next comes comparison of job quality between the three jobs. Among many dimensions, worker's current jobs tend to be slightly better than their previous and next jobs. For both outsourced and traditional workers, current jobs tend to earn higher wages, are more likely to be full-time, and more likely to come with benefits.[23] One observation to note is that currently outsourced workers are more likely to be unionized than in their previous and next job, supporting my observation that outsourced jobs are more likely to be union and not just outsourced occupations.

To get a better sense of how job quality changes as workers move between jobs, I divide

[23]Current jobs are better because my sample is of prime-aged males, who have already found relatively high quality jobs. There is likely some negative selection of workers who find new jobs at these ages.

workers by their job type transitions between previous and current job: traditional to traditional, traditional to outsourced, outsourced to traditional, and outsourced to outsourced. I compare mean log real weekly wages and percent of workers receiving health insurance, both using levels and residuals from regressions similar to those in Table A9 (see Footnote 17) but without the variable *outsourced* to differentiate outsourced from traditional jobs.[24] Results for log real weekly wages are in Figures A7 and A8 and for health insurance are in Figures A9 and A10. My levels measures reinforce what my summary statistics and regressions implied, outsourced workers are positively selected. Conditional on previous job type, workers currently outsourced had higher wages and were more likely to receive health insurance in their previous jobs than currently traditional workers. Because of this selection, controlling for observables is important; my residual plots show traditional jobs are better than outsourced jobs both at previous and current jobs. By controlling for worker fixed effects, my residuals show most workers moving from traditional to outsourced jobs show about the same magnitude of wage drop as workers moving from outsourced to traditional jobs show wage gain, further suggesting that my outsourcing regressions in Table A9 do a good job capturing the effects of outsourced jobs despite endogeneity of job transitions. My health insurance residuals show a much bigger drop for traditional to outsourced workers than the gain for outsourced to traditional, but otherwise the patterns are similar.

Finally, I return to Table A18 to compare weeks between jobs, which will be important details I want my outsourcing model to match. I measure three factors, weeks between jobs, weeks between jobs conditional on lasting longer than 1 week, and percent of job transitions lasting one week, where a worker is employed at the current job one week and the next job the next week. I refer to this last group as job-to-job transitions and they account for a little over 40% of job transitions in my sample. Notice that for all three of my measures, outsourced and traditional jobs are statistically and economically indistinguishable from one another. This suggests outsourcing does not effect the flow of workers from unemployment

[24]Results are similar for other measures of quality or if I restrict the sample to workers ever in HO occupations.

or between jobs. If workers could direct search between outsourced and traditional jobs, then theory predicts that they would only apply to lower quality outsourced jobs if these jobs were easier to find. If job flows are no different, this is strong evidence against directed search.

To explore this point further, Figure A11 and Figure A12 compare the distributions of weeks between previous job and current job for outsourced versus traditional current job.[25] Figure A11 shows all transition values while Figure A12 excludes one week transitions. In both figures, the distribution of weeks to job is extremely similar for both jobs across the distribution; if anything traditional jobs are found slightly faster. While these distributions and averages look similar, it is possible that differences could exist once I account for worker or job characteristics. To test this, I run Regression 2 for outcomes weeks between previous and current job and probability of a job-to-job transition between previous and current job for person i with previous job a in occupation b and current job j in occupation k

$$Y_{iabjk} = \beta_0 \, outsourced_a + \beta_1 \, outsourced_j + \beta_2 X_{ia} + \beta_3 X_{ij} + \alpha_i + \psi_b + \psi'_k + \gamma_t + \epsilon_{iabjk}. \quad (2)$$

Once again, my main parameters of interest are *outcourced*, which measures whether the previous or current job is outsourced (compared to traditional jobs). I also include worker, current occupation, and previous occupation fixed effects using α, ψ, and ψ' and other previous and current job characteristics and current demographic characteristics in X.[26] Table A19 shows these results. For both outcomes, both previous and current job outsourced have an economically small and statistically insignificant effect compared to traditional jobs. I conclude that outsourced jobs have the same rate of job finding and job-to-job flows as

[25] I can also compare weeks between current job and next job for outsourced versus traditional current job with similar results.

[26] Controls for current and previous job include: job type (default is traditional), hours worked per week, part-time status, log real weekly wage, union status, and whether received health insurance, retirement benefits, or any benefits. Also have quartic in tenure for previous job and a dummy for year current job began. Controls for demographic variables include: quartic in age, dummies for region, whether in an MSA or central city, marital status, and number of children total and in household. Standard errors are clustered at the demographic sampling group.

traditional jobs.

3.5 Aggregate Effects

While this paper is not the first to study differences between outsourced and traditional jobs, it is the first to emphasize that outsourcing may lead to an increased demand for workers. Furthermore, I argue the prevalence of more numerous but lower quality outsourcing jobs will have an ambiguous impact on all worker's outside options and thus wages. In this section, I empirically test these predictions. To do so, I aggregate jobs by occupation and measure how the percent of workers outsourced affects the number of jobs and the quality of traditional and outsourced jobs within that occupation. While a worker's outside option does not solely consist of jobs in their own occupation, the fact that about 35% of job switchers stay within their occupation (as shown in Table A18) suggests that these jobs are an important part of a worker's outside option. For robustness, I check some of my result with CPS data to see if they hold for a more general population.

My main independent variable of interest is percent of workers outsourced within an occupation (compared to percent traditional). My main specification measures outsourcing at the weekly level, but I also measure at the monthly level (to compare with the CPS) and the yearly level with similar results. For various outcomes Y, I run Regression (3) for occupation k in time period t

$$Y_{kt} = \beta_0 \; outsourced_{kt} + \beta_1 X_{kt} + \psi_k + \omega_t + \epsilon_{kt}. \tag{3}$$

My first conjecture is that by decreasing the costs of labor, outsourcing increases the quantity of labor demanded. I regress percent of workers employed in an occupation on percent outsourced within that occupation *outsourced*, occupation and week fixed effects ψ and ω, and other occupation level controls X.[27] The result is show in row 1 of Table A20. I find

[27] Controls include percent of workers in each job type (excluding traditional), percent Black, Hispanic, and union member, and average age. Standard errors are clustered at the occupation level.

that a 1 percentage point increase in outsourcing within an occupation leads to a significant 0.00024 percentage point increase in employment. The mean occupation makes up about .28% of all employment, so this implies a .086% increase in employment in the average occupation. To put this in perspective, I make some back-of-the-envelope comparisons to the minimum wage literature. While there is considerable debate on the employment effects of minimum wage increases, estimates by Meer and West (2016) suggest that a 10 log point increase in the minimum wage leads to a 1.5% decrease in employment (see columns 2 and 3 of Table 2, page 512). Given that outsourced jobs pay about 10 log points per week less than traditional jobs (see Table A9) and that 2-3% of workers make at or below the Federal minimum wage, this makes my effects of a 1 percentage point increase in outsourcing comparable in magnitude to theirs.[28] So while my effect is modest, it is consistent with potential effects of higher wages from the minimum wage literature and can make substantial differences in occupations where outsourcing is common.

We might worry that my results are driven by small sample sizes for any given occupation; if one or two outsourced workers appear in an occupation with few workers, they will increase measured employment in that occupation. To check for robustness, I turn to the CPS. I aggregate each month at the occupation level, taking most job information from the CPS but measures of outsourcing and other job types from the NLSY. I rerun my above regression for males age 18-65 in CPS and for males in the NLSY cohort in Table A21. The results for the larger sample are significant at the 10% level and very close to the NLSY results at 0.00021. My results are even stronger if I restrict my sample to the NLSY cohort, where my coefficient of interest becomes 0.00034. This could be because, as in KK, older workers are more likely to be contracted out, or because there are underlying contracting out patterns that differ by age. These results show that the effects of outsourcing prevalence on employment are real and my data set if anything underestimates the effects for my cohort of workers, although

[28] Percent of workers at or below the minimum wage from https://www.bls.gov/opub/reports/minimum-wage/2017/home.htm#:~:text=Together%2C%20these%201.8%20million%20workers,to%202.3%20percent%20in%202017.

these workers may be more likely to be affected than the rest of the population.

My finding that outsourcing increases employment slightly contradicts past research. Two papers study the Professional and Business Services (PBS) industry, an industry that provides services such as janitorial and human resources to other firms and about 90% of production is of intermediate goods (Berlingieri, 2013). They use BEA Annual Industry Accounts (Berlingieri, 2013) and the Survey of Occupational Employment (Bloom et al., 2018) to show that this industry is growing, but neither finds significant increases in employment in occupations employed by this sector. To shed some light on why their results may differ from mine, I break down job types for both the PBS and non-PBS industries in my NLSY sample in Table A22.[29] I find PBS jobs are over-represented in non-traditional job types, especially contracted out, independent contractor, and temp work associated with outsourcing. But many PBS workers still self-report as traditional and about 75% of contracted out jobs are not in PBS industries.[30] In Table A23, I run a regression on percent of employment with in an occupation similar to above but replace all job type information with percent of occupation employed in PBS industries. I run this in both the NLSY and CPS. My results suggest employment does increase overall as they increase in these industries at similar rates to the effects of outsourcing, although the effects in the CPS are insignificant. My result may differ from previous literature because my data is on workers while their data is on firms, especially because many in PBS industries are self-employed or independent contractors. Because of these differences, it can simultaneously be true that the past literature shows no effects of an increase in PBS employment on total employment and for me to show positive effects of both outsourcing and PBS employment.

Many search models of the labor market show that a worker's outside option affects the wage they earn at their current job. Outsourcing has an ambiguous effect on a worker's

[29] I find similar results when studying PBS versus non-PBS jobs in the CWS.

[30] The fact that so many PBS workers report being in traditional jobs is partially due to how I defined outsourced workers. If, for example, an accountant performs audits for many different clients, then they would be providing an intermediate good but working directly for their firm and would not be considered outsourced by my definition.

outside option: one one hand, outsourced jobs pay lower wages and fewer benefits which will decrease a worker's outside option; on the other hand, outsourcing increases the amount of jobs which will increase a worker's outside option. To see which effect is stronger, I measure how outsourcing within an occupation affects average job quality. My outcomes of interest are: log real hourly and weekly wage, hours worked, part-time status, job satisfaction, and receiving any benefits or health insurance. I want to focus on the effects of a changing outside option, not a change in job composition, so I measure quality separately for outsourced versus traditional jobs.[31] I again run Regression (3), focusing on percent outsourced in an occupation, but also controlling for occupation and week fixed effects and other occupation controls (see footnote 27). The results are shown in Table A20.

Overall these effects are small and insignificant. For traditional jobs, these effects tend to be positive: wages, job satisfaction, and benefit reception all increase. For outsourced jobs, these same effects tend to be negative. If a changing outside option were driving these results, I would expect job quality to move in the same direction for both traditional and outsourced workers. If these results were driven by composition effects, I would expect traditional jobs to decrease in quality, as past research has show that high quality jobs are more likely to become outsourced.[32] For future work, I plan on using Bartik instruments by region to attempt to address some endogeneity issues and see how results may potentially change.

3.6 Data Analysis Summary

In this section, I used NLSY data to show many facts about contracted out workers and jobs. Outsourcing has been increasing in the last two decades, measuring 1% of all jobs in 2001 and 2.5% of all jobs in 2016. Outsourcing is widespread, a third of all occupations had

[31] Unfortunately, this does not eliminate potential composition effects, as past literature has shown that high quality job are more likely to be outsourced. This will tend to bias any findings for traditional jobs downward.

[32] Because I do not know outsourcing status in the CPS, I have no way to separate composition effects from outside option effects, so I do not attempt any robustness checks there.

at least one outsourced worker. About 10% of men are ever outsourced and they are slightly less educated but otherwise very similar to the rest of the population. Outsourced jobs are significantly worse than traditional jobs; workers make 8.8 log points per week less and are 7.5 pp less likely to be provided with health insurance. Outsourced workers are more likely to move to outsourced jobs, but otherwise the time it takes for them to move between jobs and the comparative quality of the jobs they move from or to is similar to traditional workers. Outsourcing within an occupation significantly increases employment within an occupation and insignificantly increases traditional job quality and decreases outsourced job quality.

For the most part, my findings match the previous literature, so I highlight the few areas of disagreement. Both the CWS and KK found contracted out workers were more likely to have a bachelor's degree or more than the general population, I find they are less likely. My job quality effects are consistent with both DK and GS even though I consider a much wider variety of workers. I do find outsourced workers are more likely to be unionized, while both of these papers find the opposite. While my measure and DK's measure produces similar summary statistics, they population of workers they consider outsourced are not the same. Past work by Berlingieri (2013) and Bloom et al. (2018) have found no effect of an increase of PBS employment on total employment within an occupation, while I show positive effects of outsourcing and potentially positive effects of PBS employment. These differences may be due to definitions of outsourcing and because I use worker-side rather than firm-side data. I am unaware of any papers studying how outsourced workers transition between jobs or how the prevalence of outsourcing in a labor market affects job quality.

These facts suggest several important factors for my model and calibration. For the model, it seems a reasonable simplification to assume that all workers, whether traditional or outsourced, are the same. I want my model to allow for lower quality outsourcing jobs than traditional jobs. My model should account for the fact that despite this lower quality, outsourced jobs are not found quicker than traditional jobs. Finally, my model should show employment increases as outsourcing increases. As I show below, my model aligns with all of these facts.

4 Baseline Model

In this section, I discuss the basic model and its properties. The model is based on Ljungqvist and Sargent's (LS) textbook treatment of Davis (2001), which is built upon a standard DMP search model where workers randomly search for jobs and bargain with their employers over wages.[33] Davis (2001) adds heterogeneous firm productivity and LS extend his model to infinite periods. My model builds on this by allowing firms to avoid hiring workers by purchasing labor from outsourcers in a Walrasian market, and collapses to LS without outsourcing. I present the simplest possible version of the model to fix ideas; when calibrating I will match a slightly more complex model covered in Appendix D. While simple, the model captures three stylized facts from the literature. The first is that firms mainly use outsourcing to lower labor costs (Abraham and Taylor, 1996; Weil, 2014). The second is that more productive firms will pay their outsourceable workers higher wages (Goldschmidt and Schmieder, 2017). The third is that more productive firms are more likely to outsource (Goldschmidt and Schmieder, 2017; Drenik et al., 2020). The model focuses on a labor market for workers of one occupation, such as security guards or IT professionals. Time is discrete and infinite and I focus on the steady state. There are three types of agents: a unit measure of homogeneous workers, a measure of heterogeneous firms defined by productivity $y \in [\underline{y}, \bar{y}]$, and an endogenous measure of outsourcers. All agents discount the future at rate $\beta = (1 + r)^{-1}$.

As in a standard DMP model, firms require labor to produce; each worker matched with a firm produces y each period. While the set of firms is exogenously fixed, firm size is endogenous. A firm starts each period with a measure of positions n and must decide how many vacancies v to create. Vacancies cost $C(v; y)$, where entry costs are increasing $c(v; y) \equiv C_v(v; y) > 0$ and convex $c_v(v; y) \geq 0$. Once vacancies are created, firms can fill

[33] See Ljungqvist and Sargent (2004) pg. 953.

them in one of two ways. The first is the standard DMP way, hiring. Firms go to a frictional labor market where they randomly meet workers with probability $q(\theta)$ (θ is market tightness, defined below). These workers are hired and paid wages $w(y)$ determined by Nash bargaining each period. This model adds another way for firms to gain access to workers, outsourcing. To outsource, firms go to the outsourcing market, a Walrasian market where outsourcers and firms meet. The market is defined by the endogenous price p firms pay to outsourcers each period in exchange for access to their workers. Whether a position is hired or outsourced, the firm exogenously loses δ fraction of positions each period and so must continuously create new vacancies to stay the same size.

I conjecture, and later prove, that firms below some endogenous productivity $\hat{y}$ only hire, hiring firms, while those above only outsource, outsourcing firms. I use $n(y)$ and $v(y)$ to denote hiring firms' optimal decisions and $\hat{n}(y)$ and $\hat{v}(y)$ to denote outsourcing firms' optimal decisions. Total hiring vacancies are $v = \int_{\underline{y}}^{\hat{y}} v(x)dx$ and total outsourcing vacancies are $\hat{v} = \int_{\hat{y}}^{\bar{y}} \hat{v}(x)dx$. The cdf of hiring vacancies is $F(y) = \int_{\underline{y}}^{y} \frac{v(x)}{v}dx$ while the pdf is $f(y) = \frac{v(y)}{v}$. Similarly, total hiring and outsourcing positions are $n = \int_{\underline{y}}^{\hat{y}} n(x)dx$ and $\hat{n} = \int_{\hat{y}}^{\bar{y}} \hat{n}(x)dx$.

There is an endogenous continuum of outsourcers who cannot produce but are able to sell their worker's labor to firms in the outsourcing market. Each outsourcer consists of a single vacancy and so each can have at most one worker. Outsourcers pay free entry cost $\tilde{c}$ to create a vacancy. They fill their vacancies in the same way hiring firms do; they go to the labor market where they randomly meet workers with probability $q(\theta)$. These workers are hired and paid wages $\tilde{w}$ determined by Nash bargaining. Outsourcers exogenously loses their worker with probability δ each period. We use $\tilde{n}$ and $\tilde{v}$ to denote the optimal total number of outsourcer positions and vacancies.

The labor market contains a total of $v + \tilde{v}$ vacancies searching for workers, the fraction from outsourcers is $\pi = \frac{\tilde{v}}{v+\tilde{v}}$. Similarly, the fraction of employed workers at outsourcers is $\zeta = \frac{\tilde{n}}{n+\tilde{n}}$. The price the outsourcer receives from the firm p is set such that the outsourcing market clears $\tilde{n} = \hat{n}$.

The measure 1 of workers can be in one of three states: u are unemployed, $n = (1-u)(1-\zeta)$ are employed at firms, and $\tilde{n} = (1-u)\zeta$ are employed at outsourcers. When unemployed, workers receive the value of home production b and randomly search for a job in the labor market. They receive an offer with probability $\ell(\theta) = \theta q(\theta)$, where $\theta = \frac{v+\tilde{v}}{u}$ is market tightness defined by number of vacancies per unemployed worker. Conditional on meeting a vacancy, workers meet a firm with probability $1-\pi$ (the productivity of said firm distributed according to $F(y)$) and an outsourcer with probability π.[34] While employed with the firm (outsourcer), workers receive wage $w(y)$ ($\tilde{w}$) each period, which is determined by generalized Nash bargaining with the worker having bargaining power η. Workers lose their job with probability δ.

4.1 Defining Equilibrium

In this section, I define a steady state equilibrium and prove that optimal firm choice follows the cutoff rule at $\hat{y}$.[35] We start by defining each agent's value function, where next period's values are denoted with a plus subscript such as n_+. A hiring firm of type y with n workers has value

$$J(n;y) = n[y - w(y)] + \max_v \{-C(v;y) + \beta J(n_+;y)\} \tag{4}$$
$$\text{st. } n_+ = (1-\delta)n + q(\theta)v,$$

[34] This matching process assumes workers can not choose to apply for outsourcing versus traditional jobs. In Section 3.4 I showed that job transitions are similar for outsourced and traditional workers. This is despite the fact that outsourced jobs are significantly worse on average, as I showed in Section 3.3. If workers could choose which jobs to apply for, they would only apply to outsourcing jobs if they were easier to find (ex. Menzio and Shi (2010)) or came with some other compensating differential. I find no evidence for such differential and so random search is appropriate in this setting.

[35] For $\hat{y}$ to exist, we must assume that firm bargaining power times probability of matching is $(1-\eta)q(\theta) < 1$. Because this is true if workers have some bargaining power $\eta > 0$ or some vacancies are unmatched $q(\theta) < 1$, I do not state this in the main text, as in these cases the problem is not interesting anyway.

while an outsourcing firm has value

$$\hat{J}(n;y) = n(y-p) + \max_{v} \left\{ -C(v;y) + \beta \hat{J}(n_+;y) \right\} \tag{5}$$
$$\text{st. } n_+ = (1-\delta)n + v,$$

and outsourcer with and without a worker has value

$$O = p - \tilde{w} + \beta(1-\delta)O_+ \tag{6}$$
$$V = -\tilde{c} + \beta q(\theta) O_+, \tag{7}$$

where we have used the fact that free entry implies $V_+ = 0$.[36] For firms, each hired (outsourced) worker produces net revenue $y - w(y)$ $(y-p)$.[37] For the outsourcer, a worker produces net revenue $p - \tilde{w}$. The firm must choose how many vacancies to create, knowing tomorrow's stock of workers n_+ will consist of the $1-\delta$ fraction of workers kept from today plus the fraction $q(\theta)$ (1) of vacancies that match with a new worker (outsourcer). Matched outsourcers hope to hold onto their workers for next period, while unmatched outsourcers pays the vacancy cost $\tilde{c}$ in hopes to match with a worker. The first order conditions for each firm and outsourcer solve

$$c[v(y);y] \geq \beta q(\theta) J_n(n_+;y) \tag{8}$$
$$c[\hat{v}(y);y] \geq \beta \hat{J}_n(\hat{n}_+;y) \tag{9}$$
$$\tilde{c} \geq \beta q(\theta) O_+, \tag{10}$$

[36]With linear production, modeling firms as employing a measure of workers while outsourcers having at most one is without loss of generality. I model firms as having many workers to justify convex vacancy costs, which ensures a distribution of firms paying different wages and that outsourcing firms do not create infinite vacancies. I model outsourcers as having single workers to emphasize that outsourcers have no market power to determine match probability $q(\theta)$ or outsourcing price p.

[37]Because of the linear productivity function, wages do not depend on firm size n.

which are binding if $v(y) > 0$, $\hat{v}(y) > 0$, or $\tilde{v} > 0$, respectively. These are the free entry conditions: the LHS are the marginal costs of creating a vacancy, the RHS are the marginal benefits.[38] Notice that for firms, the marginal cost of hiring and outsourcing is the same, so the choice to outsource will be based on which gives them a higher expected marginal benefit. If outsourcing increases a firm's marginal value, they will be willing to increase vacancy creation.

