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 document three empirical facts studying men from the National Longitudinal Survey of Youth 1979: 10% ever work outsourced jobs; 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; and a 1 pp increase in outsourcing within the average occupation is associated with a .085% increase in its employment share. To explain these facts, I develop a DMP-style model where 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. I show that high productivity firms choose to outsource. As a result, workers lose access to the highest paying jobs. But outsourcing increases firm profits, increasing their demand for labor and the total number of jobs. I calibrate the model to match worker flows, wage distributions, and outsourcing employment share. I find that the employment gains of outsourcing do not make up for lower wages, 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 services 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 choose 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). Although much of this trend has been driven by globalization, where firms import to access other countries' comparative advantages (Antràs, 2003; Grossman and Helpman, 2005), 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. By focusing on contracted out jobs, I isolate the effects of being employed by one firm while performing tasks for another. 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. I focus on contracted out workers for three reasons. First, they usually work at the client's job cite, unlike workers at domestic suppliers who work at their employer. Second, they are hired by a firm, unlike independent contractors who work for themselves. Third, their jobs are expected to last many years, unlike temp workers whose jobs are short-term. For the rest of this paper, I use outsourced and contracted out interchangeably.

I use data from the National Longitudinal Survey of Youth 1979 (NLSY), which asks for self-reported outsourcing status for each job since 2002. To my knowledge, I am the first person to use this part of the NLSY. I establish three key empirical facts about domestic outsourcing in the US. First, I find that outsourced jobs are widespread, 10% of men work at least one contracted out job. Because my measure of outsourcing starts well into workers' careers, this is a lower bound on the true number of workers who are ever outsourced. Workers who are ever contracted out have slightly lower education levels but are otherwise demographically similar to the rest of the population. Second, I find that 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 find no evidence of compensating differentials. In particular, workers do not find outsourced jobs at a faster rate and they are no more likely to use these jobs as stepping stones to better opportunities. Third, I find that outsourcing is correlated with an increase in the number of jobs available. Specifically, a 1 pp increase in the percent of workers outsourced within the average occupation is associated with a .085% increase in its employment share. Outsourcing provides a trade-off for workers because these jobs are lower quality but they lead to more employment.

To study this trade-off, I develop a labor search model of domestic outsourcing. Domestic outsourcing changes who pays the worker, not who does the work. 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 bypass search frictions 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. Outsourcing allows firms to avoid search frictions and bargaining with workers, 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, so they increase their demand for labor and more overall jobs are available. In this way, the model captures the empirical trade-off we see in the data. The model 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 potentially 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).

To see how outsourcing affects economic efficiency, I study the Planner's problem. I show that outsourcing has ambiguous effects on overall efficiency. The Planner faces the same search frictions that firms do and can use outsourcing to alleviate these frictions. Compared to decentralized firms, the Planner does not need to bargain with workers but does account for how vacancy creation obstructs other firms. The Planner also wants high productivity firms to outsource because this bypasses search frictions for the most valuable (and thus most expensive) vacancies. Outsourcing can increase efficiency because the Walrasian market allows outsourcing firms make more efficient decisions. But it can decrease efficiency because too many firms choose to outsource to avoid bargaining with workers. To provide intuition behind how governments should respond to outsourcing, I show how the Planner's allocation can be decentralized using taxes and subsidies on vacancy creation. The optimal tax schedule places no taxes/transfers on outsourcing firms, as they make efficient decisions conditional on the price of outsourcing. This results suggest that if governments want to limit outsourcing, they should target outsourcers rather than outsourcing firms.

I then calibrate an extended version of the model, which includes on-the-job search, to match NLSY data and quantify the effects of outsourcing on workers. The calibration matches moments for 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 residual wage distributions, the percent of jobs that are outsourced, and the rate of worker job flows. To show how outsourcing affects worker welfare, I simulate the model with outsourcing shutdown. In a steady state without outsourcing, unemployment is 1.2% higher. But the loss of jobs is outweighed by the increase in average job quality, and eliminating outsourcing increases total welfare by 0.39%.

The rest of the paper is organized as follows: Section 2 overviews the literature, Section 3 analyzes outsourcing in the NLSY, Section 4 presents a stylized model and its properties, Section 5 calibrates the full model to NLSY data, Section 6 shows results, and Section 7 concludes. The Appendix contains supplemental data analysis, proofs, the more detailed calibrated model, and a guide to cleaning the data.

2 Literature Review

My empirical work combines two strands of the literature on domestic outsourcing: one that uses self-reported outsourcing and one that measures outsourced job quality. The self-reported measure of outsourcing starts with the CPS supplement Contingent Worker Survey (CWS), which ran 5 times from 1995-2005 and again in 2017. The NLSY questions I use come almost verbatim from the CWS. Another CWS-like survey is Katz and Krueger (2019a) (KK), who ask about alternative jobs as part of the RAND American Life Panel in 2015. By using self-reported outsourcing, each of these data sets can measure outsourcing across the entire economy. 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 measure of contracting out over time is consistent with these sources and fills in how outsourcing evolved over the gaps in their surveys (see Figure 1).

I also contribute to the literature on outsourced job quality. The closest comparison is

Dube and Kaplan (2010) (DK), who use CPS data to study janitors and security guards. Another is Goldschmidt and Schmieder (2017) (GS), who use matched worker-firm data from Germany to study workers in food, security, cleaning, and logistic services.[1] These papers need to impute outsourcing, which leads them to focus on a few, lower skilled occupations.[2] I show that workers are outsourced across the skill distribution, 33% of occupations have at least one outsourced worker. This could lead to different conclusions 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 in my sample. By studying all workers, I 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.

The closest paper to mine is Bilal and Lhuillier (2021), who also study 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 outsource while less productive hire; outsourced workers earn less than they would if hired by the same firm directly; and outsourcing increases employment. The main differences are that my outsourcing firms pay hiring costs but outsourced workers are fully productive, while their outsourcers hire for free but outsourced workers have a productivity penalty.

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

[2] One paper that has administrative records on worker outsourcing is Drenik et al. (2020), who use Argentinian data to match temp workers to their temp agency and the client firm they work for. They find that temp workers receive about half of the production rents that traditional workers do.

Their model allows for closed form distributions of worker wages and can easily accommodate many worker types.[3] On the other hand, my outsourced wages can fall anywhere in the distribution, while theirs are mechanically equal to reservation wages.[4] Both papers find lower wages in outsourcing jobs on average, so this distinction is less important in aggregate. My model might be more useful when focusing on occupations where outsourced workers earn similar or higher wages.