Using the envelope conditions and the fact that in steady state $n = n_+$, $\hat{n} = \hat{n}_+$, and $O = O_+$, we can show

$$J_n(n; y) = \frac{(1+r)[y - w(y)]}{r+\delta} \tag{11}$$

$$\hat{J}_n(n; y) = \frac{(1+r)(y-p)}{r+\delta} \tag{12}$$

$$O = \frac{(1+r)(p-\tilde{w})}{r+\delta}. \tag{13}$$

The value of each worker is the present value of the stream of revenue they generate for the firm over the expected lifetime of the match. Combining our free entry and envelope conditions in (8)-(13) implies wages and prices must satisfy

$$w(y) = y - \frac{r+\delta}{q(\theta)} c[v(y); y] \tag{14}$$

$$p = y - (r+\delta)c[\hat{v}(y); y] \tag{15}$$

$$\tilde{w} = p - \frac{r+\delta}{q(\theta)}\tilde{c}. \tag{16}$$

The wage (price) firms are willing to pay workers (outsourcers) each period is the firms' productivity minus the amortized cost of creating the match. In other words, the firm pays the cost of vacancy creation $c(\cdot; y)$ up front, then spreads its loses over the life of the match. Its ability to do so depends on the chance the firm meets a worker (increasing in $q(\theta)$), how

[38] In equilibrium, firms make 0 expected profits on marginal workers, but positive profits on inframarginal workers because of convex vacancy costs. Outsourcers make 0 expected profits.

it values the future (decreasing in r), and the expected length of the match (decreasing in δ). As each of these increase, the firm is better able to amortize and can fund more vacancy creation for a given wage (price). Outsourcers make similar decisions, but revenue is based on the price of outsourced workers.

Workers can be unemployed, employed at a firm, or employed at an outsourcer. The value of being employed at a firm of productivity y, employed at an outsourcer, or unemployed are

$$W(y) = w(y) + \beta\Big\{\delta U_+ + (1-\delta)W_+(y)\Big\} \tag{17}$$

$$\tilde{W} = \tilde{w} + \beta\Big\{\delta U_+ + (1-\delta)\tilde{W}_+\Big\} \tag{18}$$

$$U = b + \beta\left\{\ell(\theta)\left[(1-\pi)\int_{\underline{y}}^{\hat{y}} W_+(x)dF(x) + \pi\tilde{W}_+\right] + [1-\ell(\theta)]U_+\right\}. \tag{19}$$

While employed, the worker receives a wage each period and hopes to keep his job. While unemployed, he receives the flow value of home production b and searches for a job, randomly matching with a firm or an outsourcer based on the fraction of vacancies of each type. Wages are determined by Nash bargaining; workers have bargaining power η. Because firms have a measure of workers, workers and firms bargain over the marginal value of the match as in Stole and Zwiebel (1996), while workers and outsourcers bargain over the total value of match because outsourcers only have one worker. Firms and outsourcers bargain after paying vacancy costs, so their outside option is 0, while worker's outside option is unemployment. This means bargaining solves $\eta J_n(n;y) = (1-\eta)[W(y)-U]$ and $\eta O = (1-\eta)[\tilde{W}-U]$. Using these bargaining rules and the free entry conditions in (9) and (10) to solve for $W(y)-U$ and $\tilde{W}-U$, we rewrite the value of unemployment in (19) as

$$\frac{r}{1+r}U = b + \Gamma, \tag{20}$$

where

$$\Gamma \equiv \theta \frac{\eta}{1-\eta}\left[(1-\pi)\int_{\underline{y}}^{\hat{y}} c[v(x);x]dF(x) + \pi\tilde{c}\right]$$
$$= \frac{1}{u}\frac{\eta}{1-\eta}\left[\int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + \tilde{v}\tilde{c}\right], \tag{21}$$

is the value of search while unemployed. The intuition behind this value is that firms and outsourcers create vacancies until the marginal cost equals the marginal benefit, so $c[v(x);x]$ ($\tilde{c}$) is the firm's (outsourcer's) marginal benefit of creating a vacancy. The worker's benefit of a match is their relative bargaining power $\frac{\eta}{1-\eta}$ times the firm's (outsourcer's) benefit times the probability the worker meets this firm or outsourcer relative to the probability this vacancy meets a worker, which depends on the number of vacancies of this type per unemployed worker.

We can use this value of unemployment in (20), the value of working for a firm or outsourcer in steady state in (17) or (18), the firm's or outsourcer's envelope condition in (12) or (13), and the bargaining rule to show firm or outsourcer wages solve

$$w(y) = \eta y + (1-\eta)(b+\Gamma) \tag{22}$$

$$\tilde{w} = \eta p + (1-\eta)(b+\Gamma), \tag{23}$$

Each period, the worker gets her share η of revenue and must be compensated by the firm for forgoing unemployment. Notice that firm wages rise with productivity even when all workers are the same, one of the stylized facts from the literature we want to match. Another fact we want to match is that wages fall when a job goes from hired to outsourced. To see this in the model, compare the wage of the outsourced worker to the worker at the marginal outsourcing firm $\hat{y}$, which gives $w(\hat{y}) - \tilde{w} = \eta(\hat{y} - p)$. In order for $\hat{y}$ to agree to outsource, $\hat{y} - p > 0$ else the firm makes a non-positive revenue each period and will never pay to enter to market. This implies the wages outsourcing firms would pay if they were to hire are always strictly greater than wages at the outsourcer.

Before writing out the value functions, I conjectured that there exists some endogenous $\hat{y}$ below which firms only hire and above which firms only outsource. Proposition 1 proves that this is in fact the case.

Proposition 1. *In steady state, there exists a firm with endogenous productivity $\hat{y} \in [b + \Gamma, \infty)$ that is indifferent between hiring and outsourcing. Any firm with productivity below $\hat{y}$ strictly prefers to hire while any firm with productivity above $\hat{y}$ strictly prefers to outsource.*[39]

The proof is straight forward and is shown in Appendix C. The basic intuition is that, because the marginal cost of entry does not depend on whether the firm outsources or hires, we only need to compare the marginal benefits. Using the free entry and envelope conditions of the firm from (8), (9), (11), and (12), the relevant comparison becomes $q(\theta)[y - w(y)] \lesseqqgtr y - p$. Both sides increase in y, but the LHS increases slower because $q(\theta) \leq 1$ and because wages increase in y. At $\hat{y}$, these are exactly equal, below $\hat{y}$ the left is strictly greater so firms hire, and above $\hat{y}$ the right is strictly greater so firms outsource. This matches my final stylized fact from the literature: more productive firms are more likely to outsource. The Walrasian market between firms and outsourcers brings two benefits to the firm. The first is that it allows the firm to always match with workers rather than needing to overcome matching frictions. The second is that it allows the firm to avoid bargaining with the worker. More productive firms place more value on both of these perks, so they are willing to pay more to outsource. Because of market clearing, the price of outsourcing p is determined by marginal demand, which comes from the firm $\hat{y}$. Outsourcing effectively allows high productivity firms to "bargain" with the worker through the outsourcer as if they were a less productive $\hat{y}$.

The effects of outsourcing on the worker's outside option is ambiguous. On one hand, outsourcing leads to fewer vacancies from high productivity firms. These high quality va-

[39] Note that while $\hat{y}$ is guaranteed to exist, it is not guaranteed to be within $[\underline{y}, \bar{y}]$. If it is below this interval all firms will outsource, if it above all firms will hire.

cancies are replaced by outsourcing vacancies, which have lower wages. On the other hand, outsourcing firms create more vacancies than they would if hiring and to match outsourcing firms demand and ensure markets clear, outsourcers create $\frac{1}{q(\theta)}$ vacancies for each outsourcing firm vacancy. With more jobs available, outsourcing will increase employment, just as we found empirically in Subsection 3.5. While the marginal benefit of any outsourcer vacancy is less than the marginal benefit of an outsourcing vacancy $c[v(\hat{y}); \hat{y}] > \tilde{c}$, the probability of finding a job increases because more vacancies are created. In general, the effects of outsourcing on worker's outside option depend on underlying parameters.

Given all of the above, we define equilibrium in Definition 1

Definition 1. A steady state equilibrium consists of optimal firm vacancy and position policies $(v(y), n(y), \hat{v}(y), \hat{n}(y))$, optimal total aggregate outsourcer vacancies and positions $(\tilde{v}, \tilde{n})$, market tightness θ, worker value of unemployment U, and wages at firms and outsourcers and price of outsourcing $(w(y), \tilde{w}, p)$ such that

1. Given market tightness θ, worker wages $w(y)$ and $\tilde{w}$ and outsourcing price p, firms choose $(v(y), n(y), \hat{v}(y), \hat{n}(y))$ and outsourcers choose $(\tilde{v}, \tilde{n})$ to satisfy their free entry and envelope conditions in (8) - (13).

2. Given market tightness θ and bargained wages $w(y)$ and $\tilde{w}$, the value of unemployment U satisfies (19).

3. Market tightness θ is consistent with hiring firm and outsourcer choices of vacancies and positions $(v(y), n(y), \tilde{v}, \tilde{n})$.

4. Given worker's value of unemployment U, bargaining between firms and workers yields wages $w(y)$ in (22) and bargaining between outsourcers and workers yields wage $\tilde{w}$ in (23).

5. Given price of outsourcing p, the market for outsourced workers clears $\hat{n} = \tilde{n}$.

In short, steady state equilibrium requires firms and outsourcers to make optimal vacancy and position choices given market tightness, wages, and prices. These factors also determine the worker's value of unemployment. In turn, these choices and the value of unemployment must imply these same market tightness, wages, and prices.

4.2 Properties of Equilibrium

I now examine some properties of the equilibrium, starting with the surplus value of each match. For firms or outsourcers, we set the wage equation in (14) or (16) equal to the wage equation in (22) or (23) to show the total surplus of the match $y - b$ for $y \leq \hat{y}$ or $p - b$ equals

$$y - b = \Gamma + \frac{r + \delta}{(1 - \eta)q(\theta)} c[v(y); y] \tag{24}$$

$$p - b = \Gamma + \frac{r + \delta}{(1 - \eta)q(\theta)} \tilde{c}. \tag{25}$$

In each case, the surplus is split between compensating the worker for forgoing search and amortizing the firm's (outsourcer's) vacancy costs. These equations highlight another obstacle to firm's amortizing ability that was previously hidden in the wages they pay; firms bear the entire cost of vacancy creation but only get fraction $1 - \eta$ of the total surplus. As firm's bargaining power increases, they can better amortize their costs and create more vacancies at a given productivity. Additionally, we can use the price of outsourcing from (25) and the price the firm is willing to pay in (15) to show the total surplus $y - b$ for $y \geq \hat{y}$ equals

$$y - b = \Gamma + (r + \delta) \left(c[\hat{v}(y); y] + \frac{\tilde{c}}{(1 - \eta)q(\theta)} \right). \tag{26}$$

The worker and firm are compensated as before. By paying price p, the firms also compensates the outsourcer for the vacancy costs she must pay.

What determines which firm $\hat{y}$ is indifferent between hiring and outsourcing? One way to think about this question is to use the fact that this indifference implies $v(\hat{y}) = \hat{v}(\hat{y})$ and set the total surpluses for hiring in (24) and outsourcing in (26) equal to show

$$[1-(1-\eta)q(\theta)]c[v(\hat{y});\hat{y}]=\tilde{c}. \tag{27}$$

The term $1-(1-\eta)q(\theta)$ is the amortization ability of a hiring firm minus that of an outsourcing firm divided by that of the outsourcer. Intuitively, the firm likes outsourcing because it makes it easier to spread out the cost of creating a vacancy by guaranteeing a match and by avoiding bargaining with the worker. The Walrasian market between firms and outsourcers ensures that the marginal amortization gain from the marginal $\hat{y}$ firm outsourcing rather than hiring equals the marginal amortization cost of the outsourcer creating another vacancy.

To calculate $\hat{y}$ more explicitly, we use hiring/outsourcing indifference along with firm free entry and envelope conditions in (8), (9), (11), and (12) and the wage and price equations in (22) and (25) to show

$$\hat{y}=b+\Gamma+\frac{r+\delta}{(1-\eta)q(\theta)[1-(1-\eta)q(\theta)]}\tilde{c}. \tag{28}$$

The indifferent productivity is equal to the worker's outside option $b+\Gamma$ plus the outsourcer's ability to amortize her costs $\frac{r+\delta}{(1-\eta)q(\theta)}$ divided by the marginal $\hat{y}$ firm's willingness to pay the outsourcer to help amortize his costs. As outsourcing becomes cheaper, $\hat{y}$ falls and more firms outsource. As firms become less patient and matches are destroyed sooner, r and δ increase and fewer firms outsource. Finally the effect of matching probability $q(\theta)$ and firm bargaining power $1-\eta$ are ambiguous. As these increase, hiring becomes more attractive, decreasing demand for outsourcing while increasing the supply. The price of outsourcing will decrease but the change in quantity depends on which curve shifts more.

In Davis's model without outsourcing, efficiency of outcome depends on firm entry along two dimensions. The first is the overall number of vacancies created and the second is the allocation or spread of vacancies among different productivity firms. Efficient number of entries requires Hosios rule of worker bargaining power η equal to the elasticity of the matching function α, while efficient spread requires that worker bargaining power is 0. Intuitively, the optimal amount of entry follows Hosios rule to balance the congestion externality firms inflict on each other versus the benefit they provide to unemployed workers. This gives workers some bargaining power, so firms pay the entire cost of entry but only get some of the benefits. This especially hurts high productivity firms who create more expensive marginal vacancies and pay workers more. Low productivity firms do not account for how they obstruct high productivity firms from finding workers; they create too many firms and high productivity firms create too few. To see how outsourcing effects the efficiency of the model, I look at the spread and total entry of vacancies here and compare them to both LS's results and the Planner's choices in the next section.

I start by studying the spread of firm vacancies. Take two firms of productivity z and $y \geq z$. There are three cases to consider: when both firms hire $z \leq y \leq \hat{y}$, when both firms outsource $\hat{y} \leq z \leq y$, and when one firm outsources and the other hires $z \leq \hat{y} \leq y$. Solving for differences in surplus $y - z$ in each case using equations (24)-(26) gives

$$y - z = \frac{r + \delta}{(1-\eta)q(\theta)}\big(c[v(y); y] - c[v(z); z]\big) \tag{29}$$

$$y - z = (r + \delta)\big(c[\hat{v}(y); y] - c[\hat{v}(z); z]\big) \tag{30}$$

$$y - z = (r + \delta)c[\hat{v}(y); y] - \frac{r + \delta}{(1-\eta)q(\theta)}\big(c[v(z); z] - \tilde{c}\big). \tag{31}$$

In each case, the differences in surplus reflect the different levels of cost amortization that firms can achieve each period. The spread between hiring vacancies in (29) is the same as LS without outsourcers. Because $(1 - \eta)q(\theta) \leq 1$, outsourcing vacancies in (30) are more spread out than hiring vacancies; all outsourcers pay the same price, so relatively more high productivity firms enter. The spread between outsourcing and hiring vacancies in (31) depends on two factors. The first is that outsourcing vacancies can better amortize their costs, so there will tend to be a wider spread. But creating outsourcing vacancies means an outsourcer must be created, who the outsourcers pays for through p, which leads to a tighter spread. Overall, this leads to a wider spread than between two hiring firms but a tighter spread than between two outsourcing firms.[40]

I now study number of firm vacancies. It is useful to break up entrance below and above $\hat{y}$. For hiring firms $y \leq \hat{y}$ and outsourcing firms $y \geq \hat{y}$ we integrate over surplus equation (24) and (26) to show

$$\int_{\underline{y}}^{\hat{y}} (x-b)v(x)dx = \frac{r+\delta+\eta(1-\pi)\theta q(\theta)}{(1-\eta)q(\theta)} \int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + \frac{\eta(1-\pi)\theta}{1-\eta}\tilde{v}\tilde{c} \tag{32}$$

$$\int_{\hat{y}}^{\bar{y}} (x-b)\hat{v}(x)dx = \frac{\eta\pi\theta q(\theta)}{1-\eta} \int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + (r+\delta)\int_{\hat{y}}^{\bar{y}} \hat{v}(x)c[\hat{v}(x);x]dx + \frac{r+\delta+\eta\pi\theta q(\theta)}{1-\eta}\tilde{v}\tilde{c}, \tag{33}$$

where both equation use the value of search in (21) and the definition of $\pi = \frac{\tilde{v}}{\tilde{v}+v}$ and the second also uses the fact that market clearing implies $\hat{v} = q(\theta)\tilde{v}$. To get the intuition behind hiring entry in (32), divide it into two parts. The first is the previously discussed amortization ability of hiring firms $\frac{r+\delta}{(1-\eta)q(\theta)}$ times hiring costs. The second is the fraction of matching vacancies from hiring firms $1-\pi$ times the worker's value of search from (21). When other firms and outsourcers enter, they increase the worker's value of search and thus their outside option. Firms must pay their share $1-\pi$ of this increase. There is a similar logic for outsourcing entry in (33). Outsourcing firms account for their own amortization ability. By paying p to outsource, they also implicitly account for the outsourcers' decision, which is determined by their amortization ability and additional costs imposed by other firms and outsourcers as I described before. In addition, the outsourcer needs to create $\frac{1}{q(\theta)}$ vacancies for each firm vacancy because they must get their supply of workers from the labor market. In the next section, I will compare these results to the Planner's problem and see

[40] To see this, note that the spread between outsourcing firm y and firm z is wider when firm z outsources (hires) if $[1-(1-\eta)q(\theta)]c[v(z);z] > (<)\,\tilde{c}$. As we showed in (27) above, these are equal when $z = \hat{y}$ and the left hand side increases in z. When z hires, $z < \hat{y}$, so spread is tighter than if z outsourced. We can use similar logic comparing hiring z to an hiring or outsourcing y to show wider spread if y outsources.

the implications for efficiency.

4.3 Planner's Problem

To calculate the efficient spread and number of vacancies, I study the Planner's problem. Let $\mathbb{n}$, $\hat{\mathbb{n}}$, $\mathbb{v}$, and $\hat{\mathbb{v}}$ be distributions of workers hired by firms, workers outsourced to firms, hiring vacancies and outsourcing vacancies and $\tilde{n}$ and $\tilde{v}$ be outsourcer positions and vacancies. Denote the Planner's optimal choices with a superscript P, such as $n^P(y)$. I conjecture, and later prove, that the Planner also follows a cutoff strategy for hiring versus outsourcing, with $\hat{y}^P$ as the Planner's optimal cutoff.[41] Each period, the Planner inherits a distribution of workers $\{\mathbb{n}, \hat{\mathbb{n}}, \tilde{n}\}$ and chooses vacancies $\{\mathbb{v}, \hat{\mathbb{v}}, \tilde{v}\}$ to solve[42]

$$P(\mathbb{n}, \hat{\mathbb{n}}, \tilde{n}) = \max_{\{\mathbb{v}, \hat{\mathbb{v}}, \tilde{v}\}} \int_{\underline{y}}^{\hat{y}} x n(x) dx + \int_{\hat{y}}^{\bar{y}} x \hat{n}(x) dx + \left[1 - \int_{\underline{y}}^{\hat{y}} n(x) dx - \tilde{n}\right] b$$
$$- \int_{\underline{y}}^{\hat{y}} C[v(x); x] dx - \int_{\hat{y}}^{\bar{y}} C[\hat{v}(x); x] dx - \tilde{c}\tilde{v} + \beta P_+(\mathbb{n}_+, \hat{\mathbb{n}}_+, \tilde{n}_+)$$

s.t.

$$n_+(y) = (1-\delta) n(y) + q(\theta) v(y) \quad \forall\, y < \hat{y}_+ \tag{34}$$

$$\hat{n}_+(y) = (1-\delta)\hat{n}(y) + \hat{v}(y) \quad \forall\, y \geq \hat{y}_+ \tag{35}$$

$$\tilde{n}_+ = (1-\delta)\tilde{n} + q(\theta)\tilde{v} \tag{36}$$

$$\int_{\hat{y}_+}^{\bar{y}} \hat{n}_+(x) dx = \tilde{n}_+, \tag{37}$$

where the Planner internalizes market tightness

$$\theta = \frac{\int_{\underline{y}}^{\hat{y}_+} v(x) dx + \tilde{v}}{1 - \int_{\underline{y}}^{\hat{y}} n(x) dx - \tilde{n}}.$$

The Planner wants to maximize total production by firms and unemployed workers while accounting for the costs of creating vacancies and the matching frictions in the labor market.

[41] For $\hat{y}^P$ to exist, we need for some vacancies not to match $q(\theta) < 1$.

[42] The Planner also implicitly receives some outsourcing cutoff $\hat{y}^P$ and chooses a new outsourcing cutoff $\hat{y}^P_+$.

For constraints (34)-(37), let $\beta\lambda(y)$ be the multiplier on hiring firms, $\beta\mu(y)$ be the multiplier on outsourcing firms, $\beta\iota$ be the multiplier on outsourcers, and $\beta\rho$ be the multiplier on the outsourced worker market clearing.[43]

Before we continue, it is useful to define the Planner's value of a searching worker

$$\Gamma^P = \frac{1}{u^P}\frac{\alpha}{1-\alpha}\left\{\int_{\underline{y}}^{\hat{y}^P} v^P(x)c[v^P(x);x]dx + \tilde{v}^P\tilde{c}\right\} \tag{38}$$

where $\alpha = -\frac{\theta^P q'(\theta^P)}{q(\theta^P)}$ is the elasticity of the matching function with respect to workers. Compare this with the worker's private value of search in (21). In the decentralized value of search, the worker cares about the relative probability that he matches with each type of firm, which depends on number of vacancies per unemployed worker, times the value he gets from that match, which is his relative bargaining power times the firm's marginal benefit from the match. The Planner's value is similar, but she weights the marginal benefits by their effect on the matching probability of other agents. This is the basis of the well know Hosios Rule.

We solve the Planner's problem much like the decentralized problem. First we use the free entry conditions with respect to hiring vacancies $v(y)$, outsourcing vacancies $\hat{v}(y)$, and outsourcer vacancies $\tilde{v}$ to show the Planner sets marginal cost of vacancy creation equal to marginal benefit. To find the value of these vacancies, we next take the steady state envelope conditions for next period's hiring positions $n_+(y)$, outsourcing positions $\hat{n}_+(y)$, and outsourcers $\tilde{n}_+$. Combining our free entry conditions and envelope conditions, we can see how the Planner splits the surplus of the match $y-b$ or $\rho-b$ for hiring firms, outsourcing

[43]The Planner decides tomorrow's allocations today, so the β's make it easier to compare to the decentralized problem.

firms, and outsourcers

$$y - b = \Gamma^P + \frac{r+\delta}{q(\theta^P)}\left(c[v^P(y);y] + \frac{\Gamma^P}{\theta^P}\right) \quad \forall\, y \leq \hat{y} \tag{39}$$

$$y - b = \Gamma^P + (r+\delta)c[\hat{v}^P(y);y] + \frac{r+\delta}{q(\theta^P)}\left(\tilde{c} + \frac{\Gamma^P}{\theta^P}\right) \quad \forall\, y \geq \hat{y} \tag{40}$$

$$\rho - b = \Gamma^P + \frac{r+\delta}{q(\theta^P)}\left(\tilde{c} + \frac{\Gamma^P}{\theta^P}\right). \tag{41}$$

Like the decentralized surplus splitting in (24)-(26), the Planner splits the surplus between compensating the worker for forgoing search and amortizing the cost of vacancy creation. The differences are that the Planner does not worry about bargaining power but does worry about the cost that vacancy creation imposes on others by making finding workers more difficult, which is represented by $\frac{\Gamma^P}{\theta^P}$.

What is the Planner's choice of productivity cutoff $\hat{y}^P$? It is again instructive to use the fact that indifference means $v^P(\hat{y}^P) = \hat{v}^P(\hat{y}^P)$ to set the hiring surplus in (39) equal to the outsourcing surplus in (40) which gives $[1 - q(\theta^P)]c[v^P(\hat{y}^P);\hat{y}^P] = \tilde{c}$. The term $1-q(\theta^P)$ is the amortization ability of a hiring position minus that of an outsourcing position divided by that of an outsourcer position. Compared to the decentralized ratio in (27), when $q(\theta^P) > (1-\eta)q(\theta)$ (as is true for almost all reasonable parameters), the Planner values outsourcing less: she only values the improved matching ability while the firm also values the ability to avoid bargaining with the worker. The Planner chooses cost of outsourcing ρ such that the marginal benefit of an outsourcing position over a hired position for marginal firm $\hat{y}^P$ equals the marginal cost of another outsourcer position.

To calculate $\hat{y}^P$ more explicitly, we solve the hiring surplus in (39) for $c[v(\hat{y});\hat{y}]$ and plug into the outsourcing surplus in (40) show

$$\hat{y}^P = b + \Gamma^P + \frac{r+\delta}{q(\theta^P)[1-q(\theta^P)]}\tilde{c} + \frac{r+\delta}{\theta^P q(\theta^P)}\Gamma^P. \tag{42}$$

Comparing to the decentralized indifferent firm in (28) the similarities are apparent. Both depend on the worker's outside option and the ability to amortize vacancy creation costs. The difference is that the Planner does not worry about bargaining power $1-\eta$ but does account for the net effect of marginally more outsourcer vacancies on the matching ability of other firms and outsourcers.

I conjectured that the Planner uses a cutoff strategy $\hat{y}^P$ where firms below the cutoff hire and firms above outsource. Lemma 1 show this is indeed the case.

Lemma 1. In steady state, there exists a $\hat{y}^P \in [b+\Gamma^P, \infty)$ such that the Planner is indifferent between hiring and outsourcing. At productivities below $\hat{y}^P$, the Planner hires, at productivities above she outsources.

The proof is in Appendix D and is similar to the proof of the existence of $\hat{y}$ in Proposition 1. In the proof, I show the benefit of outsourcing minus the benefit of hiring is strictly increasing in productivity, is negative for low productivity and positive for high productivity.

We want to know how efficient the decentralized solution is, both overall and compared to the equilibrium without outsourcers. To make this comparison, I solve for the Planner's optimal spread of vacancies and optimal total entry each period. As before, we start with the optimal spread of vacancies for firms of productivity z and $y > z$. There are three cases to consider, when both firms hire $z \le y \le \hat{y}^P$, when both firms outsource $\hat{y}^P \le z \le y$, and when one firm outsources and the other hires $z \le \hat{y}^P \le y$. Solving for differences in surplus $y-z$ in each case using surplus equations (39), (40), and (41) gives

$$y - z = \frac{r+\delta}{q(\theta^P)}\big(c[v^P(y);y] - c[v^P(z);z]\big) \tag{43}$$

$$y - z = (r+\delta)\big(c[v^P(y);y] - c[v^P(z);z]\big) \tag{44}$$

$$y - z = (r+\delta)c[v^P(y);y] - \frac{r+\delta}{q(\theta^P)}\big(c[v^P(z);z] - \tilde{c}\big). \tag{45}$$

Like the decentralized spread in (29), the spread between hiring vacancies in (43) is the same as LS without outsourcers. As in that model, an inefficiently tight spread of vacancies arises because firms only get $1-\eta$ fraction of the total surplus. This causes low productivity firms to create too many vacancies and high productivity firms to create too few, and the only potential efficiency gains outsourcing can bring to these firms is if it causes θ to be closer to θ^P. Results are much more promising for outsourcing firms, decentralized spread in (30) is equal to the Planner's spread in (44). This is a result of the Walrasian market between firms and outsourcers, which allows for workers to be allocated in an efficient way. While the lack of frictions is an extreme assumption, this shows how outsourcing can improve overall efficiency by reducing the frictions between workers and the most productive firms. To the extent that workers get a share of these efficiency gains, their welfare can improve too. Finally, comparing the spread between outsourcing and hiring in the decentralized problem in (31) to the Planner's choice in (45) again finds us in between the two other cases. Note that difference in spreads depends on how the marginal cost of the hiring firm z. For high productivity firms, $c[v^P(z); z] - \tilde{c}$ is positive and the decentralized gap is too big. For low productivity firms, $c[v^P(z); z] - \tilde{c}$ is negative and the decentralized gap is too small. To sum up, the decentralized problem has relatively too many low productivity firms, relatively too few middle productivity firms, and the right relative amount of high productivity firms.

I now see how total entry compares to the decentralized problem. Dividing by hiring firms $y \leq \hat{y}^P$ and outsourcing firms $y \geq \hat{y}^P$, we integrate over total surplus in (39) and (40) to show

$$\int_{\underline{y}}^{\hat{y}^P} (x-b)v^P(x)dx = \frac{(r+\delta)(1-\alpha\pi^P) + \alpha(1-\pi^P)\theta^P q(\theta^P)}{(1-\alpha)q(\theta^P)} \int_{\underline{y}}^{\hat{y}^P} v^P(x)c[v^P(x);x]dx + \frac{[r+\delta+\theta^P q(\theta^P)]\alpha(1-\pi^P)}{(1-\alpha)q(\theta^P)}\tilde{v}^P\tilde{c} \tag{46}$$

$$\int_{\hat{y}^P}^{\bar{y}} (x-b)\hat{v}^P(x)dx = \frac{[r+\delta+\theta^P q(\theta^P)]\alpha\pi^P}{1-\alpha} \int_{\underline{y}}^{\hat{y}^P} v(x)c[v(x);x]dx + (r+\delta)\int_{\hat{y}}^{\bar{y}} \hat{v}(x)c[\hat{v}(x);x]dx + \frac{(r+\delta)[1-\alpha(1-\pi^P)] + \alpha\pi^P\theta^P q(\theta^P)}{1-\alpha}\tilde{v}\tilde{c}. \tag{47}$$

First we compare total hiring entry in the decentralized market (32) to the Planner's choice in (46). The main difference is that hiring firms base entry decisions on their own surplus, which depends on worker bargaining power η, while the Planner accounts for total surplus, which depends on matching elasticity α. And while the firm considers how other firms and outsourcers affect their entry, the Planner also considers how entry will affect others. In the problem without outsourcers, setting $\eta = \alpha$ was enough to make total entry efficient because firms internalized the effect they had on workers. With outsourcers, this is not enough, firms properly account for how they effect workers but not for how they effect outsourcers. We see a similar pattern when comparing outsourcer's entry in the decentralized market (33) to the Planner's choice in (47). Outsourcing firms make the efficient entry decision but the outsourcers required to support them do not for similar reasons to hiring firms. For spread of vacancies, we can return to efficiency by setting $\eta = 0$, just like LS. But for entry, LS can achieve efficient entry if $\eta = \alpha$, which is not enough here. Even if firms (outsourcers) properly account for their effect on fellow firms (outsourcers) when $\alpha = \eta$, they will not account for their effect on outsourcers (firms) and thus total entry will be too high.

The above results compared the Planner's choices to the decentralized outcome conditional on the Planner making the same hiring/outsourcing decision as the firm would. In these cases, outsourcing firms make much more efficient choices than in LS without outsourcing, while hiring firms make about as efficient choices. But the Planner values outsourcing less than the marginal firm does, so the decentralized economy has too much outsourcing as firms attempt to arbitrage rents away from workers. As a result, overall efficiency and even total welfare can decrease when outsourcing is introduced, although exact results will depend on parameters.

4.4 Decentralizing Planner's Solutions Through Transfers

In this subsection, I study if it is possible to decentralize the Planner's solution through taxes and transfers. For simplicity, I assume the Planner has perfect information about firm type thus abstract from incentive compatibility issues. I allow the Planner to tax firms and outsourcers per vacancy created and to collect lump sum taxes from all workers to balance the budget. Let $\tau(y)$ be the transfer to firms per vacancy (or tax if negative) and $\tilde{\tau}$ be the transfer to outsourcers. In Proposition 2 below I show that this is sufficient to decentralize the Planner's solution.

Proposition 2. *The Planner can decentralize her solution through the following transfer and tax schedule*

- *Hiring firm's $y \leq \hat{y}^P$ per vacancy transfers are $\tau(y) = \eta c[v^P(y); y] - T$.*
- *Outsourcing firm's $y \geq \hat{y}^P$ per vacancy transfers are $\tau(y) = 0$.*
- *Outsourcer's per vacancy transfers are $\tilde{\tau} = \eta\tilde{c} - T$.*
- *Worker's lump sum transfers balance out total transfer to firms and outsourcers.*

Where T depends on total entry of hiring firms and outsourcers

$$T = \frac{(1-\eta)\big[\alpha(r+\delta) - (\eta - \alpha - \alpha\eta)\theta^P q(\theta^P)\big]}{(1-\alpha)\big[r + \delta + \eta\theta^P q(\theta^P)\big]} \left\{(1-\pi^P)\int_{\underline{y}}^{\hat{y}^P} c[v^P(x); x] dF^P(x) + \pi^P\tilde{c}\right\}. \quad (48)$$

The proof is in Appendix C. The Planner needs to ensure the right amount of firm and outsourcer entry and that firms make the correct outsourcing decision. Hiring firms and outsourcers are compensated for the benefit of entry lost to the worker but must pay for the matching externality they impose on other firms and outsourcers. Less productive firms pay lower marginal entry costs, so they lose less to bargaining and thus pay more in taxes. This is especially clear when match elasticity equals worker bargaining power $\alpha = \eta$; then transfers to workers are zero and $T = \alpha[(1-\pi^P)\int_{\underline{y}}^{\hat{y}^P} c[v^P(x); x] dF^P(x) + \pi^P\tilde{c}]$ is match elasticity times the average marginal benefit of entry for a labor market vacancy. In this case, firms and outsourcers compensate each other depending on which has a higher average marginal benefit and the taxes on workers will be 0. If the Planner wants to change which firms outsource, they subsidize hiring or tax outsourcers directly, but taxes on outsourcing firms are zero because these firms are already making efficient choices. Workers make no decisions, so the lump sum transfers have no effect on the equilibrium outcome.

While my model is highly stylized, the main takeaway from this exercise is that if governments are worried about too much outsourcing, they should target outsourcers directly and not client firms. While firms may be using outsourcing to avoid bargaining with the worker, which the government may oppose, they are also using it to avoid matching frictions, which the government should support. By targeting outsourcers directly, the government is able to increase the price of outsourcing to ensure the latter motivation is the only reason firms outsource. Governments can then use funds raised to compensate workers for their rents lost to outsourcing.

4.5 Model Summary

In this section, I built a simple model of a labor market with outsourcing. Firm outsourcing is endogenous and in equilibrium low productivity firms hire and high productivity firms choose to outsource. Outsourcing will increase as firms become more productive, more patient, or longer lasting. Outsourcing hinders worker's ability to extract rents from firms but creates more available jobs overall, so effects on worker welfare are ambiguous. Outsourcing firms create a more efficient spread and number of vacancies which tends to increase overall efficiency, but if too many firms outsource, then efficiency and even overall welfare can decrease. The Planner can induce efficiency by taxing low productivity firms, subsidizing middle productivity firms and leaving outsourcing firms alone. To better understand the magnitude of the effects of outsourcing, in the next section, I will calibrate a more complex version of the model to NLSY data.

5 Calibration

In this section, I calibrate a version of my model to match NLSY data for workers ever in high outsourcing (HO) occupations, which have outsourcing levels greater than 4.35%. I focus on workers ever in HO occupations because they are the most likely to experience any potential equilibrium effects. The model I calibrate, detailed in Appendix D, takes the baseline model in Section 4 and adds several features. First, it allows worker bargaining power $\eta/\tilde{\eta}$ and exogenous position destruction $\delta/\tilde{\delta}$ to differ for firms and outsourcers. Separating η and $\tilde{\eta}$ allows me to better match the data on both wage levels and percent of workers outsourced.[44] Separating δ and $\tilde{\delta}$ allows me to match the different average tenure for traditional versus outsourced workers seen in the data. The second change is to allow for a distribution of outsourcing productivity $o \in [\underline{o}, \bar{o}]$ with vacancy costs $\tilde{C}(\tilde{v}; o)$. Now the market between firms and outsourcers is the market for effective labor, each unit costing p. This allows me to match the distribution of wages at outsourcers. The final major addition is on-the-job search; workers can search on the job each period with probability ξ. For simplicity, I assume that firms cannot observe any outside offers from other firms, and so a worker's outside option is always unemployment benefit U.[45] This allows me to match the fraction of job-to-job transitions I see in the data.

Each period in the model is equal to one week. My calibrated parameters are shown in Table A24. I choose β and r such that the yearly interest rate is 5%. I treat traditional and contracted out jobs in the data as hired and outsourced jobs in the model. I set job loss probabilities of hiring firms and outsourcers δ and $\tilde{\delta}$ to match the rate that traditional and outsourced workers exit to non-employment. I use a Cobb-Douglas matching function $M(s, v) = \phi s^{\alpha} v^{(1-\alpha)}$ where $s = u + (1-u)\xi[(1-\delta)(1-\zeta) + (1-\tilde{\delta})\zeta]$ are total workers searching for a job. I take matching elasticity $\alpha = 0.72$ from Shimer (2005) and calibrate match efficiency ϕ and probability of on-the-job search ξ within the model to match the probability unemployed and employed workers find a job. Following Hosios Rule, I set worker bargaining power with firms $\eta = \alpha$ and calibrate worker bargaining power with outsourcers $\tilde{\eta}$. Following

[44] While I take bargaining power as exogenous in the model, one way different bargaining powers may arise in reality is through laws that require firms provide similarly generous health insurance and retirement benefits to all employees if they want tax credits (Perun, 2010). Firms hire many different types of employees and will attract high skilled workers with generous benefits that must be extended to outsourceable workers. Outsourcing firms do not need these high skilled workers and so are not as constrained by these laws.

[45] See Flinn et al. (2017) for more details for this type of on-the-job search in DMP models. See Postel-Vinay and Robin (2002) for a model where firms can observe worker's outside option.

Hall and Milgrom (2008) and Pissarides (2009), unemployment flow b equals 0.71 times the average log real weekly wage of all ever HO traditional and outsourced jobs. I set the range of firm productivity to be $\underline{y} = 5$ to $\bar{y} = 11$ and the range of outsourcer productivity to be $\underline{o} = 0.7$ to $\bar{o} = 1.3$. For cost of entry of firms, I choose $C(v, y) = \exp(c_0 + c_1 * y)v^\gamma$ and $\tilde{C}(v, o) = \exp(\tilde{c}_0 + \tilde{c}_1 * o)v^\gamma$, where cost convexity $\gamma = 2$ and cost scalars c_0, c_1, $\tilde{c}_0$, and $\tilde{c}_1$ are calibrated within the model.

As mentioned above, I calibrate ϕ, ξ, $\tilde{\eta}$, c_0, c_1, $\tilde{c}_0$, and $\tilde{c}_1$ within the model. Flow parameters ϕ and ξ are mainly used to match the job finding rate of unemployed and employed workers. I set η, c_0, c_1, $\tilde{c}_0$, and $\tilde{c}_1$ to match the wage distribution and percent of all workers in outsourcing jobs each week ζ in the data. The model represents a labor market with homogeneous workers in one occupation, while my data comes from heterogeneous workers in many occupations. Instead of matching wage distributions directly, I remove occupation and worker fixed effects (along with other observable differences) using a regression on log real weekly wages similar to the one from equation (1) and Table A9 but without the indicator for outsourced. I run the regression on the entire sample, take the residuals from my calibration sample, plotted in Figure A13, and re-scale them by the average log real weekly wage. I match the mean and standard deviation of both residual wage distributions.

Calibration results are in Table A25. First, I check calibrated wage distributions for hired and outsourced workers; Figure A14 and Figure A15 show the model's CDF of wages compared to the data. The calibration attempts to match firm's cost of entry, but allows the amount of entry to be chosen by the firm. For this reason, the calibration has a hard time matching the lower end of the wage distribution for outsourcers because the model has a hard time rationalizing why these outsourcers would choose to enter. Given these restrictions, the model does a reasonable job of matching the wage data, although average wages for both hired and outsourced workers is too high. For my worker flow and percent outsourced moments, the model matches the data well. I then check my calibration against some untargeted moments. According to the model, the percent of vacancies from outsourcers

π is the same as the percent of outsourced jobs from unemployment, which I can calculate in the data. I can also compare the average job-to-job transition rate with the individual rates for hired and outsourced workers. The model slightly overestimates both the share of vacancies from outsourcers and the fraction of job-to-job transitions, but matches these moments relatively well.

To see what effect outsourcing has on worker welfare, I shut down outsourcers and re-run the model. Table A26 shows how model outcomes change when outsourcing is shut down. Without outsourcing, unemployment rises 1.2%. Despite this, workers still earn higher wages and worker value of search while unemployed and overall welfare increase by 1.1% and 0.39%. The increase in jobs is not enough to make up for lower average job quality, and workers are worse off. Figure A16 shows the distributions of workers by wages and makes the trade-off apparent; the simulation with outsourcing has more low wage jobs but is missing the right tail where firms start outsourcing. Do we expect the model to over- or under-estimate these welfare effects? On one hand, my estimates only include wages and job tenures, excluding the benefit differences that make outsourcing jobs even less attractive than traditional jobs. On the other hand, my simple model uses linear utility, while risk averse workers might place higher value on spending less time unemployed. While it is unclear which effect might be bigger, the model strongly suggests that workers have been harmed by the increase in outsourcing.

6 Conclusion

This paper analyzes the effects of domestic outsourcing on workers and labor markets. I use NLSY data that provides self-reported outsourcing status for each job over a 15 year period, which to my knowledge has not been used before. I use the data set to reexamine past questions and answer some new ones. Like most of the literature, I find an increase in outsourcing over the past two decades. I show that many of the results from past studies finding outsourced jobs in low skilled occupations are lower quality can be extended to all outsourcing jobs. For the first time, I show that outsourced workers transition between jobs in similar ways to traditional workers and that outsourcing increases employment within an occupation.

Using stylized facts from the literature and data, I build a model of domestic outsourcing's effects on labor markets. The model is simple but captures the main reason firms choose to outsource; to lower costs by lowering workers' share of production surplus and avoiding matching frictions. I focus on how the firm's choice to outsource affects workers. On one hand, outsourcing lowers the average job quality, on the other, it increases the amount of jobs available. These have competing effects on all workers' outside option; workers who stay hired by their firm can be affected by other workers being outsourced. After calibrating the model to match NLSY data, I find the overall effect is negative, workers would be better off if firms hired workers directly, even though it means fewer jobs are available.

While the model captures the main reason firms choose to outsource, it has less to say about why outsourcing has been increasing. Because of a lack of firm side data, the model can only explain the rise of outsourcing from exogenous changes such as lower outsourcer vacancy costs or higher firm productivity. Building a model with better microfoundations for how outsourcers reduce costs could highlight additional effects on labor markets not considered here. Another simplification of the current model is taking an occupation's outsourceability as given and ignoring the economy outside of outsourceable occupations. In reality, firms must decide which occupations to hire and which to outsource, and a firm's decision to outsource affects how it interacts with its remaining workers. While there is a general consensus that outsourceable occupations tend to be ones that are relatively generic across firms, not much work on what exactly makes some occupations more outsourceable than others. There is much more to learn about why some occupations are outsourced compared to others and how a firm's decision to outsource interacts with the rest of its operating strategy. I leave these questions to future work.

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Appendices

A Tables

Subset	Number
In Employer History Roster and Employer Supplement	69,749
Only in Employer History Roster	+219
Only in Employer Supplement	+7
	69,975
Unmatched with On Jobs	-423
Conflicting Start or Stop Dates	-1,109
Missing/Conflicting Job Types	-3,455
Total	64,988

Table A1: The matching process for the Employer History Roster/Employer Supplement of the NLSY and number of person-interview-job observations lost/gained step by step. An observation is considered matched with On Jobs if it is matched in at least one interview.

Subset	Unmatched	Total	Percent Missing
On Jobs	6,037	62,708	9.63
On Jobs with Information	3,239	30,696	10.55
On Jobs Outsourced	130	826	15.74

Table A2: The matching quality from On Jobs of the NLSY in the final data set. Observations are at the person-interview-job level. A job is matched if is connected to a job from the Employer History Roster/Employer Supplement. Jobs with information are any jobs in which the job type questionnaire loop began.