Both papers make empirical contributions. 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 NLSY data to show that outsourced workers are no quicker to find their jobs out of unemployment and that outsourcing within an occupation is associated with increased employment. Each of these findings are consistent with both models. In this way, the papers are complementary, showing many of their conclusions are robust to model specification and are supported empirically across countries.

I find that domestic outsourcing has increased in the US, a result echoed in the literature on the US and in other Western countries.[5] My model suggests that increases in outsourcing lead to increased employment, and I find a positive relationship between outsourcing and employment in the data. 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 is positively correlated with total employment.

[3]My model can accommodate multiple worker types, but it makes the analysis more difficult. I do not attempt to do so in this paper.

[4]The fact that outsourced wages can fall anywhere in the distribution may seem to contradict the fact that outsourced workers earn less than if they were hired directly. This result arrives because outsourcing firms would pay the highest wages if they were to hire, but these jobs are not available in equilibrium.

[5]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); Bergeaud et al. (2020); Bilal and Lhuillier (2021), UK and Spain: Kalleberg (2000), and Australia: Wooden (1999).

3 Data Analysis

In this section, I discuss my data analysis of outsourced jobs, including who works in outsourced jobs, the quality of outsourced jobs compared to traditional jobs, and the effects of outsourcing on total employment. I focus on the NLSY but also perform robustness checks with IPUMS CPS data, using both monthly data and the six CWS surveys. Supplemental analysis is in Appendix A. For more information about how the data is cleaned, including a list of all variables used, see Appendix E.

The NLSY follows a nationally representative group of young adults born between 1957-1964 throughout their life.[6] NLSY data consists of biennial surveys which can be used to construct a weekly employment history. Starting in 2002, the NLSY asks workers if they were employed in alternative jobs: whether they were contracted out, self-employed, an independent contractor, a temp worker, or an on-call worker. I classify a job traditional if it not reported as any other type.[7] My measure of outsourcing will be all contracted out jobs.[8] As shown in Table A3 in Appendix A.4, these jobs are the most comparable to traditional jobs in terms of wages, hours 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 as respondents complete the most recent wave of the survey.

Unfortunately, the alternative job questions are not immediately usable for researchers. The NLSY asks workers about jobs in two parts: first they ask workers to list each job since the previous interview, then they rearrange these jobs by quit date and ask about job details.

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

[7]When the NLSY introduced the alternative job questions, they assumed 90% of previously held jobs were traditional to avoid burdening respondents with extra questions. For example, workers who previously reported "regular hours, a supervisor, and so on" were assumed to be traditional by NLSY staff. For more, see https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/employment/jobs-employers. I assume these assignments are correct and label these jobs as traditional.

[8]The specific question for contracting out 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?"

The alternative job questions are asked in the first part, separate from other job details. As of this writing, there is no official link between the two parts of the survey, despite the fact that the second part is explicitly derived from the first. To use the alternative job data, I must first recreate the NLSY's sorting algorithm.[9] My sorting algorithm matches more than 90% of jobs with outsourcing information and most of these matches are high quality. Any mistakes in the matching process that miss-assigns job status to individual jobs will likely bias my estimates towards 0. For more on the matching procedure and match quality, see Appendix E.

For most of the analysis of this paper, I focus on men at the job level.[10] My data set is made up of 4,081 men in 12,358 jobs. I find similar results at the job-interview level.[11] Throughout, I weight results based on NLSY supplied weights which account for respondent's interview participation over time.

This sections analyzes the data along four different themes. First, I measure who is outsourced, documenting the prevalence of outsourcing over time and comparing workers who are ever outsourced to those who are not. Second, I compare the quality of outsourced jobs to traditional jobs based on wages and benefits. Third, I study how long it takes for workers to move between jobs, which has important implications for how job search is modeled below. Fourth, I show how outsourcing and employment within occupations are related over time.

3.1 Who is Outsourced?

In this section, I measure the prevalence of contracting out and study the demographics of outsourced workers. Figure 1 shows the percent of employed men and women working in

[9] 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 and NLS User Services have not made the first section (containing the alternative job questions) 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.

[10] If a job is present in multiple interviews, I take average or modal job characteristics.

[11] For results using job-interview observations, which are similar, email the author.

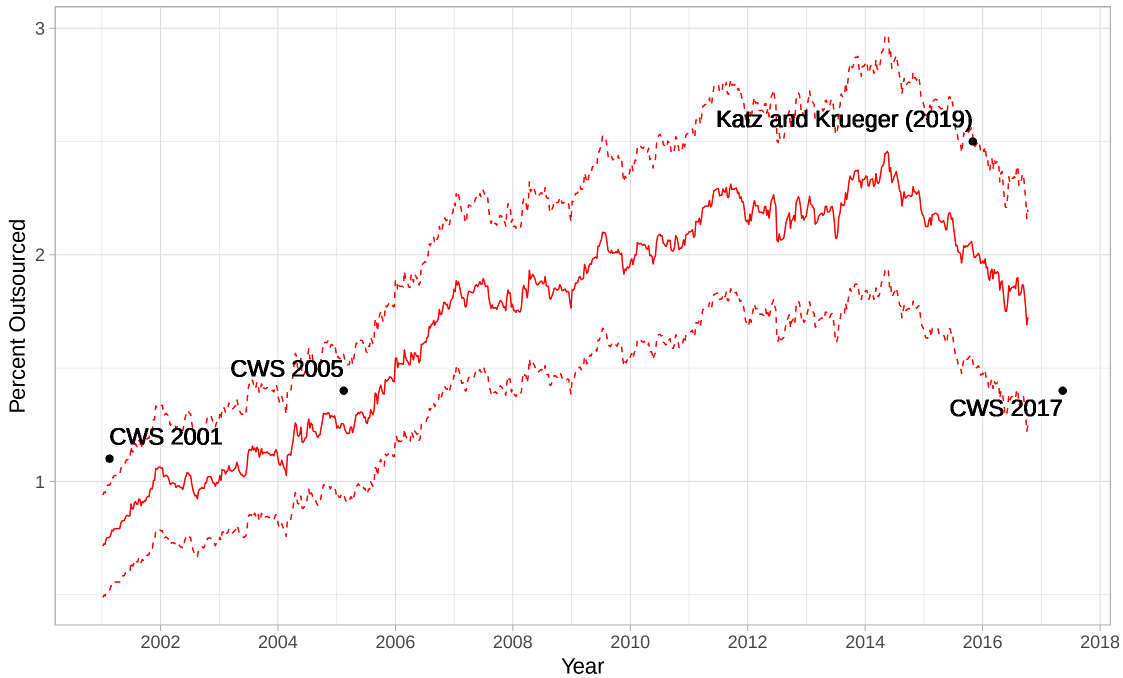

Figure 1: Percent of employed men and women contracted out each week in the NSLY. Also show point estimates from Katz and Krueger (2019b) Table 1 compiling data from the Contingent Worker Survey (CWS) and RAND American Life Panel using alternative weight 2.

outsourced jobs each week. This measure has been increasing over the last two decades, starting around 0.75% in 2001, rising to over 2% in the early 2010's before falling to 1.75% in 2016. Because my panel data only follows one cohort, we may worry that the increase in outsourcing over time is due to age effects. In Appendix A.1, I show that the increase in outsourcing holds even when holding age constant. My findings are in line with the rest of the literature that has found outsourcing is increasing in the US.

The figure also compares to past surveys from the CWS and KK as reported in Katz and Krueger (2019b), Table 1. My data set is different from theirs in important ways. First, my survey follows a cohort from ages 37-44 to ages 51-59 rather than all working-aged Americans. Some results in the CWS and KK suggest that older workers are more likely to be contracted out. Second, my respondents are repeatedly interviewed over time and fill out each survey on their own behalf. KK show that proxy respondents (i.e. spouses) 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. Third, when the NLSY introduced the alternative job questions, they assumed 90% of previously held jobs were traditional (see Footnote 7). I assume these assignments are correct, which could bias my measure of outsourcing downwards, especially for earlier years. With these caveats, my measure of contracting out matches well with these sources. While my measure of outsourcing is significantly below the CWS in 2001, both the 2005 CWS and KK are within my confidence interval and the 2017 CWS would be if my data extended that far. Despite the fact that they are measured about a year and a half apart, KK's level of contracting out is more than 1 pp greater than the one found by CWS 2017. While some of these differences may come from the underlying samples or how the questions were asked, KK theorize that the strong labor market over this time could contribute to the difference. My findings back up this claim, outsourcing noticeably drops after 2014. Overall, my measure of outsourcing is in line with past research while also showing how outsourcing evolved over previous gaps in the data.

Who works in outsourced jobs or in occupations that tend to be outsourced? In Table 1, I look at men's demographics based on their job histories. The first two columns divide workers by ever outsourced versus never outsourced.[12] The last two columns divide workers by those ever employed in a high outsourcing (HO) occupation, a proxy for workers likely to be outsourced. Overall, 9.9% of men are ever outsourced in my sample and 32.5% ever work in a HO occupation. My measure of outsourcing starts when workers are aged 37-44, well into their careers. These measures are then lower bounds for workers ever experiencing outsourcing or working in HO occupations, especially as most job transitions occur when young (Keane and Wolpin, 1997). Ever outsourced workers are significantly more likely to be Black in my sample, although the difference does not carry through to ever in a HO Occupation. Ever outsourced or HO occupation workers are slightly more likely to have a

[12]When measuring ever outsourced, I include all workers who ever report working an outsourced job, including jobs that I am unable to match in the final data set.

high 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.

In Appendix A.2, I use monthly CPS data from 2001-2016 to see how these results generalize to the rest of the population. While the monthly CPS does not have a measure of outsourcing, I can divide workers using my measure of HO occupations from the NLSY. I show that men in the NLSY cohort (born between 1957-1964) have both similar demographic characteristics and similar differences between the ever and never HO samples to my NLSY sample. I also show that all men age 18-65 are similar to the NLSY cohort. 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.

3.2 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. I first compare summary statistics of contracted out jobs to other types of traditional jobs. Then I use worker and occupation fixed effects regressions to examine if the comparison changes after controlling for potential underlying differences. All data in this section uses men. Throughout this subsection, I compare my results to DK and GS. These papers must impute outsourcing, and so only study low skilled workers (janitors and security guards for DK; food, security, cleaning, and logistic services (FCLS) for GS). I will show how the implications for job quality do and do not change when we expand our scope to all workers.

I start with summary statistics. Table 2 compares outsourced jobs to traditional jobs. In both wages and hours worked, outsourced jobs are statistically indistinguishable from

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

Table 1: Demographic statistics from the NLSY for men who are ever outsourced versus those who never are and for men 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 ***.

traditional jobs.[13] When I broaden my measure to other measures of job quality, these jobs

[13] 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.

do not perform so well. Traditional workers are more likely to receive every benefit, usually significantly so. This includes a significant 8-10 pp gap for receiving any benefits 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 6 year average tenure of traditional jobs. 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.[14]

Outsourced jobs look, on average, worse than traditional jobs despite being held by demographically similar people. Do these effects hold after controlling for observables? To find out, 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. Equation (1) shows my main specification 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.[15] All standard errors are clustered by demographic sample, which the NLSY used when creating the data set to ensure it was nationally representative.

[14]Higher rates of unionization could arise from the type of occupations outsourced workers are employed in. In Table A10 from Appendix A.6, I show workers are more likely to be unionized in their current outsourced job than their previous or next job.

[15]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.

	Outsourced	Traditional
Log Real	3.02	3.06
Hourly Wage	(0.05)	(0.01)
Log Real	6.69	6.75
Weekly Wage	(0.06)	(0.02)
Hours Worked	42.01	42.74
Weekly	(0.73)	(0.20)
Part Time	0.12	0.12
	(0.02)	(0.00)
Tenure	121.62	306.94***
(Weeks)	(7.62)	(5.73)
Union	0.09	0.04***
	(0.02)	(0.00)
Job Satisfaction	1.88	1.85
(Lower Better)	(0.04)	(0.01)
Any Benefits	0.73	0.81***
	(0.02)	(0.01)
Health	0.65	0.73***
Insurance	(0.03)	(0.01)
Retirement	0.51	0.61***
Plan	(0.03)	(0.01)
Subsidized	0.05	0.07
Childcare	(0.01)	(0.00)
Dental	0.56	0.63***
Insurance	(0.03)	(0.01)
Flex	0.36	0.43***
Schedule	(0.03)	(0.01)
Life	0.56	0.62**
Insurance	(0.03)	(0.01)
Maternity	0.43	0.54***
Leave	(0.03)	(0.01)
Profit	0.18	0.21*
Sharing	(0.02)	(0.01)
Training	0.28	0.41***
	(0.02)	(0.01)
Observations	455	9,103

Table 2: Summary statistics of jobs in the NLSY divided by outsourced and traditional jobs. Observations are at the person-job level, where jobs observed more than once use average or modal 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 ***.