Match Quality	Overall	Outsourced
1. Matched start date, end date, and rank	4,398	178
2. Matched start date and end date	343	17
3. Matched start date and rank	29,407	940
4. Matched end date and rank	12,006	73
5. Matched start date	197	6
6. Matched end date	2,012	19
7. Only unmatched job in year	14,067	96
8. Only unmatched job type in year	286	0
9. Matched rank	2,272	73
Total	64,988	1,402

Table A3: Match quality of final NLSY dataset. Observations are at the person-interview-job level. Match quality for each job is measured by the highest quality match across interviews.

Job Type	NLSY	CWS 2005	Katz and Krueger (2019)
Contracted Out	2.17	1.40	2.50
	(0.20)		
Independent Contractor	1.52	7.00	7.20
	(0.19)		
Temp Worker	0.60	0.90	1.70
	(0.07)		
On-Call Worker	1.26	1.70	2.40
	(0.16)		
Self-Employed	14.76	10.80	9.20
	(0.65)		
Traditional Employee	79.70	–	–
	(0.71)		

Table A4: Percent of weekly job-person observations in each job type for men in the NLSY. Observations weighted at the person level. Other values are from Katz and Krueger (2019b) Table 1 using data from the Contingent Worker Survey (CWS) 2005 and the RAND American Life Panel using alternative weight 2, which reweights to match the CPS in self-employment and multiple job holders. Both of these samples include men and women age 18 and older. My NLSY data separates self-employment as its own job type while both CWS and KK do not, so I could not determine how many workers are in traditional jobs for these sources.

Variable	Value
All Occupations	
Number	443
Percent of Workers Outsourced	2.17
Occupations with any Outsourcing	145
High Outsourcing Occupations ($\geq$4.35%)	
Number	58
Percent of Jobs	13.09
Percent of Workers Outsourced	8.94

Table A5: Outsourcing prevalence among occupations and workers in the NLSY.

Variable	Outsourced Ever	Outsourced Never	HO Occupation Ever	HO Occupation Never
Percent Ever HO Occupation	0.59 (0.03)	0.29*** (0.01)	1	0
Percent Ever Outsourced	1	0	0.16 (0.01)	0.05*** (0.00)
Black	0.21 (0.02)	0.13*** (0.00)	0.15 (0.01)	0.13 (0.01)
Hispanic	0.08 (0.01)	0.07 (0.00)	0.07 (0.01)	0.07 (0.00)
No HS Diploma	0.10 (0.02)	0.09 (0.01)	0.09 (0.01)	0.09 (0.01)
HS Diploma	0.60 (0.03)	0.56 (0.01)	0.56 (0.02)	0.56 (0.01)
AA Degree	0.08 (0.01)	0.08 (0.01)	0.09 (0.01)	0.07** (0.01)
BA Degree	0.14 (0.02)	0.17 (0.01)	0.18 (0.01)	0.17 (0.01)
Post Graduate Degree	0.06 (0.01)	0.07 (0.01)	0.05 (0.01)	0.08*** (0.01)
Single	0.16 (0.02)	0.16 (0.01)	0.15 (0.01)	0.16 (0.01)
Married	0.57 (0.03)	0.62* (0.01)	0.61 (0.02)	0.62 (0.01)
Total Number of Children	1.80 (0.08)	1.80 (0.03)	1.86 (0.05)	1.77* (0.03)
Children in Household	0.74 (0.06)	0.88*** (0.02)	0.86 (0.04)	0.88 (0.03)
Observations	403	3,678	1,325	2,756

Table A6: Demographic statistics from the NLSY for those who are ever outsourced in On Jobs versus those who never are and for those who ever work in high outsourcing (HO) occupations versus those who never do. Observations are at the person level from an individual's first survey post-2000 and summary statistics are weighted at the person level. Stars represent significant difference at the .10 level *, .05 level **, and .01 level ***.

	Whole Workforce		NLSY Cohort	
	HO Occupation	Other Occupation	HO Occupation	Other Occupation
Log Real	2.84	2.75^{***}	3.02	2.91^{***}
Hourly Wage	(0.0017)	(0.0007)	(0.0037)	(0.0016)
Log Real	6.69	6.71^{***}	6.92	6.92
Weekly Wage	(0.0020)	(0.0008)	(0.0037)	(0.0016)
Part-Time	0.09	0.09^{***}	0.09	0.08^{***}
	(0.0004)	(0.0001)	(0.0008)	(0.0003)
Union	0.12	0.10^{***}	0.15	0.12^{***}
	(0.0008)	(0.0003)	(0.0020)	(0.0007)
Age	39.96	40.23^{***}	47.80	47.67^{***}
	(0.0162)	(0.0061)	(0.0141)	(0.0055)
Percent	0.11	0.11^{***}	0.10	0.10
Black	(0.0004)	(0.0002)	(0.0009)	(0.0004)
Percent	0.16	0.16^{***}	0.11	0.13^{***}
Hispanic	(0.0005)	(0.0002)	(0.0010)	(0.0004)
Less	0.11	0.12^{***}	0.09	0.10^{***}
High School	(0.0004)	(0.0002)	(0.0008)	(0.0003)
High School	0.56	0.49^{***}	0.55	0.48^{***}
	(0.0006)	(0.0002)	(0.0014)	(0.0005)
Associates	0.11	0.08^{***}	0.12	0.09^{***}
Degree	(0.0004)	(0.0001)	(0.0009)	(0.0003)
Bachelor's	0.17	0.21^{***}	0.17	0.21^{***}
Degree	(0.0005)	(0.0002)	(0.0011)	(0.0004)
Plus	0.06	0.11^{***}	0.07	0.12^{***}
Degree	(0.0003)	(0.0002)	(0.0007)	(0.0004)
Single	0.30	0.30	0.11	0.12^{***}
	(0.0006)	(0.0002)	(0.0009)	(0.0004)
Married	0.58	0.59^{***}	0.72	0.72
	(0.0006)	(0.0002)	(0.0013)	(0.0005)
Observations	792,601	5,510,498	165,173	1,133,065

Table A7: Summary statistics from the January 2001 - October 2016 CPS for all employed men age 18-65 and for those born between 1957-1964 (NLSY cohort). Workers are divided by if they work in a high outsourcing (HO) occupation (all occupations with outsourcing more than 4.34% in the NLSY). Statstics are weighted at the person level. Stars represent significant difference from HO occupations at the .10 level *, .05 level **, and .01 level ***.

Variable	Outsourced	Traditional	Self-Employed	Ind. Contractor	On-Call	Temp
Log Real	3.02	3.06	2.92**	2.98	2.63***	2.38***
Hourly Wage	(0.05)	(0.01)	(0.04)	(0.07)	(0.05)	(0.04)
Log Real	6.69	6.75	6.28***	6.25***	5.96***	6.00***
Weekly Wage	(0.06)	(0.02)	(0.05)	(0.08)	(0.09)	(0.04)
Hours Worked	42.01	42.74	38.04***	34.69***	35.37***	39.14***
Weekly	(0.73)	(0.20)	(0.73)	(1.38)	(1.43)	(0.57)
Part Time	0.12	0.12	0.38***	0.39***	0.41***	0.17*
	(0.02)	(0.00)	(0.01)	(0.03)	(0.03)	(0.02)
Tenure	121.62	306.94***	342.18***	122.13	117.68	58.24***
(Weeks)	(7.62)	(5.73)	(11.81)	(9.50)	(12.73)	(5.42)
Union	0.09	0.04***	0.01***	0.06	0.04***	0.03***
	(0.02)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
Job Satisfaction	1.88	1.85	1.51***	1.82	1.80	2.11***
(Lower Better)	(0.04)	(0.01)	(0.02)	(0.05)	(0.05)	(0.05)
Any Benefits	0.73	0.81***	0.10***	0.35***	0.37***	0.32***
	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Health	0.65	0.73***	0.07***	0.18***	0.30***	0.30***
Insurance	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
Retirement	0.51	0.61***	0.04***	0.11***	0.23***	0.10***
Plan	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)
Subsidized	0.05	0.07	0.01***	0.02**	0.04	0.02**
Childcare	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Dental	0.56	0.63***	0.04***	0.12***	0.26***	0.19***
Insurance	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
Flex	0.36	0.43***	0.07***	0.25***	0.20***	0.15***
Schedule	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Life	0.56	0.62**	0.05***	0.12***	0.22***	0.13***
Insurance	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)
Maternity	0.43	0.54***	0.02***	0.10***	0.18***	0.07***
Leave	(0.03)	(0.01)	(0.00)	(0.02)	(0.02)	(0.02)
Profit	0.18	0.21*	0.04***	0.06***	0.08***	0.02***
Sharing	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Training	0.28	0.41***	0.03***	0.09***	0.16***	0.07***
	(0.02)	(0.01)	(0.00)	(0.02)	(0.02)	(0.02)
Observations	455	9,103	1,472	452	415	461

Table A8: Summary statistics of jobs in the NLSY divided by job types. Observations are at the person-job level, where jobs observed more than once use average characteristics. All statistics are weighted at the person level. Stars represent significant difference from outsourced jobs at the .10 level *, .05 level **, and .01 level ***.

Outcome	Outsourced	R^2	Observations
Log Real Hourly Wages	-0.053^{**} (0.019)	0.83	9,741
Log Real Weekly Wages	-0.088^{**} (0.034)	0.79	9,753
Hours Worked Per Week	-0.915 (0.808)	0.65	9,738
Part-Time	-0.005 (0.024)	0.61	10,635
Job Satisfaction (Lower Better)	0.037 (0.060)	0.57	9,691
Any Benefits	-0.077^{*} (0.037)	0.70	10,570
Health Insurance	-0.075^{**} (0.031)	0.70	10,559

Table A9: Regressions of worker outsourcing status on job outcomes in the NLSY. All regressions include controls for job type (traditional job is default), worker and occupation fixed effects, a quartic in age and job tenure, dummies for year started and ended job, union status, dummies for region, whether in an MSA or central city, marital status, and number of children total and in household. Regressions for log real hourly wages and job satisfaction also include controls for hours worked per week and part-time status. All observations are at the person-job level, where jobs observed more than once use average characteristics. All regressions are weighted at the person level and all standard errors are clustered by demographic sample. Stars represent significant at the .10 level *, .05 level **, and .01 level ***.

Outcome	Outsourced Currently	R^2	Observations	Outsourced Previously	R^2	Observations
Log Real Hourly Wages	-0.069 (0.044)	0.88	4,823	-0.002 (0.034)	0.87	4,823
Log Real Weekly Wages	-0.091^{**} (0.036)	0.87	4,823	-0.037 (0.032)	0.86	4,823
Hours Worked Per Week	-0.861 (1.055)	0.75	4,823	-1.622^{*} (0.863)	0.75	4,823
Part-Time	-0.022 (0.024)	0.71	5,224	0.013 (0.022)	0.71	5,224
Job Satisfaction (Lower Better)	0.086 (0.089)	0.63	4,813	0.039 (0.058)	0.62	4,813
Any Benefits	-0.091^{***} (0.023)	0.74	5,214	-0.030 (0.048)	0.69	5,214
Health Insurance	-0.091^{***} (0.023)	0.75	5,205	-0.024 (0.062)	0.70	5,205

Table A10: Regressions of worker outsourcing status on job outcomes in the NLSY. All regressions include controls for job type (traditional job is default) in current (left three columns) or previous (right three columns) job. Additional controls are worker and occupation fixed effects, a quartic in age and tenure, dummies for year started and ended job, union status, dummies for region, whether in an MSA or central city, marital status, and number of children total and in household. Regressions for log real hourly wages and job satisfaction also include controls for hours worked per week and part-time status. All observations are at the person-job level, where jobs observed more than once use average characteristics. All regressions are weighted at the person level and all standard errors are clustered by demographic sample. Stars represent significant at the .10 level *, .05 level **, and .01 level ***.

	Outsourced	Self-Employed	Full
Outsourced	-0.004	-0.048	-0.088^{**}
	(0.037)	(0.033)	(0.034)
Self-Employed	–	-0.723^{***}	-0.733^{***}
		(0.056)	(0.061)
Independent Contractor	–	-0.357^{***}	-0.385^{***}
		(0.084)	(0.071)
On-Call	–	–	-0.369^{***}
			(0.038)
Temp Worker	–	–	-0.339^{***}
			(0.026)
R^2	0.77	0.78	0.79
Observations	9,793	9,793	9,793

Table A11: Regressions of job type on log real weekly wages in the NLSY. Missing type in final row is traditional jobs. All regressions use worker and occupation fixed effects and include a quartic in age and job tenureand year started and ended job, union status, dummies for region, whether in an MSA or central city, marital status, and number of children in household and total. All observations are at the person-job level, where jobs observed more than once use average characteristics. All regressions are weighted at the person level and all standard errors are clustered by demographic sample. Stars represent significant at the .10 level *, .05 level **, and .01 level ***.

Variable	Self-Reported (This Paper) Outsourced	Self-Reported (This Paper) Not Outsourced	Industry-Occupation (Dube and Kaplan) Outsourced	Industry-Occupation (Dube and Kaplan) Not Outsourced
Log Real	2.13	2.50***	2.45	2.49
Hourly Wage	(0.08)	(0.04)	(0.12)	(0.04)
Log Real	5.21	5.98***	5.70	6.02***
Weekly Wage	(0.13)	(0.06)	(0.17)	(0.06)
Hours Worked	23.71	35.36***	29.37	36.34***
per Week	(2.71)	(0.92)	(2.12)	(1.05)
Part Time	0.72	0.33***	0.61	0.28***
	(0.12)	(0.03)	(0.07)	(0.04)
Any Benefits	0.18	0.62***	0.28	0.69***
	(0.10)	(0.04)	(0.06)	(0.04)
Health Insurance	0.18	0.50**	0.18	0.56***
	(0.10)	(0.04)	(0.06)	(0.04)
Union	0.00	0.06	0.06	0.06
	(0.00)	(0.01)	(0.03)	(0.01)
Job Satisfaction	1.76	1.85	1.88	1.84
(Lower Better)	(0.20)	(0.05)	(0.10)	(0.06)
No HS Diploma	0.11	0.20	0.15	0.21
	(0.07)	(0.03)	(0.05)	(0.04)
HS Diploma	0.89	0.65*	0.73	0.64
	(0.07)	(0.04)	(0.07)	(0.04)
AA Degree	0.00	0.07	0.03	0.08
	(0.00)	(0.02)	(0.02)	(0.02)
BA Degree	0.00	0.03	0.06	0.02**
	(0.00)	(0.01)	(0.04)	(0.01)
Post Graduate	0.00	0.01	0.01	0.01
Degree	(0.00)	(0.00)	(0.01)	(0.00)
Black	0.59	0.31**	0.42	0.29**
	(0.17)	(0.03)	(0.08)	(0.04)
Hispanic	0.06	0.07	0.05	0.07
	(0.04)	(0.01)	(0.02)	(0.01)
Age	48.50	47.71	47.75	47.73
	(1.10)	(0.34)	(0.59)	(0.39)
Observations	14	326	75	265

Table A12: Summary statistics for janitors (occupation 4220) who are outsourced vs not outsourced in the NLSY. In the left two columns, outsourced is self-reported by the worker as in the rest of this paper. In the right two, it is inferred if the worker is in services to buildings and dwellings (industry 7690) following Dube and Kaplan (2010). Observations are at the person-job level and summary statistics are weighted at the person level. Stars represent significant difference from outsourced of same determination method at the .10 level *, .05 level **, and .01 level ***.

Variable	Self-Reported (This Paper) Outsourced	Not Outsourced	Industry-Occupation (Dube and Kaplan) Outsourced	Not Outsourced
Log Real	2.38	2.64***	2.42	2.74***
Hourly Wage	(0.08)	(0.05)	(0.05)	(0.08)
Log Real	5.86	6.06	5.92	6.12*
Weekly Wage	(0.13)	(0.10)	(0.08)	(0.15)
Hours Worked	34.94	34.19	35.29	33.51
per Week	(2.09)	(1.70)	(1.46)	(2.40)
Part Time	0.28	0.27	0.23	0.30
	(0.10)	(0.05)	(0.06)	(0.07)
Any Benefits	0.54	0.64	0.59	0.66*
	(0.10)	(0.05)	(0.06)	(0.07)
Health Insurance	0.41	0.53*	0.44	0.57**
	(0.09)	(0.05)	(0.06)	(0.08)
Union	0.11	0.06	0.09	0.05
	(0.07)	(0.02)	(0.03)	(0.02)
Job Satisfaction	2.12	1.83**	2.05	1.73***
(Lower Better)	(0.13)	(0.08)	(0.12)	(0.07)
No HS Diploma	0.22	0.06***	0.15	0.03***
	(0.11)	(0.02)	(0.07)	(0.02)
HS Diploma	0.59	0.70	0.69	0.67
	(0.12)	(0.05)	(0.07)	(0.07)
AA Degree	0.13	0.17	0.08	0.24***
	(0.09)	(0.05)	(0.04)	(0.07)
BA Degree	0.06	0.05	0.04	0.06
	(0.06)	(0.02)	(0.03)	(0.03)
Post Graduate	0.00	0.01	0.01	0.00
Degree	(0.00)	(0.01)	(0.01)	(0.00)
Black	0.33	0.36	0.43	0.29**
	(0.10)	(0.06)	(0.08)	(0.06)
Hispanic	0.05	0.09	0.08	0.09
	(0.04)	(0.02)	(0.03)	(0.03)
Age	48.74	47.18	46.78	48.04*
	(1.11)	(0.59)	(0.73)	(0.77)
Observations	30	162	97	95

Table A13: Summary statistics for security guards (occupation 3920) who are outsourced vs not outsourced in the NLSY. In the left two columns, outsourced is self-reported by the worker as in the rest of this paper. In the right two, it is inferred if the worker is in protective services (industry 7680) following Dube and Kaplan (2010). Observations are at the person-job level and summary statistics are weighted at the person level. Stars represent significant difference from outsourced of same determination method at the .10 level *, .05 level **, and .01 level ***.

Self-Reported	Industry-Occupation (Dube and Kaplan) Outsourced	Not Outsourced	Total
Contracted Out	7	7	14
Independent Contractor	2	4	6
Temp Worker	5	14	19
On-Call Worker	3	13	16
Self-Employed	13	5	18
Traditional Employee	45	222	267
Total	75	265	340

Table A14: Counts of Dube and Kaplan (2010) (DK) method of measuring outsourcing versus NLSY self-reported job type for janitors (occupation 4220) in the NLSY. For columns, following DK, workers are consider outsourced if they are in services to buildings and dwellings (industry 7690). For rows, we show the worker's self-reported job type. Observations are at the person-job level.

Self-Reported	Industry-Occupation (Dube and Kaplan) Outsourced	Not Outsourced	Total
Contracted Out	23	7	30
Independent Contractor	7	3	10
Temp Worker	1	2	3
On-Call Worker	9	3	12
Self-Employed	4	0	4
Traditional Employee	53	80	133
Total	97	95	192

Table A15: Counts of Dube and Kaplan (2010) (DK) method of measuring outsourcing versus NLSY self-reported job type for security guards (occupation 3920) in the NLSY. For columns, following DK, workers are consider outsourced if they are in protective services (industry 7680). For rows, we show the worker's self-reported job type. Observations are at the person-job level.

Self-Reported	Industry-Occupation (Dube and Kaplan) Outsourced	Not Outsourced	Total
Contracted Out	83	36	119
Independent Contractor	184	28	212
Temp Worker	12	33	45
On-Call Worker	21	61	82
Day Laborer	2	6	8
Self-Employed	53	23	76
Traditional Employee	644	3309	3953
Total	1316	4432	5748

Table A16: Counts of Dube and Kaplan (2010) (DK) method of measuring outsourcing versus CWS self-reported job type for janitors (occupation 753) in the CWS. For columns, following DK, workers are consider outsourced if they are in industry 722. For rows, we show the worker's self-reported job type.

Self-Reported	Industry-Occupation (Dube and Kaplan) Outsourced	Not Outsourced	Total
Contracted Out	193	16	209
Independent Contractor	25	6	31
Temp Worker	10	5	15
On-Call Worker	14	21	35
Day Laborer	1	0	1
Self-Employed	7	0	7
Traditional Employee	464	822	1286
Total	896	1078	1974

Table A17: Counts of Dube and Kaplan (2010) (DK) method of measuring outsourcing versus CWS self-reported job type for security guards (occupation 726) in the CWS. For columns, following DK, workers are consider outsourced if they are in industry 744. For rows, we show the worker's self-reported job type.

	Outsourced Currently			Traditional Currently		
	Previous	Current	Next	Previous	Current	Next
Outsourced	0.18***	1	0.25***	0.03***	0	0.04***
	(0.03)		(0.04)	(0.00)		(0.00)
Same Occupation	0.28	–	0.32	0.26	–	0.25
	(0.03)		(0.04)	(0.01)		(0.01)
Same Industry	0.32	–	0.39	0.30	–	0.29
	(0.04)		(0.05)	(0.01)		(0.01)
Log Real Hourly Wage	3.04	3.05	3.00	3.01***	3.11	2.98***
	(0.05)	(0.05)	(0.07)	(0.02)	(0.01)	(0.02)
Log Real Weekly Earnings	6.79	6.77	6.69	6.73***	6.85	6.67***
	(0.05)	(0.05)	(0.08)	(0.02)	(0.02)	(0.02)
Hours Worked Weekly	44.23	43.48	41.94	43.93	44.10	43.01***
	(0.71)	(0.69)	(0.84)	(0.28)	(0.19)	(0.30)
Part Time	0.08	0.08	0.12	0.10***	0.08	0.14***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)
Union	0.04***	0.09	0.07	0.04**	0.04	0.04
	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Job Satisfaction (Lower Better)	1.93	1.87	1.88	1.94***	1.83	1.83
	(0.05)	(0.04)	(0.06)	(0.02)	(0.01)	(0.02)
Health Insurance	0.69	0.69	0.63*	0.67***	0.78	0.63***
	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)
Any Benefits	0.77	0.76	0.71*	0.73***	0.85	0.71***
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Weeks To Find Job	22.31	–	22.38	22.76	–	23.63
	(2.82)		(2.67)	(0.82)		(0.81)
Weeks To Find Job (> 1 week)	39.32	–	37.38	40.44	–	41.66
	(4.51)		(4.13)	(1.27)		(1.25)
Job-to-Job Transition	0.44	–	0.41	0.45	–	0.44
	(0.03)		(0.04)	(0.01)		(0.01)
Observations		391			7,550	

Table A18: Job summary statistics in the NLSY at previous, current, and next job for workers who are currently outsourced compared to those who are currently in traditional jobs. Observations are at the person-job level and summary statistics are weighted at the person level. Stars represent significant difference from current job (except for outsourced which represents significant difference from 0) at the .10 level *, .05 level **, and .01 level ***.