Results are reported in Table 3. 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.[16] Outsourced

[16]This suggests that outsourced workers are positively rather than negatively selected for productivity. I

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 3: 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 ***.

workers make 8.8 log points per week less than traditional workers, which will be the outcome of interest in my calibrated model. They are also 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.

These regressions use worker fixed effects, so the outsourcing effect is estimated by workers

provide more evidence for this assertion in Appendix A.3.

moving in and out of outsourced jobs. Because worker job transitions are endogenous, we might worry this biases the outcomes. I perform several robustness checks to confirm that outsourced jobs are lower quality. The first, in the spirit of Card et al. (2013), compares wage residuals based on current and previous outsourcing status. Specifically, I run regression (1) for log real weekly wages but without the variable *outsourced* to differentiate outsourced from traditional jobs. In Figure 2, I plot average residuals from these regressions by current and previous job types. The figure shows that the residual wages lost by those moving from traditional to outsourced jobs are of similar magnitude as the gains of those moving from outsourced to traditional. In Appendix A.3, I perform similar exercises for wage levels and for health insurance with similar results. Another robustness check reported in the Appendix is to regress my job quality measures on previous rather than current job type in the vein of Gibbons and Katz (1992). These regressions show that the job quality penalty for previously outsourced workers is less than a third of the penalty for currently outsourced workers and is 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.

Contracted out jobs are clearly worse than traditional jobs, but how do they compare to other types of jobs? In Appendix A.4, I compare contracted out jobs to independent contractor, temp, self-employed, and on-call jobs. In summary statistics, contracted out jobs earn similar wages to traditional jobs but are 6-10 pp less likely to receive most benefits. Many other job types have significantly lower earnings and are 30-70 pp less likely to receive benefits (although self-employed workers have significantly higher job satisfaction). By controlling for other job types, the regressions in Table 3 compare outsourced jobs to traditional jobs. I rerun these regression for log real weekly wages without controlling for other job types, comparing outsourced jobs to all other jobs. The wage penalty for outsourced work becomes very small and insignificant. While contracted out jobs are lower quality than traditional jobs, they are much more comparable than other alternative job types.

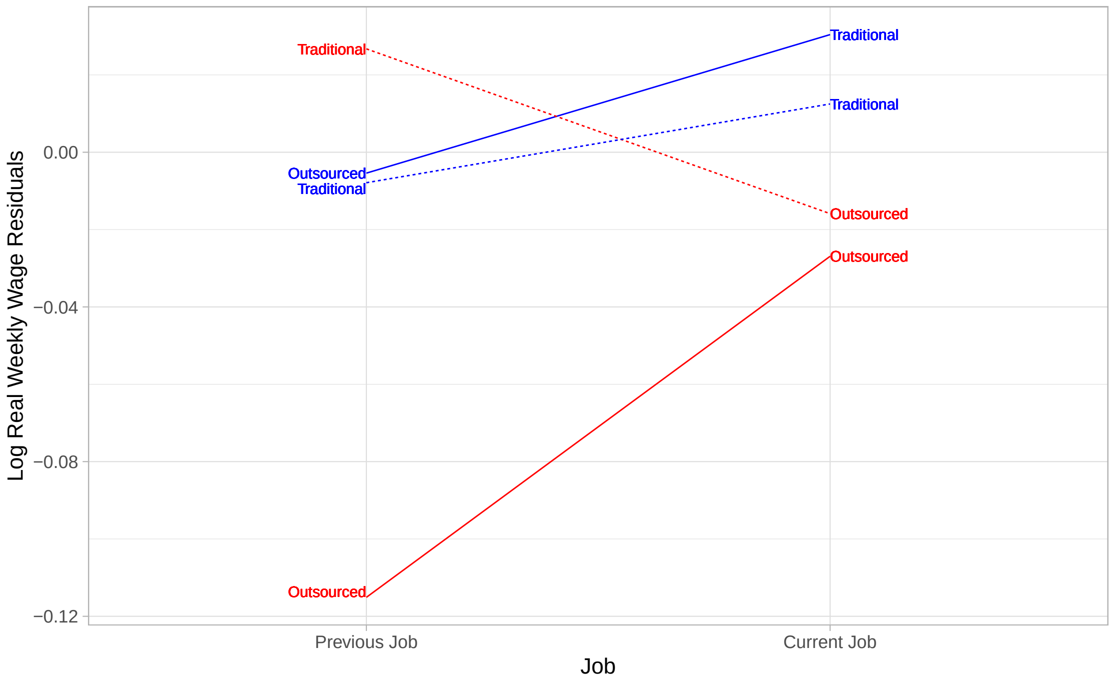

Figure 2: Mean log real weekly wage residuals at previous and current job by current and previous job type. Residuals come from a regression similar to the one described in Table 3 but without the variable *outsourced*, which indicated if a job was outsourced (see Footnote 15).

Despite using a different population and a different method of measuring outsourcing, most of my results are similar to the past literature. The most direct comparison is to DK, who study security guards and janitors in the monthly CPS. Without a direct measure of outsourcing, they instead follow Abraham (1990) and impute outsourcing status using occupation and industry. The intuition is that certain industries specialize in selling worker services, so any workers in these industries must be outsourced, for example the industry *Protective Services* and occupation security guards. While this rule can only be applied to a few occupations, it has the benefit of using commonly available data rather than less common self-reported measures. If industry-occupation rules are good proxies for self-reported outsourcing, then these measures can be reliably used elsewhere, at least for certain occupations.

With this goal in mind, Appendix A.5 compares my measure of outsourcing to DK's for janitors and security guards. When using their definition of outsourcing, my data set has

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 4: 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.

similar rates of outsourcing and summary statistics to their results. But when comparing how workers are classified using my self-reported method and their industry-occupation method, the amount of outsourcing is very different. Table 4 shows how security guards report their job type compared to their industry. Of the 30 contracted out security guards in the survey, 7 would not be outsourced by DK's method, while of the 133 who are classified as traditional (that is, did not report an alternative job type), 53 would be considered outsourced. In Appendix A.5, I show similar discrepancies for janitors and using data from the 6 waves of the CWS. I conclude that self-reporting and industry-occupation are fundamentally different measures of outsourcing.

3.3 Job Transitions

The previous subsection found outsourced jobs are worse along a number of important dimensions. One potential compensating differential is job finding probability. If workers find outsourced jobs quicker, then any negative effects of lower quality would be overstated. Workers may be willing to accept lower quality jobs if they are more likely to get them, as in a directed search model such as Menzio and Shi (2010). To study how job transitions differ between outsourced and traditional jobs, I order jobs chronologically using NLSY start and

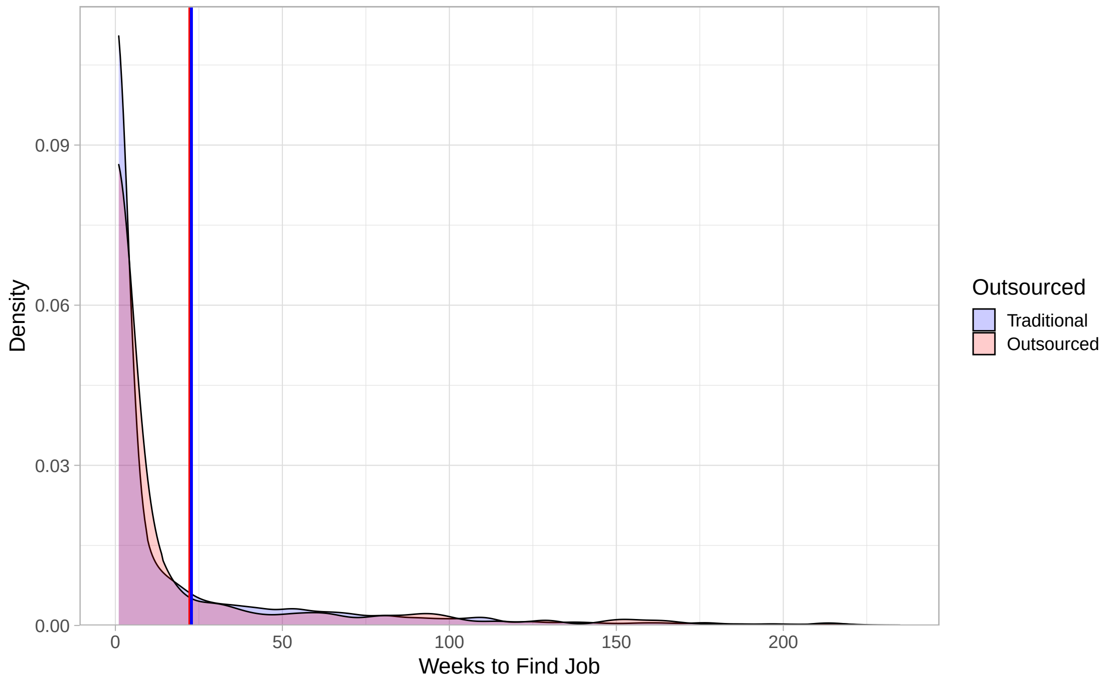

Figure 3: Weeks between previous job and current job for currently outsourced and currently traditional workers. Vertical lines are average weeks for outsourced and traditional. Graph excludes the top 1% longest transitions.

stop weeks. This allows me to study how many weeks workers take between finding jobs. More details on how I link job histories can be found in Appendix E.

I start with summary statistics. Figure 3 shows the distribution of weeks between the previous and current job for all traditional and outsourced workers. The solid line shows the mean of each distribution. Traditional jobs are more concentrated around 1 week transitions, which I call job-to-job transitions, but the distributions and means are similar. In Appendix A.6, I show that the average weeks between jobs and probability of job-to-job transition are statistically indistinguishable. I also show that the distributions are similar if we condition on non-job-to-job transitions (transitions that take more than one week).

To see if these lack of differences hold after controlling for observables, I run regression (2) below. The outcomes I analyze are weeks between previous and current job, both unconditionally and conditional on non-job-to-job transition, and probability of job to job transition. 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'. Other previous and current job characteristics and current demographic characteristics are in X.[17] Table 5 shows these results. For all outcomes, the effect of having a previous or current job outsourced is small and statistically insignificant. I conclude that outsourced jobs have the same rate of job finding and job-to-job flows as traditional jobs. Workers are not compensated for lower job quality with faster job finding rates.

3.4 Employment Effects

As I argue in my model bellow, if firms use outsourcing to increase production or lower costs, then their demand for labor will increase. While I lack the firm side data to test this hypothesis directly, I can test one of its implications by looking at employment.[18] In this section, I regress percent of workers employed in an occupation each month on the percent of workers outsourced within that occupation. For robustness, I test how well my NLSY measure of outsourcing predicts employment shares in the monthly CPS.

Regression (3) details my specification. For occupation k in month t

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

[17]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.

[18]For direct evidence that outsourcing firms increase productivity, see Bilal and Lhuillier (2021).

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 5: 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 ***.

The outcome Y is the share of workers employed in each occupation. The main independent variable is again *outsourced*, which now measures the share of workers outsourced within an occupation each month. I also include occupation and week fixed effects ψ and ω and other occupation level controls X.[19] The result is shown in row 1 of Table 6. I find that a 1 percentage point increase in outsourcing within an occupation is associated with 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.[20] Note that 2-3%

[19]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.

[20]See columns 2 and 3 of Table 2, page 512 (Meer and West, 2016).

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

Table 6: 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 ***.

of workers make at or below the Federal minimum wage.[21] Given that outsourced jobs pay about 10 log points per week less than traditional jobs (see Table 3), this makes my outsourcing regression results comparable in magnitude to theirs. So while this 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 these 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 monthly CPS. I run the same regression as above, taking the measure of percent of workers outsourced (or in other alternative jobs) from the NLSY but the remaining variables from the CPS. I rerun my above regression for males age 18-65 and for males in the NLSY cohort, the results are in row 2 and 3 of Table 6. The association for the full sample is significant at the 10% level and very close to the NLSY results at 0.00021. The results are stronger when I restrict the sample to the NLSY cohort, where the coefficient of interest becomes 0.00034.

[21]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.`

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 associations of outsourcing prevalence on employment are real and my data set if anything underestimates the effects for my cohort of workers, although these workers may be more likely to be affected than the rest of the population.

The finding that employment increases with outsourcing conflicts with past research by Berlingieri (2013) and Bloom et al. (2018). These papers study Professional and Business Services (PBS) industry, an industry that provides services such as security and human resources to other firms. About 90% of PBS production is of intermediate goods, so this industry is closely associated with outsourcing (Berlingieri, 2013). Both show that this industry has been increasing over time but argue its growth has had no employment effects. In Appendix A.7, I investigate why I reach different conclusions. I find PBS jobs are over-represented in non-traditional job types, especially for contracting out. Still, many PBS workers self-report as traditional and about 75% of contracted out jobs are not in PBS industries. Some of the differences may reflect different underlying populations. I also run regressions similar to regression (3) on employment share but replace percent outsourced (or other job type) with percent of workers in PBS industries. In both the NLSY and CPS, I find effect sizes similar to those for outsourcing, albeit with marginal significance. So there is some evidence that PBS employment is in fact associated with higher employment.