Variables	Weeks to Job	Weeks to Job (> 1)	Job-Job Transition
Outsourced	-3.92	-8.97	0.02
Current	(7.20)	(22.78)	(0.04)
Outsourced	-3.67	-10.98	-0.04
Previous	(7.21)	(25.90)	(0.07)
Job Info	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes
R^2	0.75	0.86	0.73
Obs	3,543	1,833	3,883

Table A19: Regressions of outsourced at current and previous job on weeks to find current job (both overall and conditional on taking more than one week) and probability of job to job transition in the NLSY. Each regression contains current and previous job variables: job type (reported coefficients are compared to traditional jobs), fixed effects for occupation, hours worked per week, part-time status, log real weekly wage, union status, and whether received health insurance, retirement benefits, or any benefits. They also contain a quartic of previous tenure and a dummy for year current job began. They contain demographic variables: a quartic in age, dummies for region, whether in an MSA or central city, marital status, and number of children total and in household. All observations are at the person-job level and regressions are weighted at the person level. All standard errors are clustered by demographic sampling group. Stars represent significant at the .10 level *, .05 level **, and .01 level ***.

Dependent Variable	Outsourced Percent	R^2	Observations
Percent of Workers in Occupation	0.00024** (0.00012)	0.98	261,022
Traditional Jobs			
Log Real Hourly Wage	0.0007 (0.0005)	0.90	249,695
Log Real Weekly Wage	0.0007 (0.0009)	0.88	249,695
Hours Worked	−0.0123 (0.0192)	0.76	249,695
Part-Time Status	−0.0001 (0.0004)	0.68	251,859
Job Satisfaction (Lower Better)	−0.0013 (0.0013)	0.70	251,859
Any Benefits	0.0007 (0.0005)	0.68	251,859
Health Insurance	0.0007 (0.0006)	0.76	251,859
Outsourced Jobs			
Log Real Hourly Wage	−0.0014 (0.0011)	0.89	38,214
Log Real Weekly Wage	−0.0001 (0.0014)	0.89	38,214
Hours Worked	0.0460 (0.0324)	0.79	38,214
Part-Time Status	−0.0013 (0.0008)	0.70	39,710
Job Satisfaction (Lower Better)	0.0019 (0.0018)	0.73	39,445
Any Benefits	−0.0004 (0.0010)	0.70	39,443
Health Insurance	−0.0012 (0.0016)	0.74	39,443

Table A20: Occupation level regressions of percent outsourced within occupation each week on average job characteristics in the NLSY. Each regression contains controls for percent in other alternative job types (ie. independent contractor, temp workers), percent Black, Hispanic, and union member, average age, and occupation and week fixed effects. Regressions use robust standard errors clustered at the occupation level. Stars represent significant difference from 0 at the .10 level *, .05 level **, and .01 level ***.

Data Set	Outsourced Percent	R^2	Observations
CPS	0.00021*	0.93	56,856
	(0.00012)		
NLSY 79	0.00024**	0.98	60,460
	(0.00012)		
CPS (NLSY 79 Cohort)	0.00034**	0.91	44,309
	(0.00016)		

Table A21: Occupation level regressions of percent outsourced each month (as measured in the NLSY) on percent of workers in an occupation. Data sets used are the CPS, the NLSY, and the CPS with only workers born between 1957-1964 (the same cohort as the NLSY). Each regression contains controls for percent in other alternative job types (ie. independent contractor, temp workers; also from NLSY), percent Black, Hispanic, and union member, average age, and occupation and month fixed effects. Data runs from January 2001 to October 2016. Regressions use robust standard errors clustered at the occupation level. Regressions use robust standard errors clustered at the occupation level. Stars represent significant difference from 0 at the .10 level *, .05 level **, and .01 level ***.

Self-Reported	PBS	Not PBS	Total
Contracted Out	121	302	423
Independent Contractor	75	335	410
Temp Worker	225	176	401
On-Call Worker	40	321	361
Self-Employed	286	1151	1437
Traditional Employee	812	7637	8449
Total	1559	9922	12358

Table A22: Job types of workers in Professional Business Service (PBS) industries versus all other industries in the NLSY. PBS Industries have Census 2000 Industry Codes between 7270 and 7790.

Data Set	PBS Percent	R^2	Observations
CPS	0.00015	0.94	82,212
	(0.00012)		
NLSY 79	0.00025*	0.98	60,628
	(0.00014)		

Table A23: Occupation level regressions of percent in Professional Business Services (PBS) industries within an occupation on percent of workers in an occupation. PBS Industries in the CPS have Census 1990 Industry Codes between 721 and 760. PBS Industries in the NLSY 79 have Census 2000 Industry Codes between 7270 and 7790. Each regression contains controls for percent Black, Hispanic, and union member, average age, and occupation and month fixed effects. Regressions use robust standard errors clustered at the occupation level. Stars represent significant difference from 0 at the .10 level *, .05 level **, and .01 level ***.

Variable	Value	Description
Outside Model		
r	0.001	5% yearly interest rate
b	4.67	71% average wage Hall and Milgrom (2008)
δ	0.0039	Traditional Job Loss
$\tilde{\delta}$	0.0044	Outsourced Job Loss
α	0.72	Shimer (2005)
η	0.72	Hosios Rule
γ	2	
$\underline{y}$	5	
$\bar{y}$	11	
$\underline{o}$	0.7	
$\bar{o}$	1.3	
Inside Model		
c_0	-20.00	Traditional workers residual wages mean
c_1	3.77	Traditional workers residual wages sd
$\tilde{c}_0$	-16.63	Outsourced workers residual wages mean
$\tilde{c}_1$	26.80	Outsourced workers residual wages sd
$\tilde{\eta}$	0.58	Relative number of outsourced workers
ϕ	0.060	Job finding rate
ξ	0.21	Job-to-job transition rate

Table A24: Calibration parameters.

Moment	Model	Data
Targeted		
Mean Hired Wage Residual (Plus Mean Wage)	6.71	6.67
SD of Hired Wage Residuals	0.36	0.38
Mean Outsourced Wage Residual (Plus Mean Wage)	6.67	6.59
SD of Outsourced Wage Residuals	0.38	0.39
Weekly EE Rate	0.0021	0.0020
Weekly UE Rate	0.028	0.028
Fraction of Employed who are Outsourced	0.072	0.072
Untargeted		
Fraction of Jobs from Unemployment that are Outsourced	0.085	0.084
Weekly EE Rate Hired	0.0020	0.0020
Weekly EE Rate Outsourced	0.0024	0.0020

Table A25: Calibration results.

Value	Percent Change Without Outsourcing
Unemployment	1.17%
Mean Wage	0.41%
Value of Search while Unemployed	1.07%
Total Welfare	0.39%

Table A26: Percent change in model outcomes when outsourcing is eliminated.

B Figures

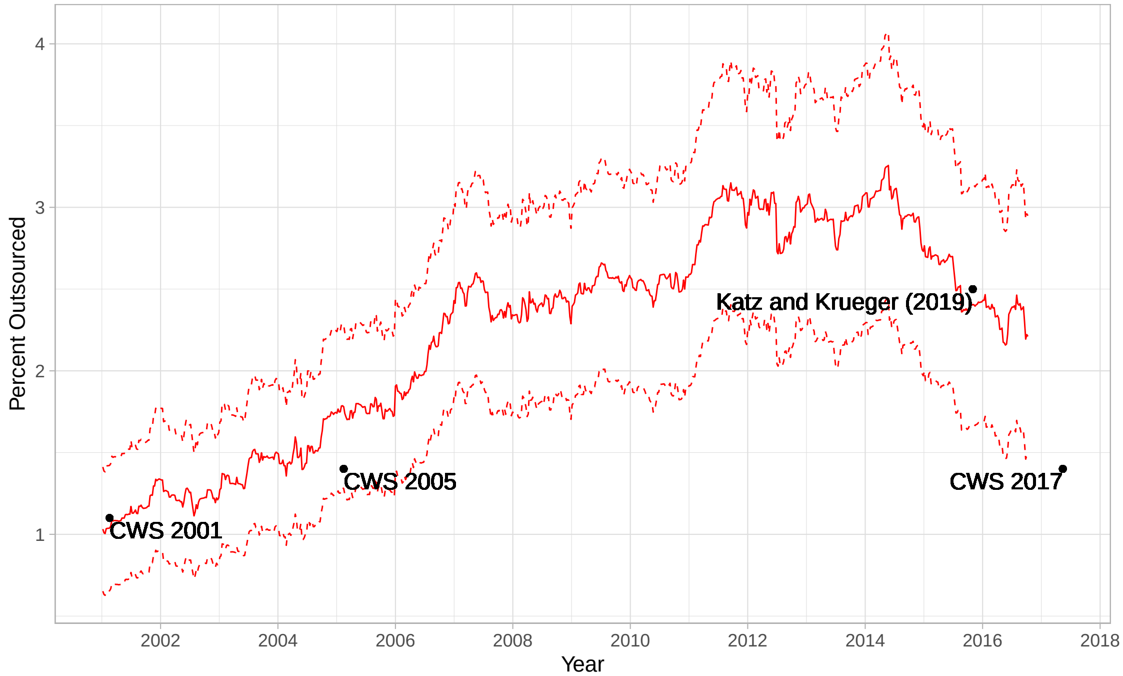

Figure A1: Percent of employed workers outsourced each week in the NSLY. Also show point estimates from Katz and Krueger (2019b) Table 1 compiling data from the Contingent Worker Survey (CWS) and RAND American Life Panel using alternative weight 2.

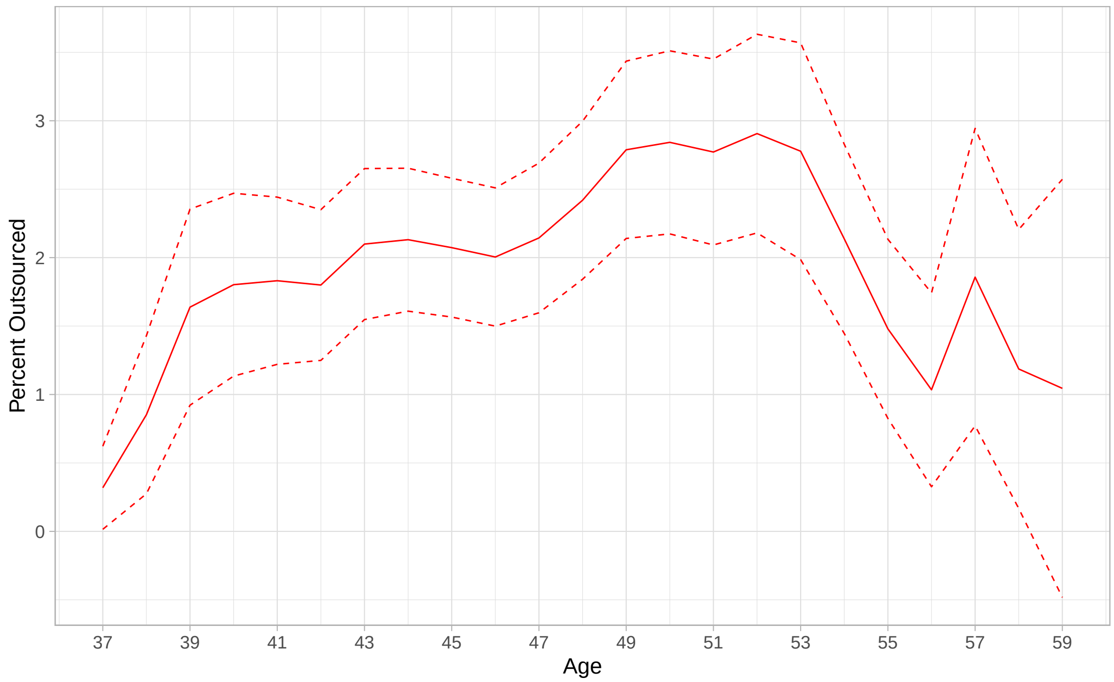

Figure A2: Percent of employed workers outsourced by age.

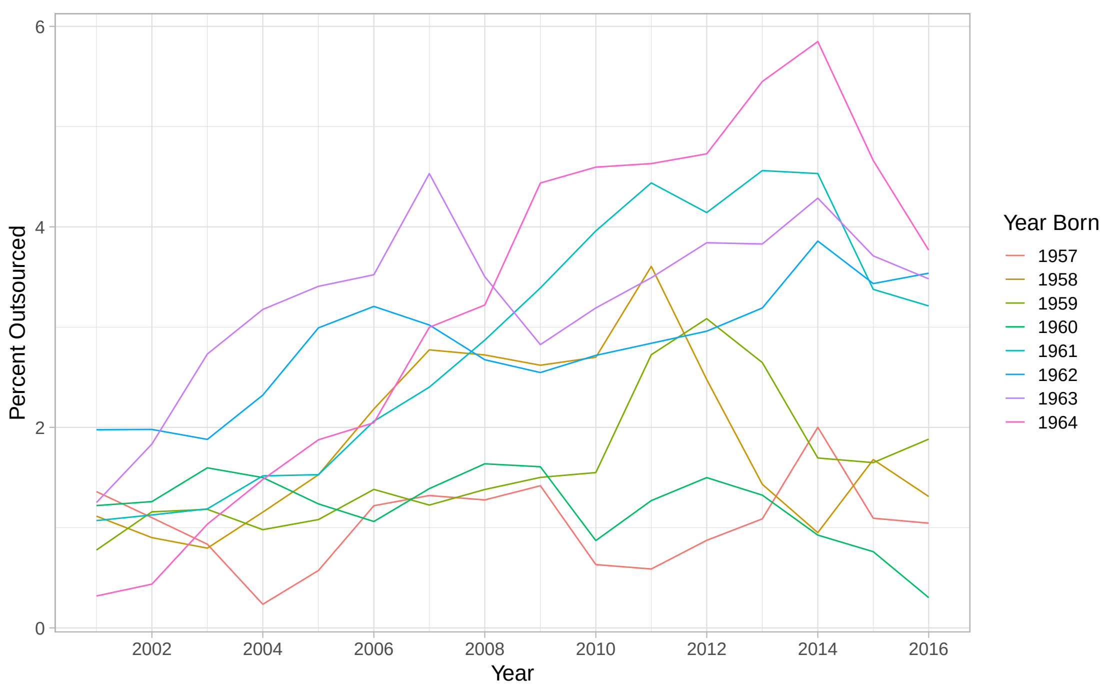

Figure A3: Percent of employed workers outsourced each year by year born.

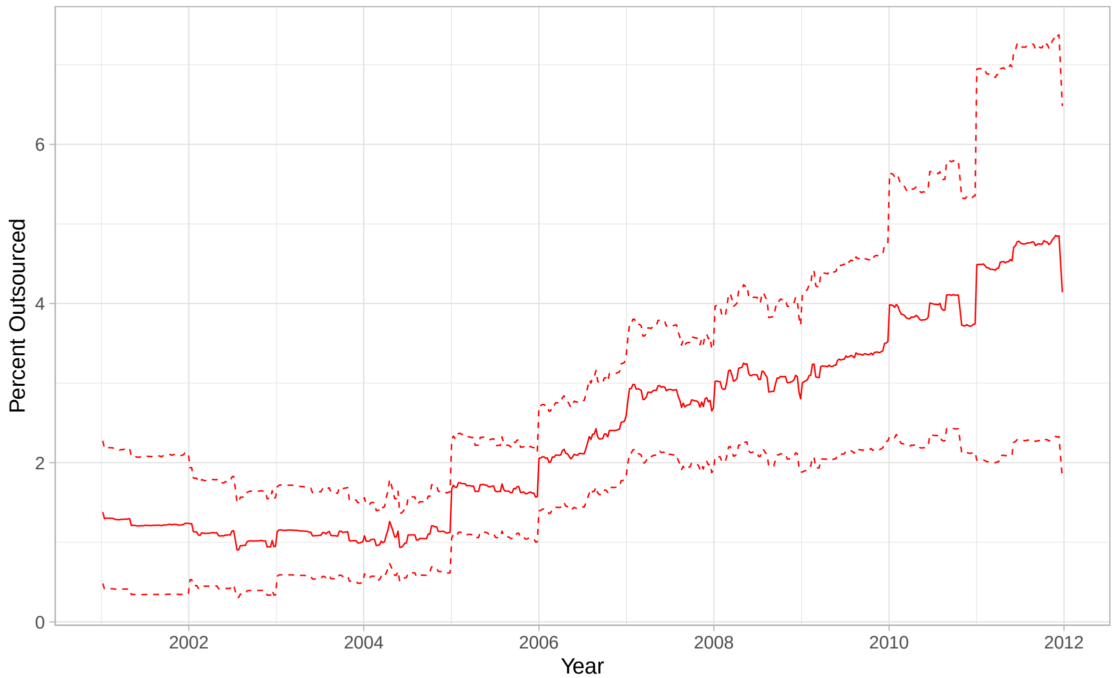

Figure A4: Percent of employed workers age 43-47 outsourced each week.

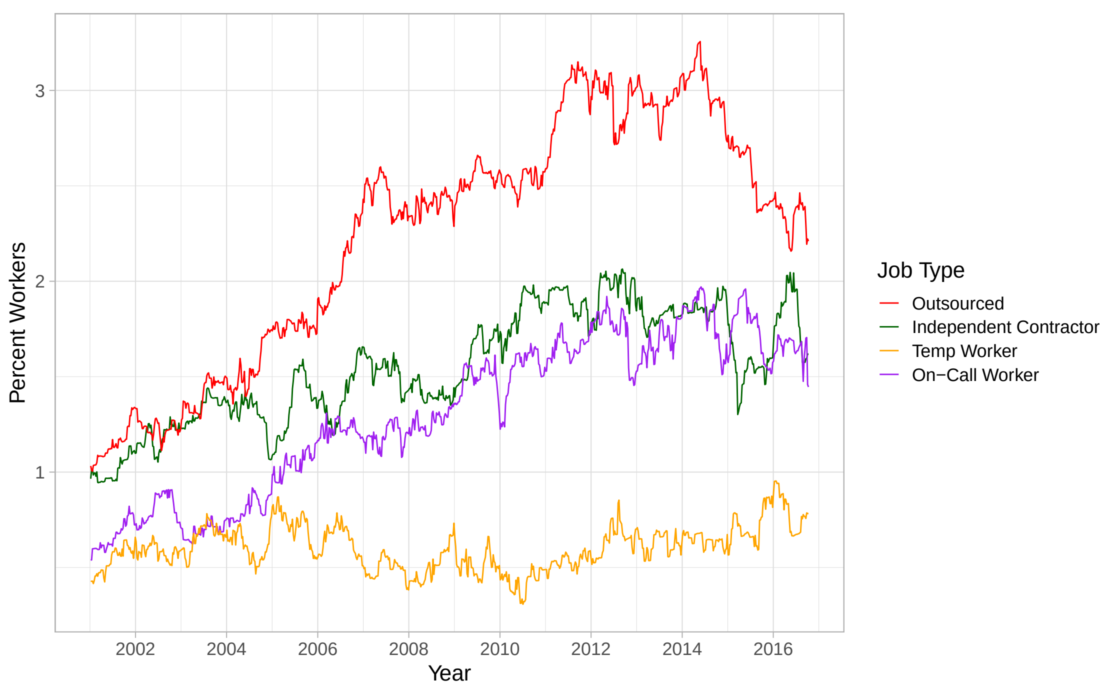

Figure A5: Percent of employed workers in each job type each week.

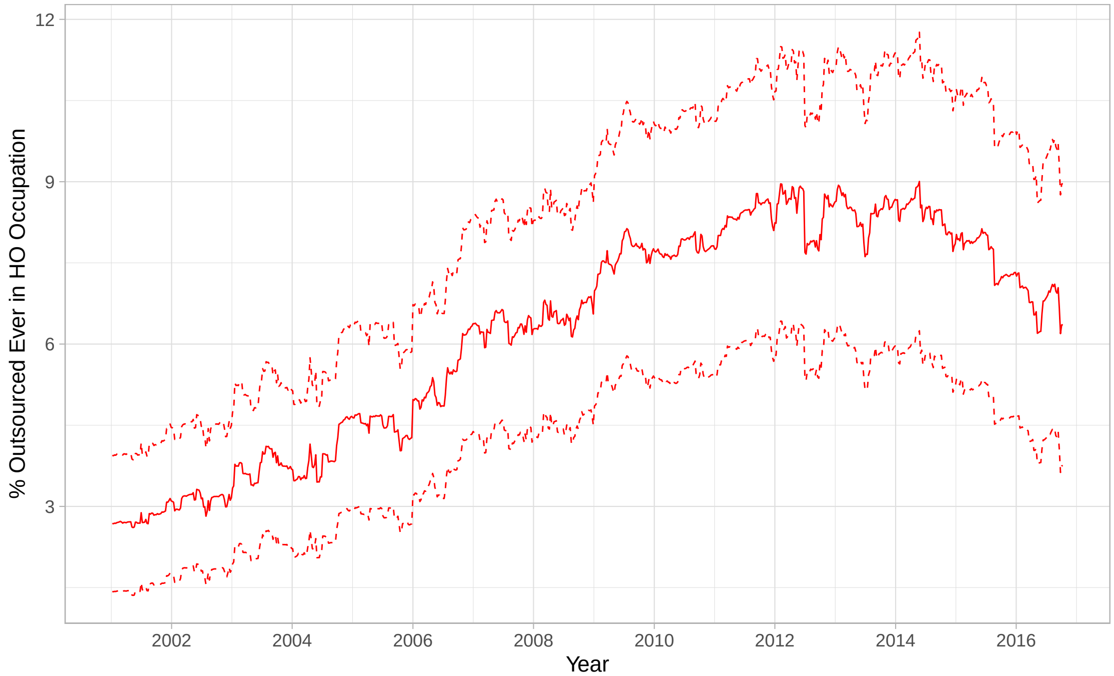

Figure A6: Percent of employed workers who ever work in a high outsourcing occupation who are outsourced each week.