3.5 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, making up 0.75% of all jobs in 2001 and 1.75% of all jobs in 2016. Outsourcing is widespread, a third of all occupations have at least one outsourced worker. A lower bound of 10% of men are ever outsourced. 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. Despite this lower quality, workers are no quicker to find outsourced jobs. Outsourcing within an occupation is associated with increased employment. My findings are mostly in line with past literature. I add to the self-reported outsourcing literature of the CWS and KK by showing the trend in outsourcing between these surveys. I add to the literature of job quality of DK and GS by showing that all jobs are worse than traditional jobs, and the penalties are similar overall as they are for the low skilled jobs that they study.

These empirical facts suggest three important factors for my model. First, I want my model to allow for lower quality outsourcing jobs than traditional jobs. Second, my model should account for the fact that, despite this lower quality, outsourced jobs are not found quicker than traditional jobs. Third, my model should show employment increases as outsourcing increases.[22] My model aligns with all three of these facts.

4 Baseline Model

In this section, I discuss the baseline model and its properties. The model is based on Ljungqvist and Sargent's (LS) textbook treatment of Davis (2001). Both are built upon a standard DMP search model where workers randomly search for jobs and bargain with their employers over wages.[23] Davis (2001) adds heterogeneous firm productivity and LS extend his model to infinite periods. My model builds on LS by allowing firms to avoid hiring workers by purchasing labor from outsourcers in a Walrasian market. Without outsourcing, it collapses to LS. I present a stylized version of the model to fix ideas. When calibrating I will match the full model covered in Appendix D. While simple, the model is able to capture my three empirical facts above, outsourced workers make lower wages and find their jobs at the same rate, but outsourcing increases employment. It also matches three stylized facts from the literature. The first is that firms mainly use outsourcing to lower labor costs

[22] Additionally, because demographics are so similar for outsourced versus non-outsourced workers, it is a reasonable simplification to assume that all workers are the same.

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

(Abraham and Taylor, 1996; Weil, 2014). The second is that more productive firms 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). All proofs are in Appendix C.

I model a labor market of one occupation, such as security guards or IT professionals. All analysis is of the steady state. There are three types of agents: a unit measure of homogeneous workers, a uniform measure of heterogeneous firms defined by productivity $y \in [\underline{y}, \bar{y}]$, and an endogenous measure of outsourcers. Time is discrete and infinite and 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 $C(v; y)$ with marginal cost $c(v; y) \equiv C_v(v; y)$. These costs are increasing $c(v; y) > 0$ and convex $c_v(v; y) \geq 0$. Once vacancies are created, firms can fill them in one of two ways. The first is the standard DMP way, hiring. Firms enter 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 enter 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 remain the same size.

I conjecture, and later prove, that firms below some endogenous productivity $\hat{y}$ only hire, call them hiring firms, while those above only outsource, call them outsourcing firms. I use $n(y)$ and $v(y)$ to denote hiring firms' decisions and $\hat{n}(y)$ and $\hat{v}(y)$ to denote outsourcing firms' 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 entry cost $\tilde{c}$ to create a vacancy. They fill their vacancies in the same way hiring firms do, by entering 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 lose their worker with probability δ each period. We use $\tilde{n}$ and $\tilde{v}$ to denote the total number of outsourcer positions and vacancies.

The labor market contains a total of $v + \tilde{v}$ vacancies searching for workers, where 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 $\tilde{n} = \hat{n}$.

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.[24] 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.

[24]This matching process assumes workers cannot choose to apply for outsourcing versus traditional jobs. This ensures that workers find outsourcing jobs at similar rates as traditional jobs, one of my empirical facts I want to match. Because outsourcing jobs are worse on average, 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)).

4.1 Defining Equilibrium

In this section, I specify value functions, show how the model satisfies my facts from my data analysis and the literature, prove that optimal firm choice follows the cutoff rule at $\hat{y}$, and define a unique steady state equilibrium. For $\hat{y}$ to exist, we must make the following assumption.

Assumption 1. $(1-\eta)q(\theta) < 1$.

This assumption is extremely mild, it is true if workers have some bargaining power $\eta > 0$ or some vacancies are unmatched $q(\theta) < 1$.

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

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

An outsourcing firm has value

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

And an 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 $V_+ = 0$.[25] For firms, each hired (out-

[25] 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,

sourced) worker produces net revenue $y - w(y)$ $(y - p)$.[26] 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

$$c[v(y); y] \geq \beta q(\theta) J_n(n_+; y) \tag{8}$$

$$c[\hat{v}(y); y] \geq \beta \hat{J}_n(\hat{n}_+; y) \tag{9}$$

$$\tilde{c} \geq \beta q(\theta) O_+, \tag{10}$$

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.[27]

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

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.

[26] Because the productivity function is linear, wages do not depend on firm size n. Production can be concave with little change to the substantive results, other than requiring that firms must only outsource or only hire rather than having the ability to choose both.

[27] 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.

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 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

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

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

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

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 having 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). Workers and outsourcers bargain over the total value of the 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

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

is the value of search while unemployed. The value of search is made up of three parts. The first is the worker's relative bargaining power $\frac{\eta}{1-\eta}$. The second is the marginal cost of a vacancy $c[v(x); x]$ ($\tilde{c}$), which equals the firm's (outsourcer's) marginal benefit of creating a vacancy due to free entry. The third is the relative probability of meeting a particular firm (outsourcer), which is the number of vacancies per unemployed worker $\frac{v(y)}{u}$ ($\frac{\tilde{v}}{u}$). The worker's value of search is the product of these three values.

We can use this value of unemployment in (20), the value of working for a firm and outsourcer in steady state in (17) and (18), the firm's or outsourcer's envelope condition in

(12) and (13), and the bargaining rule to show firm and 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 firm $\hat{y}$ to choose outsourcing, $\hat{y} - p > 0$ else the firm makes a non-positive revenue each period and will never pay to enter the market. This implies the wages outsourcing firms would pay if they were to hire are always strictly greater than wages at the outsourcer. One of my empirical facts I want to match is that outsourced jobs are worse than traditional jobs on average. While my model does not guarantee this result, I argue this fact is satisfied because the model allows it to be true.[28]

Knowing wages, we can solve for the surplus value of each match, which is the firm or outsourcer's revenue minus the worker's home production. For hiring firms and outsourcers, we set the wage equation in (14) and (16) equal to the wage equation in (22) and (23) to show the total surplus of each match 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

[28]Depending on parameters, outsourced wages can be greater than or less than the average traditional job. This will depend on the number of hiring vacancies with productivities greater or less than p.

amortizing the firm's or 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. We can use outsourcing surplus from (25) and the price the firm is willing to pay to outsource in (15) to show the total surplus for outsourcing firms is

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

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.