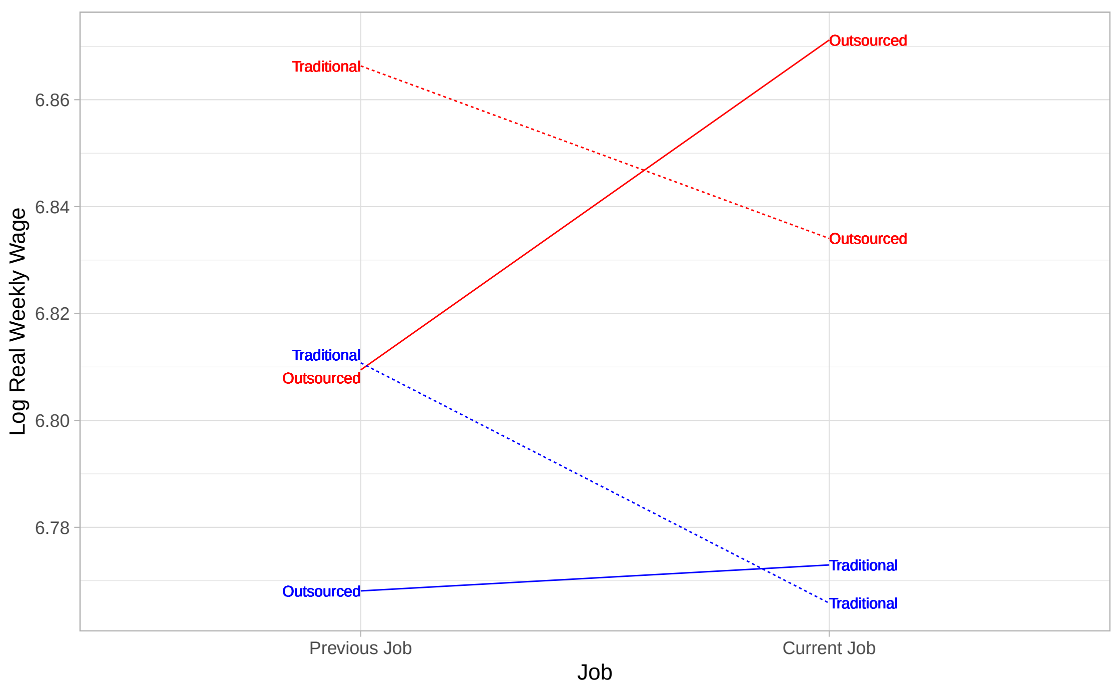

Figure A7: Mean log real weekly wages at previous and current job by current and previous job type.

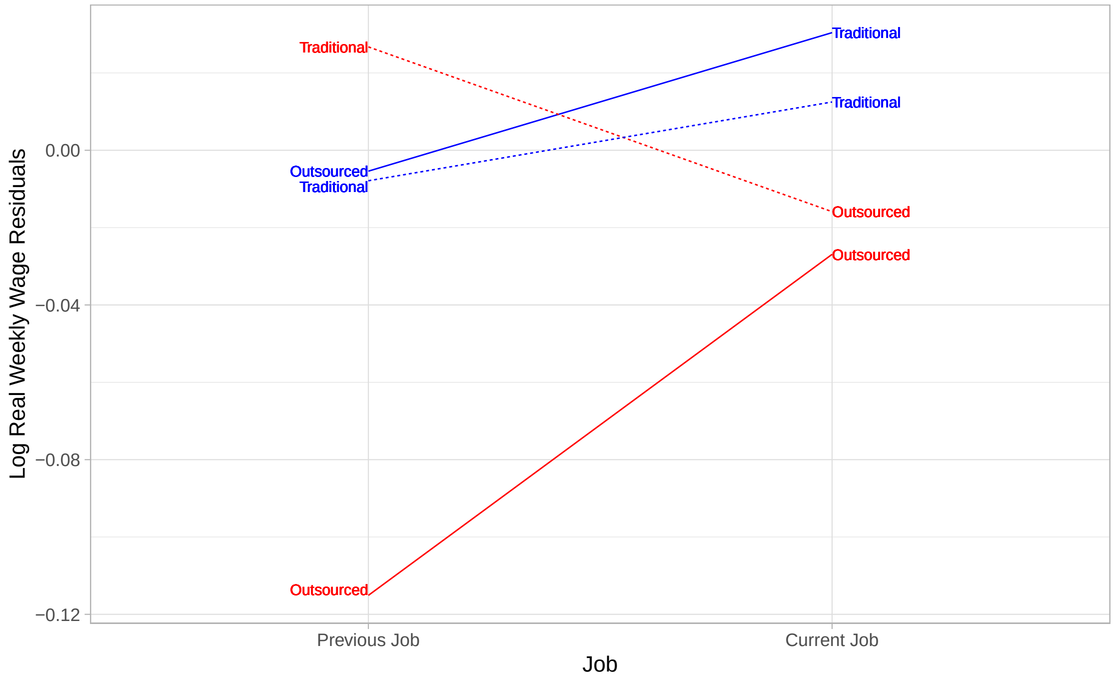

Figure A8: Mean log real weekly wage residuals at previous and current job by current and previous job type. Residuals come from a regression similar to the one described in Table A9 but without the variable *outsourced*, which indicated if a job was outsourced (see Footnote 17).

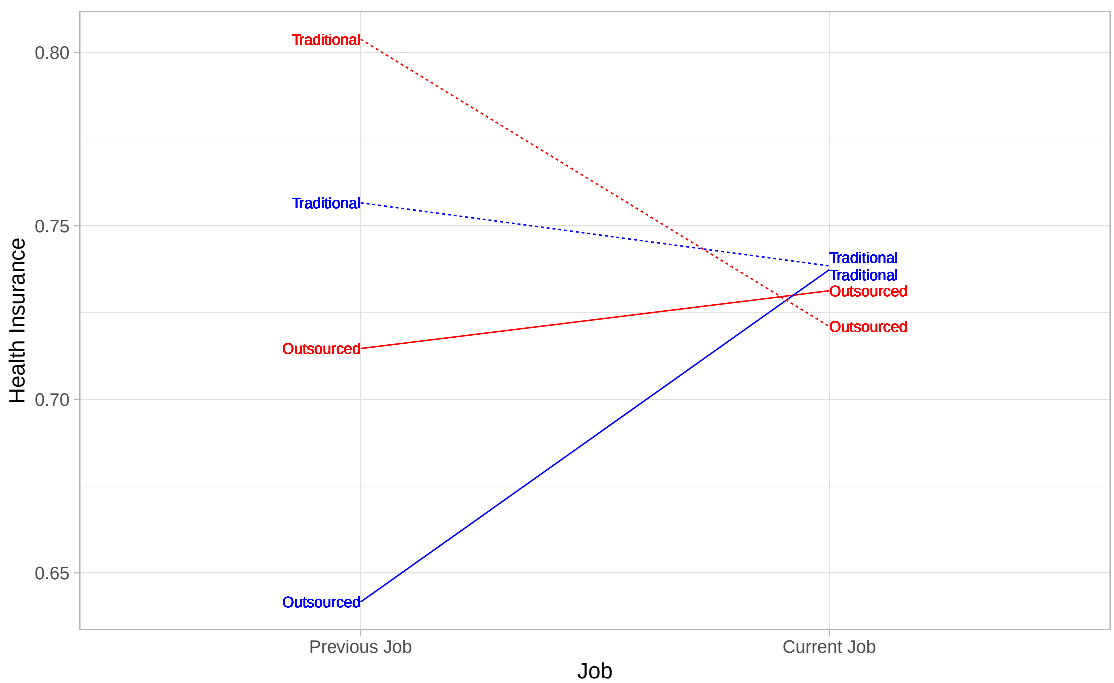

Figure A9: Percent of workers receiving health insurance at previous and current job by current and previous job type.

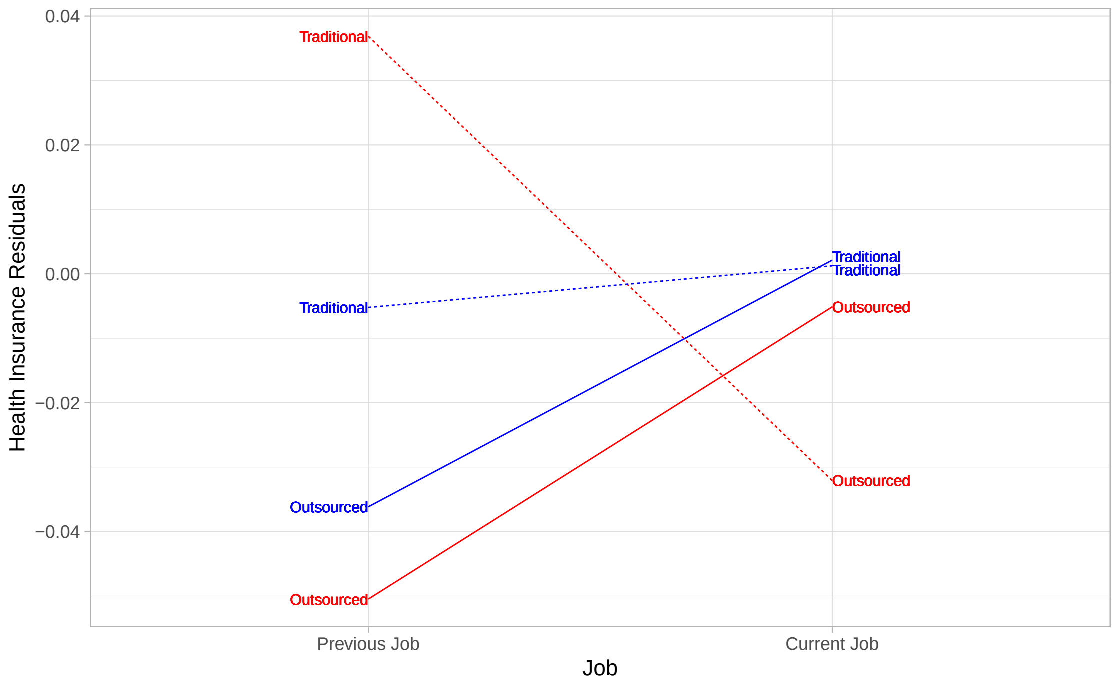

Figure A10: Mean chance of receiving health insurance residuals at previous and current job by current and previous job type. Residuals come from a regression similar to the one described in Table A9 but without the variable *outsourced*, which indicated if a job was outsourced (see Footnote 17).

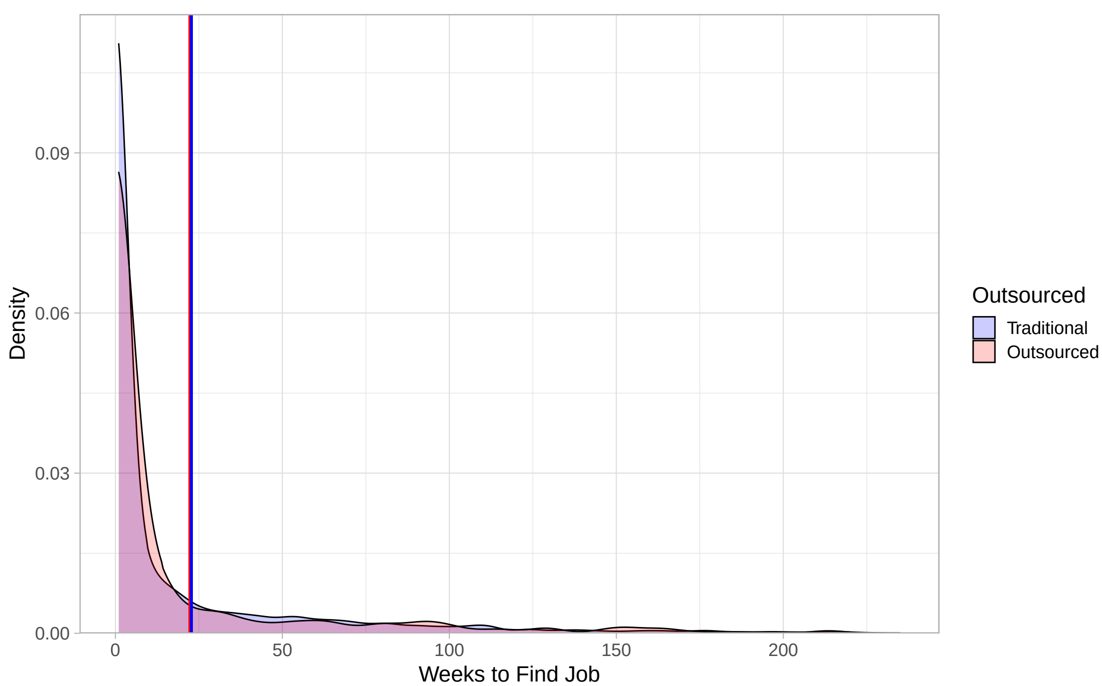

Figure A11: Weeks between previous job and current job for currently outsourced and currently traditional workers. Vertical lines are average weeks for outsourced and traditional. Graph excludes the top 1% longest transitions.

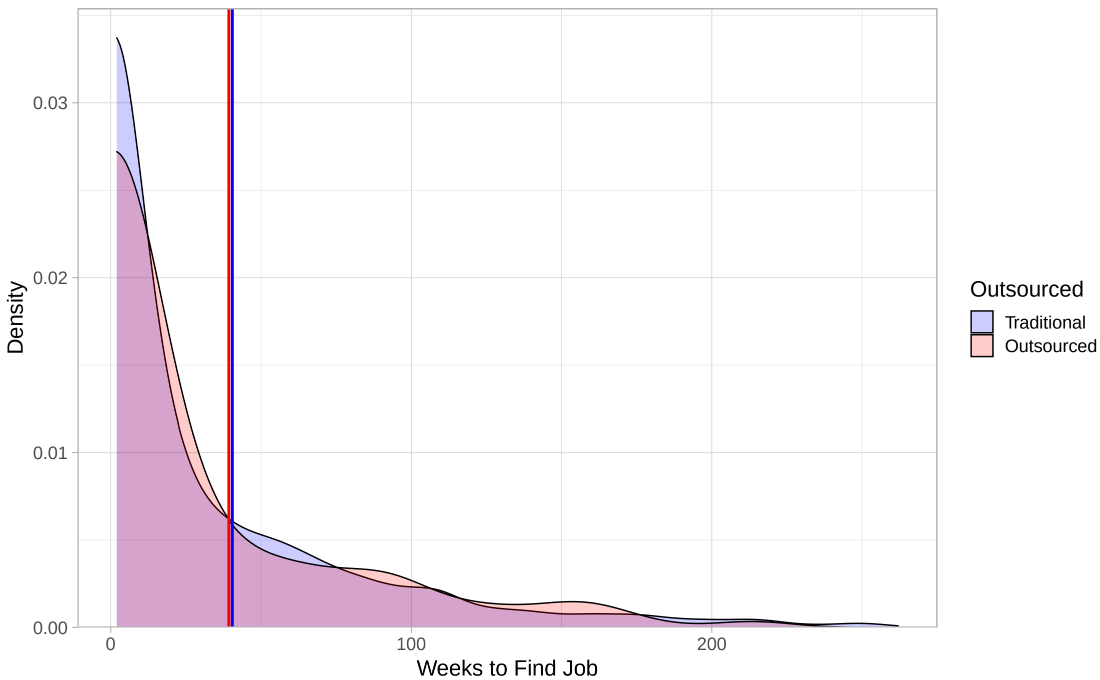

Figure A12: Weeks between previous job and current job excluding one week transitions for currently outsourced and currently traditional workers. Vertical lines are average weeks for outsourced and traditional. Graph excludes the top 1% longest transitions.

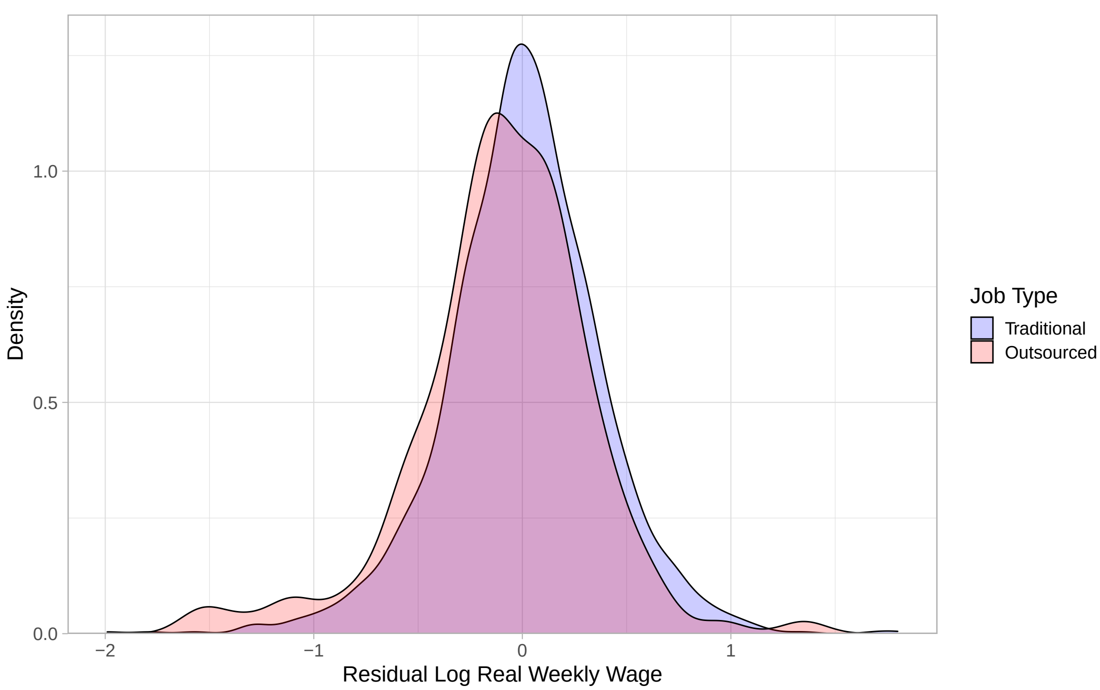

Figure A13: Residuals for outsourced and traditional jobs from a regression on log real weekly wages. All observations come from workers who were ever employed in a high outsourcing occupation. Residuals come from a regression similar to the one described in Table A9 but without the variable *outsourced*, which indicated if a job was outsourced (see Footnote 17).

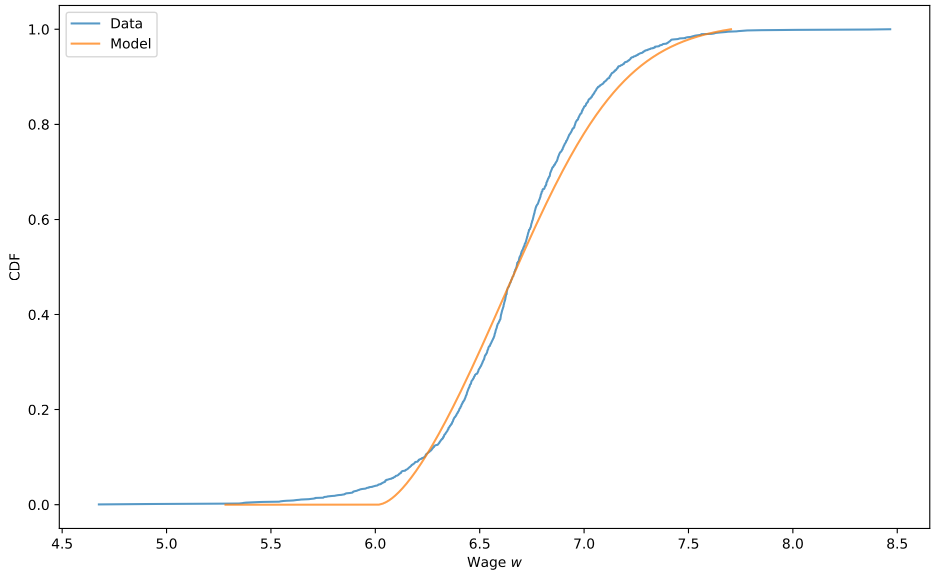

Figure A14: Distribution of log real weekly wage residuals for traditional jobs versus distribution of weekly wages at hiring firms in calibrated model.

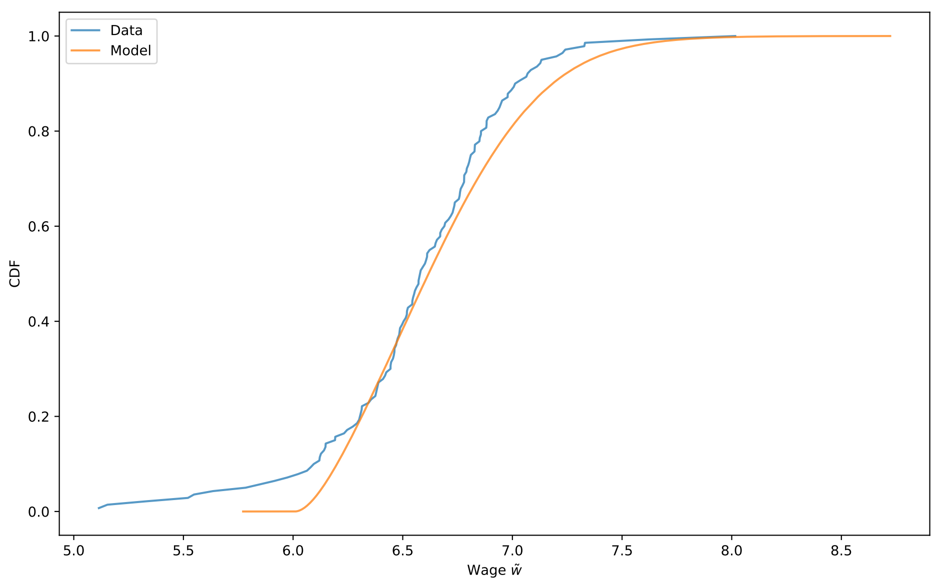

Figure A15: Distribution of log real weekly wage residuals for outsourced jobs versus distribution of weekly wages at outsourcers in calibrated model.