The effects of outsourcing on workers are ambiguous. On one hand, outsourcing leads to fewer vacancies from high productivity firms. These high quality vacancies are replaced by outsourcing vacancies, which have lower wages. On the other hand, outsourcing increases firm profitability. These firms respond by creating more vacancies than they would if hiring. On top of this, outsourcers must create $\frac{1}{q(\theta)} > 1$ vacancies for each outsourcing firm vacancy to match demand. With more jobs available, outsourcing will increase employment, the final empirical fact we wanted to match. In general, the effects of outsourcing on worker's welfare depends on underlying parameters.

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 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.*[29]

[29] 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.

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 $q(\theta)[y-w(y)] \lesseqgtr y-p$. 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. The Walrasian market between firms and outsourcers brings two benefits to the firm. The first is that it avoids matching frictions and guarantees access to a worker. 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. This matches my final stylized fact from the literature: more productive firms are more likely 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 $\hat{y}$.

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.

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 worker 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 the same market tightness, wages, and prices.

4.2 Efficiency of Equilibrium

Search frictions mean the decentralized equilibrium is not necessarily Pareto optimal. In a standard DMP model, Hosios rule, which sets worker bargaining power η equal to the elasticity of the matching function α, is necessary and sufficient for efficiency. In LS's model, heterogeneous productivity means Hosios rule is not enough, as low productivity firms create too many vacancies and high productivity firms too few. In general, efficiency cannot be achieved. In this section, I examine how outsourcing affects the efficiency of the economy. To do so, I first solve a Planner's problem. I show that, under light assumptions, the Planner also demands outsourcing. In the decentralized economy, firms outsource to avoid matching frictions, which leads to more efficient entry decisions. But they also outsource to avoid bargaining with workers, which can lead to less efficient entry decisions.

To study efficiency, we must first solve the Planner's problem. The Planner chooses vacancy creation for all firms and outsourcers but still faces search frictions. Workers hired at outsourcers can be used to fill any empty vacancy. The main differences between the Planner's choices and the decentralized economy are that the Planner does not need to bargain over wages but she accounts for how vacancy creation affects other firms and outsourcers.

Let $\mathbb{n}$, $\hat{\mathbb{n}}$, $\mathbb{v}$, and $\hat{\mathbb{v}}$ be vectors of hiring positions, outsourcing positions, hiring vacancies, and outsourcing vacancies. Let $\tilde{n}$ 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 under Assumption 2 below, the Planner follows a cutoff strategy for hiring versus outsourcing, with $\hat{y}^P$ as the Planner's optimal cutoff. Each period, the Planner inherits filled positions $\{\mathbb{n}, \hat{\mathbb{n}}, \tilde{n}\}$ and chooses vacancies $\{\mathbb{v}, \hat{\mathbb{v}}, \tilde{v}\}$ to solve[30]

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

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

s.t.

$$n_+(y) = (1-\delta)n(y) + q(\theta)v(y) \tag{29}$$

$$\hat{n}_+(y) = (1-\delta)\hat{n}(y) + \hat{v}(y) \tag{30}$$

$$\tilde{n}_+ = (1-\delta)\tilde{n} + q(\theta)\tilde{v} \tag{31}$$

$$\int_{\hat{y}_+}^{\bar{y}} \hat{n}_+(x)dx = \tilde{n}_+, \tag{32}$$

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. Define ρ as the Planner's (implicit) price of outsourcing. When solving the Planner's problem, $\beta\rho$ is the multiplier on the outsourcing market clearing condition in (32).[31] We are interested in equilbria where the Planner has positive demand for outsourcing and $\hat{y}^P$ exists. To ensure this, we must assume that the Planner faces matching frictions.

Assumption 2. $q(\theta^P) < 1$.

The Planner values outsourcing for avoiding matching frictions, so if these are not binding, then her demand for outsourcing will be zero.

[30]The Planner implicitly receives some outsourcing cutoff $\hat{y}^P$ and chooses a new outsourcing cutoff $\hat{y}^P_+$. These are reflected in the Planner's choices for firms. Hiring vacancies and positions $\tilde{v}^P(y)$ and $\tilde{n}^P(y)$ are zero for firms below $\hat{y}^P$ and outsourcing vacancies and positions $v^P(y)$ and $n^P(y)$ are zero for firms above $\hat{y}^P$. Because the Planner follows a cutoff rule, this representation is without loss of generality.

[31]The Planner ensures tomorrow's outsourcing market clears today, so including β in the multiplier makes it easier to compare the Planner's price ρ to the decentralized price p.

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

$$\Gamma^P = \frac{1}{u^P}\frac{\alpha}{1-\alpha}\left\{\int_{\underline{y}}^{\hat{y}^P} v^P(x)c[v^P(x);x]dx + \tilde{v}^P\tilde{c}\right\} \tag{33}$$

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). The decentralized value of search depends on the relative probability a worker matches with a firm, the worker's relative bargaining power, and the marginal benefit of each vacancy. The Planner's value is similar, but she weights the marginal benefits by their effect on the matching probability of other agents, $\frac{\alpha}{1-\alpha}$. 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 firms, and outsourcers

$$y - b = \Gamma^P + \frac{r+\delta}{q(\theta^P)}\left(c[v^P(y);y] + \frac{\Gamma^P}{\theta^P}\right) \quad \forall\, y \leq \hat{y} \tag{34}$$

$$y - b = \Gamma^P + (r+\delta)c[\hat{v}^P(y);y] + \frac{r+\delta}{q(\theta^P)}\left(\tilde{c} + \frac{\Gamma^P}{\theta^P}\right) \quad \forall\, y \geq \hat{y} \tag{35}$$

$$\rho - b = \Gamma^P + \frac{r+\delta}{q(\theta^P)}\left(\tilde{c} + \frac{\Gamma^P}{\theta^P}\right). \tag{36}$$

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 $\frac{\Gamma^P}{\theta^P}$.