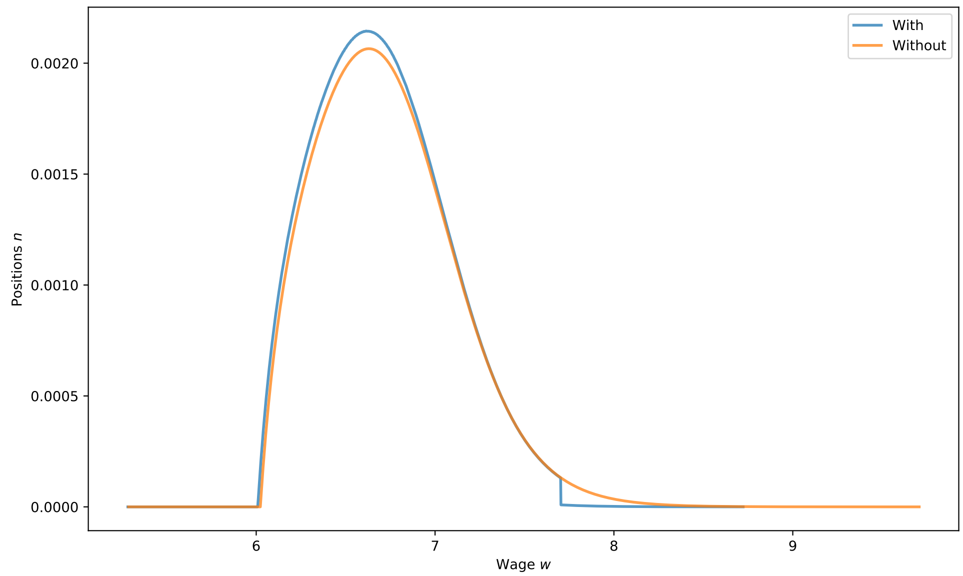

Figure A16: Distribution of workers by wages using parameters from calibrated model with and without outsourcers.

C Proofs

C.1 Proof of Proposition 1

Proof. This is the proof of Proposition 1. The marginal cost of creating a vacancy to hire or outsource is $c(v + \hat{v}, y)$, so marginal costs do not depend on how the vacancy is filled. This means the firm only needs to compare marginal benefits. Using the free entry and envelope conditions of the firm from (8), (9), (11), and (12), the relevant comparison becomes

$$\frac{q(\theta)[y - w(y)]}{r + \delta} \lesseqgtr \frac{(y - p)}{r + \delta}.$$

The left hand side is the benefit of hiring, which is the probability $q(\theta)$ of matching with a worker times the present value of the net revenue the firm gets from the match each period. The right hand side is the benefit of outsourcing, which is the present value of the net revenue the firm gets from outsourcing each period. Both sides are increasing in productivity y, but using bargained wages in (22), the left monotonically increases at rate $\frac{(1-\eta)q(\theta)}{(r+\delta)} < \frac{1}{r+\delta}$, the right's rate of increase. Define $y_{low} = b + \Gamma$, where $w(y_{low}) = y_{low}$ and $J_n(n; y_{low}) = 0$. Because the outsourcer must pay the worker his outside option but must also be compensated for entering, $p \geq y_{low}$ and $\hat{J}_n(n; y_{low}) \leq 0$ (with strict inequality if $\tilde{c} > 0$). Both marginal values are unbounded above, so there must be some y_{high} such that the RHS is greater. Therefore, because the LHS is greater for some y_{low}, the RHS is great for some $y_{high} > y_{low}$, both sides monotonically increase in y, and the RHS increases faster, these lines must cross exactly once where the firm is indifferent. I denote this point $\hat{y} \in [b + \Gamma^U, \infty)$, below which the LHS is greater and firms hire, and above which the RHS is greater and firms outsource. □

C.2 Proof of Lemma 1

Proof. This is the proof of Lemma 1. The marginal cost of creating a vacancy to hire or outsource is $c(v^P + \hat{v}^P, y)$, so marginal costs do not depend on how the vacancy is filled. This means the Planner only needs to compare marginal benefits. Using the match surplus of hiring and outsourcing firms in (39) and (40), the marginal benefit of outsourcing minus the marginal benefit of hiring is

$$[1 - q(\theta^P)][y - b - \Gamma^P] - \frac{r + \delta}{q(\theta^P)}\tilde{c} - \frac{(r + \delta)[1 - q(\theta^P)]}{\theta^P q(\theta^P)}\Gamma^P.$$

This difference is clearly negative for some y, for example $y_{low} = b - \Gamma^P$. If $q(\theta^P) < 1$, it is also clearly positive for some y_{high}, strictly increasing in y, and unbounded above. Therefore, there exists a $\hat{y}^P \in [b + \Gamma^P, \infty)$ such that the Planner is indifferent between hiring and outsourcing. Below $\hat{y}^P$, the difference is negative and the Planner prefers to hire, above $\hat{y}^P$, the difference is positive and the Planner prefers to outsource. □

C.3 Proof of Proposition 2

Proof. This is the proof of Proposition 2. To begin, note that workers make no decisions, so any taxes or transfers can be used to balance the budget without effecting the equilibrium. The Planner chooses per vacancy transfers such that firm and outsourcers spread and total entry are efficient. To ensure efficient spread for firms of productivity z and $y \geq z$, compare decentralized spread in (29)-(31) to Planner's spread in (43)-(45) if both firms hire $z \leq y \leq \hat{y}^P$, both firms outsource $\hat{y}^P \leq z \leq y$, or if one hires and the other outsources $z \leq \hat{y}^P \leq y$ to show

$$\tau(y) - \tau(z) = \eta\big(c[v^P(y); y] - c[v^P(z); z]\big) \tag{49}$$

$$\tau(y) - \tau(z) = 0 \tag{50}$$

$$(1-\eta)q(\theta)\tau(y) - \tau(z) + \tilde{\tau} = -\eta\big(c[v^P(z); z] - \tilde{c}\big). \tag{51}$$

Because low productivity hiring firms inflict a negative externality on high productivity hiring firms, they pay more in taxes. Outsourcing firms were already making efficient relative entry decisions, so they all must pay the same taxes. Taxes on outsourcers ensure the efficient spread between hiring and outsourcing firms.

To ensure efficient entry for hiring and outsourcing firms, compare decentralized entry in (32) and (33) to Planner's entry in (46) and (47) to show total entry must be

$$\begin{aligned}
&\int_{\underline{y}}^{\bar{y}} [v^P(x) + \hat{v}^P(x)](x-b)dx = \\
&\quad \frac{r+\delta+\eta\theta^P q(\theta^P)[1-\pi^P+\pi^P q(\theta^P)]}{(1-\eta)q(\theta^P)} \int_{\underline{y}}^{\hat{y}^P} v^P(x)\big(c[v^P(x); x] - \tau(x)\big)dx \\
&\quad + (r+\delta)\int_{\hat{y}^P}^{\bar{y}} \hat{v}^P(x)\big(c[\hat{v}^P(x); x] - \tau(x)\big)dx \\
&\quad + \frac{r+\delta+\eta\theta^P[1-\pi^P+\pi^P q(\theta^P)]}{1-\eta}\tilde{v}^P(\tilde{c}-\tilde{\tau}).
\end{aligned} \tag{52}$$

It is easy to show that my proposed transfer schedule satisfies my spread and entry requirements. $\square$

D Calibrated Model

In this section, I build upon the baseline model from Section 4 to create the model I calibrate to the data. The model adds a few key features:

1. I allow for worker bargaining power η and exogenous job loss δ to differ among firms and outsourcers.

2. Outsourcers now have heterogeneous productivity $o \in [\underline{o}, \bar{o}]$ with which they supply effective labor to the outsourcing market.

3. Workers can now search on-the-job with probability ξ. For simplicity, I do not allow firms to compete for workers a là Postel-Vinay and Robin (2002). Instead, the worker's outside option is always unemployment U.

Below, I define value functions and define an equilibrium for the calibrated model. Most of the notation is covered in the main text, so I will only note where it differs.

D.1 Model Overview

Previously, all firms and outsourcers had the same bargaining power with workers $1-\eta$ and exogenous firing probability δ. Firms still inherit these characteristics, but now outsourcers' bargaining power is $1-\tilde{\eta}$ and firing probability is $\tilde{\delta}$. I let outsourcers have different bargaining power with workers and have different exogenous job loss to better match wages and tenure at outsourcers.

There is an exogenous continuum of outsourcers of type $o \in [\underline{o}, \bar{o}]$ which determines how effective they are at providing effective labor to the outsourcing market. Let $\tilde{C}(v; o)$ be the outsourcer's cost of creating vacancies with $\tilde{c}(v; o) \equiv \tilde{C}_v(v; o) > 0$ as the marginal cost and $\tilde{c}_v(v; o) > 0$. Let $\tilde{v}(o)$ and $\tilde{n}(o)$ be an outsourcer's optimal vacancies and size. Total outsourcing vacancies are $\tilde{v} = \int_{\underline{o}}^{\bar{o}} \tilde{v}(a)da$. The cdf of outsourcers by type is $\tilde{F}(o) = \int_{\underline{o}}^{o} \frac{\tilde{v}(a)}{\tilde{v}}da$ with pdf $\tilde{f}(o) = \frac{\tilde{v}(o)}{\tilde{v}}$. Outsourcing firms now create $n(y)$ positions to fill with effective labor and pay p per unit of effective labor they buy, so market clearing requires $\int_{\underline{o}}^{\bar{o}} a\tilde{n}(a)da = \int_{\hat{y}}^{\bar{y}} \hat{n}(x)dx$.

Workers now search on-the-job with probability ξ each period (if they are not fired first). For simplicity, I assume firms cannot observe outside offers, so the worker's outside option is always the value of unemployment U. Recall that fraction $\zeta = \frac{\tilde{n}}{n+\tilde{n}}$ of employed workers are at an outsourcer and fraction $\pi = \frac{\tilde{v}}{v+\tilde{v}}$ vacancies are from the outsourcer. The measure of job seekers is now $s = u + \xi(1-u)[(1-\zeta)(1-\delta) + \zeta(1-\tilde{\delta})]$ and market tightness is number of vacancies per job seeker $\theta = \frac{v+\tilde{v}}{s}$. Workers only leave their job for a better one; they always go from a less productive firm (outsourcer) to a more productive firm (outsourcer) but need to decide when to change job types. Let $R(y)$ be the productivity of an outsourcer such that a hired worker at firm y is indifferent and $\tilde{R}(o) \equiv R^{-}(o)$ denote this choice from the outsourced worker's side. The distribution of better job offers is $D(y) = 1-(1-\pi)F(y) - \pi\tilde{F}[R(y)]$ when working at a firm and $\tilde{D}(o) = 1-(1-\pi)F[\tilde{R}(o)] - \pi\tilde{F}(o)$ when working at an outsourcer. Firms and outsourcers hire all unemployed workers they meet plus those working at inferior jobs. The probability a worker accepts a hiring firm's offer is $G(y) = \frac{1}{s}\left\{u + \xi\left[(1-\delta)\int_{\underline{y}}^{y} n(x)dx + (1-\tilde{\delta})\int_{\underline{o}}^{R(y)} \tilde{n}(a)da\right]\right\}$ and an outsourcer's offer is $\tilde{G}(o) = \frac{1}{s}\left\{u + \xi\left[(1-\delta)\int_{\underline{y}}^{\tilde{R}(o)} n(x)dx + (1-\tilde{\delta})\int_{\underline{o}}^{o} \tilde{n}(a)da\right]\right\}$. These all have corresponding pdfs $d(y)$, $\tilde{d}(o)$, $g(y)$, and $\tilde{g}(o)$.

D.2 Defining Equilibrium

I now cover the value functions and define equilibrium. I again conjecture, and prove below, that there exists some firm $\hat{y}$ that is indifferent between outsourcing and hiring, that less productive firms hire and more productive firms outsource. Before I do, I make Assumption D1

Assumption D1. The value of the best hired job is weakly greater than the value of the best outsourced job $W(\hat{y}) \geq \tilde{W}(\bar{o})$.

This assumption implies that the marginal firm indifferent between hiring and outsourcing could hire any worker it meets.

A hiring firm with productivity y and n workers has value

$$J(n; y) = n[y - w(y)] + \max_{v} \{-C(v; y) + \beta J(n_+; y)\} \tag{53}$$
$$\text{st. } n_+ = (1 - \delta)[1 - \xi\ell(\theta)D(y)]n + q(\theta)G(y)v,$$

an outsourcing firm with productivity y and n positions has value

$$\hat{J}(n; y) = n(y - p) + \max_{v} \left\{-C(v; y) + \beta \hat{J}(n_+; y)\right\} \tag{54}$$
$$\text{st. } n_+ = (1 - \delta)n + v,$$

and an outsourcer with productivity o and n workers has value

$$O(n; o) = n[op - \tilde{w}(o)] + \max_{v} \left\{-\tilde{C}(v; o) + \beta O(n_+; o)\right\} \tag{55}$$
$$\text{st. } n_+ = (1 - \tilde{\delta})[1 - \xi\ell(\theta)\tilde{D}(o)]n + q(\theta)\tilde{G}(o)v.$$

The intuition is similar to before, but now outsourcer's revenue is the price times her productivity and hiring firms and outsourcers must worry about their workers leaving for better jobs and will not hire every worker they meet. As before, we can take the free entry and envelope conditions of (53)-(55) in steady state to show

$$c[v(y); y] \geq \beta q(\theta) G(y) J_n(n; y) \tag{56}$$

$$c[\hat{v}(y); y] \geq \beta \hat{J}_n(n'; y) \tag{57}$$

$$\tilde{c}[\tilde{v}(o); o] \geq \beta q(\theta) \tilde{G}(o) O_n(n'; o) \tag{58}$$

$$J_n(n; y) = \frac{(1+r)[y - w(y)]}{r + \delta + (1-\delta)\xi \ell(\theta) D(y)} \tag{59}$$

$$\hat{J}_n(n; y) = \frac{(1+r)(y-p)}{r+\delta} \tag{60}$$

$$O_n(n; o) = \frac{(1+r)[op - \tilde{w}(o)]}{r + \tilde{\delta} + (1-\tilde{\delta})\xi \ell(\theta) \tilde{D}(o)} \tag{61}$$

$$w(y) = y - \frac{r + \delta + (1-\delta)\xi \ell(\theta) D(y)}{q(\theta) G(y)} c[v(y); y] \tag{62}$$

$$p = y - (r+\delta) c[\hat{v}(y); y]. \tag{63}$$

$$\tilde{w}(o) = op - \frac{r + \tilde{\delta} + (1-\tilde{\delta})\xi \ell(\theta) \tilde{D}(o)}{q(\theta) \tilde{G}(o)} \tilde{c}[\tilde{v}(o); o]. \tag{64}$$

The interpretation is mostly unchanged from the main text. Firms and the outsourcer set marginal cost of entry equal to marginal benefit, value matches for the present value of net revenue over the expected life of the match, and are willing to pay revenue minus amortization costs each period.

Workers can be unemployed, employed at a firm, or employed at an outsourcer. The value of being employed at a firm of productivity y, at an outsourcer of productivity o, or unemployed are

$$W(y) = w(y) + \beta\Bigg\{\delta U + (1-\delta)\xi\ell(\theta)\left[(1-\pi)\int_y^{\hat{y}} W(x)dF(x) + \pi\int_{R(y)}^{\bar{o}} \tilde{W}(a)d\tilde{F}(a)\right] \\ + (1-\delta)[1-\xi\ell(\theta)D(y)]W(y)\Bigg\} \quad (65)$$

$$\tilde{W}(o) = \tilde{w}(o) + \beta\Bigg\{\tilde{\delta}U + (1-\tilde{\delta})\xi\ell(\theta)\left[(1-\pi)\int_{\tilde{R}(o)}^{\hat{y}} W(x)dF(x) + \pi\int_o^{\bar{o}} \tilde{W}(a)d\tilde{F}(a)\right] \\ + (1-\tilde{\delta})[1-\xi\ell(\theta)\tilde{D}(o)]\tilde{W}(o)\Bigg\} \quad (66)$$

$$U = b + \beta\left\{\ell(\theta)\left[(1-\pi)\int_{\underline{y}}^{\hat{y}} W(z)dF(z) + \pi\int_{\underline{o}}^{\bar{o}} \tilde{W}(a)d\tilde{F}(a)\right] + [1-\ell(\theta)]U\right\}. \quad (67)$$

Workers now have the ability to search on-the-job, which makes employment more valuable, but otherwise the interpretation is the same as the main text. Note that for Assumption D1 to hold, we need either $w(\hat{y}) \geq \tilde{w}(\bar{o})$ or δ to be sufficiently smaller then $\tilde{\delta}$ so the worker makes more each period or the match is expected to last longer. In the data, $w(\hat{y}) \approx \tilde{w}(\bar{o})$ and $\delta < \tilde{\delta}$, which is sufficient.

As in Stole and Zwiebel (1996), workers and firms (outsourcers) Nash bargain over the marginal value of the match, with workers having bargaining power η ($\tilde{\eta}$). Firms (outsourcers) bargain after paying vacancy costs, so their marginal outside option is 0, while worker's outside option is unemployment. This means $\eta J_n(n;y) = (1-\eta)[W(y)-U]$ and $\tilde{\eta}O_n(n;o) = (1-\tilde{\eta})[\tilde{W}(o)-U]$. Using these bargaining rules, the first order conditions in (56) and (58) to solve for $W(y)-U$ and $\tilde{W}(o)-U$, we rewrite the value of unemployment in (67) as

$$\frac{r}{1+r}U = b + \Gamma^U, \quad (68)$$

where $\Gamma^U \equiv \Gamma(\underline{y}, \underline{o})$ is the value of search while unemployed and

$$\Gamma(y,o) \equiv \theta \left\{ \frac{\eta}{1-\eta}(1-\pi) \int_y^{\hat{y}} \frac{c[v(x);x]}{G(x)} dF(x) + \frac{\tilde{\eta}}{1-\tilde{\eta}} \pi \int_o^{\bar{o}} \frac{\tilde{c}[\tilde{v}(a);a]}{\tilde{G}(a)} d\tilde{F}(a) \right\}$$
$$= \frac{1}{s} \left\{ \frac{\eta}{1-\eta} \int_y^{\hat{y}} \frac{v(x)c[v(x);x]}{G(x)} dx + \frac{\tilde{\eta}}{1-\tilde{\eta}} \int_o^{\bar{o}} \frac{\tilde{v}(a)\tilde{c}[\tilde{v}(a);a]}{\tilde{G}(a)} da \right\}, \tag{69}$$

is the value of search at a given job. Workers split the marginal benefit of the firm they match with, but they only take the job if it is better than their current option, which is either $(y, R(y))$ or $(\tilde{R}(o), o)$ depending on if the worker is at a firm or an outsourcer.

To find the wage at a hiring firm or outsourcer we can use the value of unemployment (68), the value of working for a firm or outsourcer in steady state in (65) or (66), the firm's or outsourcer's envelope condition in (59) or (61), and the bargaining rule to solve

$$w(y) = \eta y + (1-\eta)\Big(b + \Gamma^U - (1-\delta)\xi\Gamma[y, R(y)]\Big) \tag{70}$$
$$\tilde{w}(o) = \tilde{\eta} op + (1-\tilde{\eta})\Big(b + \Gamma^U - (1-\tilde{\delta})\xi\Gamma[\tilde{R}(o), o]\Big). \tag{71}$$

The worker gets his share of the total revenue and must be compensated for forgoing unemployment less the value he gains from searching on the job.

The key to determining how workers find new jobs at firms (outsourcers) is the reservation productivity of the outsourcer (firm) $R(y)$ ($\tilde{R}(o)$) the worker is indifferent to. For a worker to be indifferent between a firm and outsourcer job, they need $W(y) - U = \tilde{W}[R(y)] - U$. Using the value of employment at the firm (65) and outsourcer (66) in steady state, the value of unemployment in (68), and the fact that $D(y) = \tilde{D}[R(y)]$, we can show this comparison implies

$$\tilde{w}[R(y)] = \frac{X(y;\tilde{\delta})w(y) + (\tilde{\delta} - \delta)\left\{\xi\Gamma[y, R(y)] - [1 - \xi\ell(\theta)D(y)](b + \Gamma^U)\right\}}{X(y;\delta)}, \tag{72}$$

where $X(y;\delta) \equiv r + \delta + (1-\delta)\xi\ell(\theta)D(y)$. The worker considers the expected wage over the life of the match plus the value of avoiding unemployment. When $\delta = \tilde{\delta}$, this collapses to $\tilde{w}[R(y)] = w(y)$ because the worker only compares wages. When $\delta \neq \tilde{\delta}$, the worker puts more value on the job where they are less likely to be fired. We can define the outsourced worker's reservation wage similarly.

I now want to prove my conjecture that $\hat{y}$ is indifferent between hiring and outsourcing and that firms below hire and firms above outsource. Because the cost of creating a vacancy to fill with a direct or outsourced worker is the same, the firm's choice of obtaining workers depends on the greater benefit. Using the free entry and envelope conditions from (56), (59), (57), and (60), the relevant comparison is

$$q(\theta)G(y)\frac{y - w(y)}{r + \delta + (1-\delta)\xi\ell(\theta)D(y))} \lesseqgtr \frac{y-p}{r+\delta}.$$

By Assumption D1, the marginal hiring firm offers better terms than all outsourcers (it already offers better terms than all other hiring firms), so the firm hires every worker it meets $G(y) = 1$ and $g(y) = 0$ and never loses its workers to others $D(y) = 0$ and $d(y) = 0$. Taking the derivative of both sides with respect to y using the hiring wage in (70) gives $(1-\eta)q(\theta) < 1$, which is true. The value of outsourcing increases in productivity faster than the value of hiring, but both are monotone increasing and unbounded. There exists a $y_{low} = b + \Gamma^U - (1-\delta)\xi\Gamma[y_{low}, R(y_{low})]$ such that the LHS is 0 and the RHS is negative. Therefore, there exists a unique $\hat{y}$ where these are equal and the firm is indifferent between hiring and outsourcing, below $\hat{y}$ firms prefer to hire, and above firms prefer to outsource.[46]

Given all of the above, I define my equilibrium in Definition 2

Definition 2. A steady state equilibrium consists of optimal firm vacancy and position policies $(v(y), n(y), \hat{v}(y), \hat{n}(y))$, optimal outsourcer vacancy and position policies $(\tilde{v}(o), \tilde{n}(o))$, market tightness θ, worker value of unemployment U and reservation values $(R(y), \tilde{R}(o))$ and wages at firms and outsourcers and price of outsourcing $(w(y), \tilde{w}(o), p)$ such that

[46]While the assumptions made were reasonable, they are sufficient but not necessary for $\hat{y}$ to exist, as implied by the proof.

1. Given market tightness θ, worker reservation values $(R(y), \tilde{R}(o))$, worker wages $w(y)$ and $\tilde{w}(o)$, and outsourcing price p, firms choose $(v(y), n(y), \hat{v}(y), \hat{n}(y))$ and outsourcers choose $(\tilde{v}(o), \tilde{n}(o))$ to satisfy the firm free entry and envelope conditions in (56)-(61).

2. Given market tightness θ and bargained wages $w(y)$ and $\tilde{w}$, the value of unemployment U satisfies (67) and worker reservation values $(R(y), \tilde{R}(o))$ satisfy (72).

3. Market tightness θ is consistent with firm and outsourcer choices of vacancies and positions.

4. Given the workers value of unemployment U and reservation values $(R(y), \tilde{R}(o))$, bargaining between the firm and the worker yields wage $w(y)$ in (70) and bargaining between the outsourcer and the worker gives wage $\tilde{w}(o)$ in (71).

5. The market for effective outsourced labor clears.

In short, steady state equilibrium requires firms and outsourcers to make optimal vacancy and position choices given market tightness, worker reservation values, wages, and prices. These factors also determine the worker's value of unemployment. In turn, these choices and the value of unemployment must imply these same market tightness, reservation values, wages, and prices.

E Data Cleaning

In this section, I describe the data cleaning process, including the algorithm I use to match On Jobs to the Employer Supplement. In Subsection E.3, I list all of the variables used. The data sets used are the National Longitudinal Survey of Youth 1979 (NLSY), NLSY custom weights generated at `https://www.nlsinfo.org/weights/nlsy79` using option "The respondents are in any or all of the selected years" for 2002-2016, FRED's CPIAUCSL to measure annual CPI for years 1979-2016, and IPUMS Current Population Survey (CPS).

For the NLSY, I use data for all male respondents from 2002-2016, where respondents are surveyed every 2 years.[47] My analysis focuses on 3 questionnaires within the sample: On Jobs (sometimes On Jobs New or On Employers), Employer Supplement, and Employer History Roster.[48] On Jobs provides data on whether a worker was outsourced at a job, the Employer Supplement provides most other job details, and the Employer History Roster is a retrospective data set that records when a worker is employed at the weekly level. My main challenge is to match On Jobs to the Employer Supplement by recreating the NLSY's sorting process.

E.1 Matching On Jobs to the Employer Supplement

Respondents first go through On Jobs, where they are asked about jobs they held at date of last interview (DLI), if they resumed any jobs they held prior to the date of last interview (here called PLI but NLSY calls PDLI),[49] and new jobs not reported previously (here call NJ but NLSY calls NEWEMP).[50] The main part of this questionnaire asks if the respondent is still working at this job and, if not, when he stopped working. Starting in 2002, respondents are also asked if their job is non-traditional: contracted out, self-employed, an independent contractor, a temp worker, or an on-call worker.[51] If respondents start this loop (Q6-8E_1A for DLI), they are asked a series of questions about their job type. Typically, if they answer affirmatively to one type, then they are not asked about subsequent job types, so I take non-responses of people who started the loop to be 0's.[52] I use this measure to find the

[47] I retrieved most NLSY data from the public use investigator at https://www.nlsinfo.org/investigator/pages/search but also from errata at https://www.nlsinfo.org/content/cohorts/nlsy79/other-documentation/errata/errata-1979-2016-data-release.

[48] See https://www.nlsinfo.org/content/cohorts/nlsy79/other-documentation/questionnaires for details about the questionnaires of the NLSY.

[49] This means any jobs they did not currently hold when interviewed last. It can include jobs respondents reported working in last interview but were not working at the time of last interview.

[50] Interview years 2014 and 2016 do not have a PLI or NJ section, all jobs are lumped together in DLI.

[51] When the NLSY 79 added the new section on non-traditional jobs, they purposefully skipped many jobs they believed were definitely traditional. Question Q8-8F (for DLI) and Q6-16F (for PLI) record if these jobs were skipped (about 90% of jobs), which I assume are traditional.

[52] Some respondents went back and changed their answers to these questions, which are coded as a new variable. If the respondent changed their answer, I take this answer as the true response.

job type of each worker; if they do not indicate their job is non-traditional, I assume it is a traditional job. I call a worker outsourced if he answers affirmatively to Q6-8H_A5A (for DLI) indicating that he is contracted out at this job.

Respondents then fill out the questionnaire for the Employer Supplement. The order jobs are listed for the Employer Supplement is derived by ranking the jobs from On Jobs by quit date, from most recent to least, with any jobs currently worked listed first. These jobs are matched by employer UID to past jobs or given a new employer UID based on survey year and job number.[53] In the Employer Supplement, respondents are asked a rich subset of questions about the first 5 listed jobs, including: wages, hours worked, occupation, industry, weeks of tenure, and various benefits. Through employer UID and Employer History Roster, these statistics can be connected throughout a respondent's career.

To link the On Jobs and Employer Supplement, I will attempt to recreate sorting process that originally transformed the On Jobs roster into the Employer Supplement roster. This ranking follows[54]

1. Current main job, as reported in ONJS-8800.

2. Other current jobs, as reported in Q6-8I (for DLI).

3. Date stopped working job, most to least recent, as recorded in Q6-9 (for DLI).

I break ties by type, DLI then PLI then NJ.[55] I have three main ways of matching On Jobs to Employer Supplement: start month, end month, and rank; although many jobs are missing one or more of these variables in the On Jobs section.[56] I therefore match several different ways, from highest to lowest quality, as follows:

[53] For more on how the Employer Supplement roster is created for these years, see Appendix 8 for the NLSY 1997 https://www.nlsinfo.org/content/cohorts/nlsy97/other-documentation/codebook-supplement/appendix-8-instrument-rosters/page/0/1.

[54] For an example of how sorting works from the NLSY 1997, see https://www.nlsinfo.org/content/cohorts/nlsy97/other-documentation/codebook-supplement/appendix-8-instrument-rosters/page/0/1

[55] It seems like the NLSY breaks ties this way, but I was unable to find how priority is determined explicitly.

[56] For example, if a job began before last interview and ends after the current interview, then the Employer Supplement lists the start and end month as the date of the last and current interview respectively, while On Jobs leaves these blank.

1. Start and end month and job rank all match.
2. Start and end month both match.[57]
3. Start month and rank.[58]
4. End month and rank.
5. Start month.
6. End month.
7. Only jobs in both On Jobs and Employer Supplement for this person in this interview year left unmatched.[59]
8. If all unmatched jobs within a year are of one type (say all traditional), assume all jobs are this type.
9. Rank.

I allow for Employer Supplement jobs to be matched multiple times across interviews. Once I have my matches, I keep the highest quality match for each Employer Supplement job. If a job has more than one highest quality match within the same year, I drop all matches. Because the alternative job questions are usually only answered at the first interview, I fill in missing job types with answers from other years, dropping matches if there are conflicting non-missing responses.[60] I also drop any conflicting start or end months between the data sets. Table A3 below shows the number of matches by each quality Table A1 shows the number of observations added/subtracted at each step of the matching process from

[57] I prioritize start and end month matching over rank as rank is imputed and could be incorrect.

[58] I prioritize matches by start month because these are mainly new jobs and often respondents only go through the job type loop in the first interview.

[59] Most of these jobs are the only jobs a respondent reports in an interview.

[60] Some respondents respond to multiple job types in the same survey year, most notably self-employed and independent contractors. I give each worker a single job type using the hierarchy: independent contractor, outsourced, temp worker, self employed, on-call workers.

the Employer Supplement/Employer History Roster Side, while Table A2 shows the match quality from the On Jobs side.

E.2 Creating data sets

In the following subsection, I comment on how the data is cleaned. I create five main data sets using the NLSY: one with data by person-job-interview, one with data by person-job, one weekly timeline of a person's job history, one that links current job to previous and next jobs, and one that averages all respondents' job characteristics by occupation each week. I start by creating my person-job-interview data set and use this to create the others, so most of the explanation will cover how this data set is created.

I first cover variables from On Jobs, which are listed in Table E1. Most of them have been previously mentioned, and are mainly used to determine job type or to match On Jobs with the Employer Supplement. I use this data to divide respondents into those who ever worked an outsourced job to those who did not, including those who work unmatched outsourced jobs.

I next cover variables in the Employer History Roster, which are listed in Table E3.[61] From these variables, I can find start and stop week of job spells, weeks of job tenure, hours worked at job per week, industry and occupation using 2000 census codes, if job is part of union, and hourly wage. I use FRED's measure of CPI, CPIAUCSL, to make wages real in 2016 dollars.[62] I multiply hourly wage by weekly hours worked to obtain weekly wages, and measure wages in logs. I drop wages of people making less than \$3.30 (Federal minimum wage in 2002 was \$5.15, which is equivalent to about \$6.60 in 2016) or more than \$400 in real hourly wages or working 0 hours or more than 80 hours per week. I classify a worker as part time if they work less than 35 hours a week.

[61] This data is collected retrospectively, and much of it comes from the Employer Supplement or On Jobs. I often take data from here as it is more likely to be cleaned and corrected. For more on the Employer History Roster, see https://nlsinfo.org/content/cohorts/nlsy79/topical-guide/employment/nlsy79-employer-history-roster.

[62] Access the CPI data at https://fred.stlouisfed.org/series/CPIAUCSL#0.

I also use the history roster variable EMPLOYERS_ALL_STATUS_WK_NUM, which is a weekly measure of labor market activity, for weeks 1202 - 2024 which correspond to January 2001 - October 2016. Weekly data starts to become scarce after October 2016, so I drop weeks after this month. Each week, I measure if a worker reports being employed, unemployed, or not working.[63] After creating the person-job data set, I use weeks started and stopped working each job to match to the job worked each week. If multiple jobs are reported, I break ties using the following hierarchy: hours worked per week, tenure, real weekly wage, highest occupation code, lowest employer UID. With this timeline, I can see what percent of workers are outsourced in the average week. This is my main measure of overall outsourcing. I look at this for each occupation, and define an occupation as high outsourcing if more than twice the average number of workers are outsourced each week (over 4.34%). I define ever high outsourcing workers as those who ever work in such an occupation.

I next cover variables in the Employer Supplement, which are listed in Table E4. These are job variables that are not listed in the Employer History Roster. I look at respondent's job satisfaction, which is rated from 1 to 4, 1 being the most satisfied. This proxies for total job satisfaction summarized by wages, earnings, other compensation, and working conditions. I also look at dummies for whether a job provides various benefits: health, life, or dental insurance; maternity leave; retirement benefits; flexible hours; profit sharing; training or education; and company provided child care. I then combine these together to record if respondent received any benefits.[64]

I finally cover variables from the rest of the NLSY, which are listed in Table E5. These are mostly demographic variables. I record sample ID, which is the demographic portion (based on sex, race, family income, and military) that the respondent comes from; the NLSY over-samples Hispanics, Blacks, and military members. I often cluster regressions using this

[63] This measure also reports which job the respondent was working at, but the measure is confusing and it is not always clear which job is being referenced. As a result I do not use this information.

[64] I use the NLSY's measure of any benefits only to confirm that a worker received no benefits (these people are not asked any of these benefit questions). If workers received benefits not in the sample, I do not count them as receiving any.

variable. I measure race/ethnicity as Hispanic, Black, or neither. I measure birth year, which I use to construct age for each year. I measure if the person is in an MSA (or MSA central city) and what region of the country they are from.[65] Each year, I take marital status and record if single or married (vs divorced/widowed/separated), the number of kids respondent ever had, and number of kids in respondent's household.

Every interview, the NLSY asks highest degree received, but often skips responses if answer has not changed from previous year. Two years with reliable updates for most respondents are 1988 and 2008. After these years, I update education only if the respondent answers this question. For 1988, I assume those with a valid skip (-4) had a high school education or less, as this is not given as an option; 2008 does not have this problem. Given this highest degree, I divide the sample into education bins: less than high school, high school diploma, associates degree, bachelors degree (of arts or science), and higher/other degree.

Once I clean all of the data, I go thorough my matching process described in Subsection E.1 above to create my person-job-year data set. To create my job-year data set, I use average and modal job characteristics over each interview.[66] I then use job start and end weeks to match my job-year data set to my timeline data set.[67] To create my data set linking current job to previous and next jobs, I rank timeline jobs by start and end date and keep all jobs with the same rank.[68] I then link current jobs to the previous and next job. Finally, I group my timeline data by occupation and week to create my aggregate occupation data set.

I also use IPUMS CPS data in two different ways. The first is to use the main survey to compare to my timeline of workers, the second is to use the Contingent Worker Supplement

[65] I do not use restricted state-level data.

[66] If there is no modal outcome, I use the observation from the first interview.

[67] I also aggregate at the month level to compare with the CPS. For robustness, I match my person-job-year data set, which allows job characteristics to change with each interview. Email author for details.

[68] Because workers can be employed at multiple jobs simultaneously, overlapping jobs can look like job transitions even when no transition has occurred. Keeping only jobs with the same ranked start and end date drops these occurrences.

(CWS) to compare to my measure of outsourcing. The variables I use for both analyses are in Table E6, for only the timeline are in Table E7, and for only the CWS are in Table E8. For the timeline, I use the monthly survey from January 2001 - October 2016, looking only at men aged 18-65. I match NLSY definitions for each variable such as race/ethnicity and education. For my timeline, the CPS uses 2010 occupation codes while the NLSY uses 2000 codes, so I use a crosswalk to match occupations.[69] I use this timeline to create two data sets. The first divides jobs into high outsourcing occupations and examines how different they are from the general population overall and for the NLSY cohort born between 1957-1964. The second averages job characteristics of each occupation by month, taking percent of workers in each job type (such as outsourced) from the NLSY.

For CWS, I use both men and women from all 6 rounds of the supplement: 1995, 1997, 1999, 2001, 2005, and 2017. I divide workers by self-report job type, including self-employed, and grouping together CWCONTRACTIC and CWSEEMP under independent contractors. Any worker without a type is reported as traditional. I then use occupation and industry codes to measure outsourcing as in Dube and Kaplan (2010), which classifies janitors and security guards (occupations 453 and 426) as outsourced if they are in certain industries (722 and 740).

E.3 Variables Used

In this section, I list the variables used in each data subset, a brief description, and years used. For years, "All" means 2002-2016. I also used FRED's CPIAUCSL from 1979-2016 `https://fred.stlouisfed.org/series/CPIAUCSL#0`, NLSY 79 custom weights generated at `https://www.nlsinfo.org/weights/nlsy79` using option "The respondents are in any or all of the selected years" for 2002-2016, and IPUMS CPS data from January 2001 - October 2016.

[69] The crosswalk is the file "integrated_ind_occ_crosswalks.xlsx" which can be found at `https://usa.ipums.org/usa/volii/occ_ind.shtml` using the hyperlink "Crosswalk" from the bullet reading, "Crosswalks for OCC1950, OCC1990 or OCC2010 to the contemporary OCC codes and for IND1950 or IND1990 to the contemporary IND codes."

Variable	Description	Years
Q6-15	Date began job (PLI)	2002
PDLI-15	Date began job (PLI)	2004-2012
Q6-27A	Date began job (NJ)	2002-2012
Q6-8I	Currently working job (DLI)	2002-2014
Q6-8	Currently working job (DLI)	2016
Q6-16I	Currently working job (PLI)	2002-2012
Q6-27I	Currently working job (NJ)	2002-2012
Q6-9	Last stopped working job (DLI)	All
Q6-17	Last stopped working job (PLI)	2002-2012
Q6-27K	Last stopped working job (NJ)	2002-2012
ONJS-8800	Current job worked most	All
Q6-8E_1A (Only end .01)	Began question loop (DLI)	All
Q6-16E_1A (Only end .01)	Began question loop (PLI)	2002-2012
Q6-27D_1A (Only end .01)	Began question loop (NJ)	2002-2012
Q6-8F	Job preassigned traditional (DLI)	2002-2010
Q6-16F	Job preassigned traditional (PLI)	2002-2012
Q6-8H_A1	Self-employed (DLI)	All
Q6-16H_A1	Self-employed (PLI)	2002-2012
Q6-27E_A1	Self-employed (NJ)	2002-2012
Q6-8H_A2	Independent contractor (DLI)	All
Q6-16H_A2	Independent contractor (PLI)	2002-2012
Q6-27E_A2	Independent contractor (NJ)	2002-2012
Q6-8H_A3	Temp worker (DLI)	All
Q6-16H_A3	Temp worker (PLI)	2002-2012
Q6-27E_A3	Temp worker (NJ)	2002-2012
Q6-8H_A4A (B)	On-call worker (DLI)	All
Q6-16H_A4A (B)	On-call worker (PLI)	2002-2012
Q6-27E_A4A (B)	On-call worker (NJ)	2002-2012
Q6-8H_A5A (B)	Contracted (DLI)	All
Q6-16H_A5A (B)	Contracted (PLI)	2002-2012
Q6-27E_A5A (B)	Contracted (NJ)	2002-2012

Table E1: These are the variables I take from the On Jobs section.

Variable	Description	Years
Q6-15	Date began job (PLI)	2002
Q6-16I	Currently working job (PLI)	2002
Q6-9	Last stopped working job (DLI)	2002
Q6-17	Last stopped working job (PLI)	2002
Q6-8E_1A (Only end .01)	Began question loop (DLI)	2002-2004
NEWEMP_STARTDATE	Date began job (NJ) (Eqiv Q6-27A)	2012
NEWEMP_CURFLAG	Currently working job (NJ) (Eqiv Q6-27I)	2012

Table E2: These are the variables from the On Jobs section that I took from the Errata https://www.nlsinfo.org/content/cohorts/nlsy79/other-documentation/errata/errata-1979-2016-data-release.

Variable	Description	Years/Weeks
UID	Employer UID	Once
STOPDATE	Employer stop date this questionnaire	All
STADATE	Employer start date this questionnaire	All
STOPWEEK	Employer stop week this questionnaire	All
STARTWEEK	Employer start week this questionnaire	All
TENURE	Weeks Tenure at interview	All
HOURSWEEK	Hours worked per week at job	All
IND	Industry (2000 Census Codes)	All
OCC	Occupation (2000 Census Codes)	All
UNION	Union (or employee contract)	All
HRLY_WAGE	Hourly wage	All
STATUS_WK_NUM	Working/Unemployment Status By Week	1202 - 2024

Table E3: These are the variables I take from the Employer History Roster (XRND), which is an NLSY created history of employment by job number. All variables start with EMPLOYERS_ALL_, which is omitted for clarity. Weeks 1202-2082 correspond to January 2001 - October 2017, but weekly data after October 2016 becomes slim, so I drop these weeks.

Variable	Description	Years
JOB_UID_EMPROSTER	Employer UID	All
QES-84D	Any Benefits	2002-2004
QES-84E	Health insurance	2002-2004
QES-84F	Life insurance	2002-2004
QES-84G	Dental insurance	2002-2004
QES-84H	Maternity leave	2002-2004
QES-84I	Retirement benefits	2002-2004
QES-84J	Flexible hours	2002-2004
QES-84K	Profit sharing	2002-2004
QES-84L	Training or education	2002-2004
QES-84M	Company provided childcare	2002-2004
QES-84E (.Job)∼(Benefit)	All above benefits grouped	2006-2016
QES-89	Job Satisfaction	All

Table E4: These are the variables taken from the Employer Supplement

Variable	Description	Years
SAMPLE_ID	Sample respondent part of	Once
SAMPLE_RACE	Hispanic or Black	Once
SAMPLE_SEX	Sex	Once
Q1-3_A∼Y	Birth year	Once(1979)
SMSARES	MSA status	All
REGION	Region of US	All
Q3-10B	Highest degree received	1988 - 2006
Q3-10D	Highest degree received	2008 - 2016
MARSTAT-COL	Marital status	All
NUMKID	Total number of children	All
NUMCH	Number of children in HH	All

Table E5: Remaining variables taken from other parts of NLSY 79

Variable	Description
YEAR	Survey Year
MONTH	Survey Month
WTFINL	Person Survey Weight
CPSIDP	Person ID
AGE	Age
SEX	Sex
RACE	Race
MARST	Marital Status
HISPAN	Hispanic
EMPSTAT	Employment Status
WKSTAT	Full/Part-Time
EDUC	Education
EARNWT	Earnings Weight
HOURWAGE	Hourly Wage
UNION	Union Status
EARNWEEK	Weekly Earnings

Table E6: These are variables from IPUMS:CPS that I use in both applications. I use the monthly survey from January 2001 - October 2016, looking only at men aged 18-65.

Variable	Description
OCC2010	Occupation, 2010 Basis

Table E7: These are variables from IPUMS:CPS that I use with the monthly survey from January 2001 - October 2016, looking only at men aged 18-65.

Variable	Description
OCC1990	Occupation, 1990 Basis
IND1990	Industry, 1990 Basis
CLASSWKR	Measure Self-Employed
CWPDTAG	Temporary Worker
CWONCALL	On-call worker
CWDAYLAB	Day Laborer
CWCONTRACT	Contracted out
CWCONTRACTIC	Independent contractor
CWSEEMP	Self-employed as freelancer
CWSUPPWT	CWS weights

Table E8: These are variables from IPUMS:CPS that I use with the Contingent Worker Survey for years 1995, 1997, 1999, 2001, 2005, and 2017 for all workers.