I conjectured that the Planner uses a cutoff strategy $\hat{y}^P$, where firms below the cutoff hire and firms above outsource. Proposition 2 show this is indeed the case.

Proposition 2. *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 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 and is negative for low productivity and positive for high productivity. This implies that low productivity firms hire and high productivity firms outsource, just like the decentralized economy.

What is the Planner's choice of productivity cutoff $\hat{y}^P$? To calculate $\hat{y}^P$, we solve the hiring surplus in (34) for $c[v(\hat{y}); \hat{y}]$ and plug into the outsourcing surplus in (35) to show

$$\hat{y}^P = b + \Gamma^P + \frac{r + \delta}{q(\theta^P)[1 - q(\theta^P)]}\tilde{c} + \frac{r + \delta}{\theta^P q(\theta^P)}\Gamma^P. \tag{37}$$

Comparing to the decentralized indifferent firm in (28) the similarities are apparent. The Planner does not worry about wage bargaining but does account for how outsourcer vacancies affect others. 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 $q(\theta^P) > (1 - \eta)q(\theta)$, the Planner values outsourcing less.

Now that we know the Planner's choices, we can measure the efficiency of the decentralized problem. In LS's model without outsourcing, efficiency of outcome depends on firm entry along two dimensions. The first is the spread of vacancies among different productivity firms and the second is the overall number of vacancies created. I will show how outsourcing affects both of these margins.

We start with the spread of vacancies, whether each individual firm creates the right amount of vacancies relative to other firms. 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 $z \leq \hat{y} \leq y$. For the decentralized problem, we can solve for differences in surplus $y - z$ in each case using equations (24) and (26)

$$y - z = \frac{r + \delta}{(1 - \eta)q(\theta)}\big(c[v(y); y] - c[v(z); z]\big) \quad \forall z \leq y \leq \hat{y} \tag{38}$$

$$y - z = (r + \delta)\big(c[\hat{v}(y); y] - c[\hat{v}(z); z]\big) \quad \forall \hat{y} \leq z \leq y \tag{39}$$

$$y - z = (r + \delta)c[\hat{v}(y); y] - \frac{r + \delta}{(1 - \eta)q(\theta)}\big(c[v(z); z] - \tilde{c}\big) \quad \forall \hat{y} \leq z \leq y. \tag{40}$$

Similarly, we can use the Planner's surplus equations (34) and (35) to show her optimal spreads solve

$$y - z = \frac{r + \delta}{q(\theta^P)}\big(c[v^P(y); y] - c[v^P(z); z]\big) \quad \forall z \leq y \leq \hat{y}^P \tag{41}$$

$$y - z = (r + \delta)\big(c[v^P(y); y] - c[v^P(z); z]\big) \quad \forall \hat{y}^P \leq z \leq y \tag{42}$$

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

How efficient is the decentralized spread of vacancies? We start with hiring firms. Comparing the decentralized spread in (38) to the Planner's spread in (41), the difference comes from the amortization abilities $(1-\eta)q(\theta)$ and $q(\theta^P)$. Given optimal market tightness $\theta = \theta^P$, the decentralized spread is only efficient when worker bargaining power η is 0. Otherwise, the decentralized spread is too small, low productivity firms create too many vacancies and high productivity firms too few. This result echoes LS without outsourcers and the intuition is the same. If workers have some bargaining power, firms pay the entire cost of vacancy creation but only receive some of the benefits. This is especially costly for high productivity firms, whose vacancies have the highest marginal benefit and therefore the highest marginal costs. Low productivity firms do not properly account for how they obstruct higher productivity vacancies.

The results are more promising for outsourcing firms. In fact, the decentralized spread in (39) is exactly the same as the Planner's spread in (42). 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.

Last, we look at the spread between hiring and outsourcing firms. Both the decentralized spread in (40) to the Planner's spread in (43) account for the outsourcer vacancy that must be created for firms to outsource. Again, if market tightness is optimal, the decentralized spread is only efficient when worker bargaining power η is 0. The difference in spreads depends on 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 because these firms outsource instead of hire.

Next we study total firm entry, whether firms create the right amount of vacancies overall. To do so, we integrate over firm surplus for hiring firms and outsourcing firms weighted by vacancy creation.[32] We first solve for decentralized entry. For hiring firms $y \leq \hat{y}$ and

[32]In steady state, this is proportional to weighting by firm positions. I weight by vacancies because this form is more easily interpretable.

outsourcing firms $y \geq \hat{y}$ we integrate over surplus equation (24) and (26) to show

$$\int_{\underline{y}}^{\hat{y}} (x-b)v(x)dx = \frac{r+\delta+\eta(1-\pi)\theta q(\theta)}{(1-\eta)q(\theta)} \int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + \frac{\eta(1-\pi)\theta}{1-\eta}\tilde{v}\tilde{c} \tag{44}$$

$$\int_{\hat{y}}^{\bar{y}} (x-b)\hat{v}(x)dx = \frac{\eta\pi\theta q(\theta)}{1-\eta} \int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + (r+\delta)\int_{\hat{y}}^{\bar{y}} \hat{v}(x)c[\hat{v}(x);x]dx + \frac{r+\delta+\eta\pi\theta q(\theta)}{1-\eta}\tilde{v}\tilde{c}, \tag{45}$$

Similarly, we integrate over the Planner's surplus equations in (34) and (35) to show

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

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

To get the intuition behind decentralized hiring entry in (44), 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. Compare this to the Planner's choice of entry in (46). Instead of making decisions based on individual surplus, which depends on worker bargaining power η, the Planner accounts for total surplus, which depends on matching elasticity α. While the firm considers how other firms and outsourcers affect their entry, the Planner also considers how entry will affect others. In LS, setting $\eta = \alpha$ is enough to make total entry efficient because firms internalized the effect they had on workers and other vacancies. In my setting, firms properly account for how they affect other firms but not for how they affect outsourcers.

Because of this, when there is outsourcing, $\eta = \alpha$ does not achieve efficient entry.

There is a similar logic for outsourcing entry in (45) and (47). Decentralized outsourcing firms account for their own amortization ability. Because of the Walrasian market, their entry rule is the same as the Planner's. But by paying p to outsource, they also implicitly account for the outsourcers' decision, which is similar to hiring firms'. Outsourcer's decisions are inefficient in the same way hiring firm's are, they fail to account for their effect on other vacancies. For outsourcing firms, $\eta = \alpha$ does not achieve efficient entry either.[33]

The effects of outsourcing on efficiency are ambiguous. Firms outsource to avoid market frictions and bargaining with workers. This first reason increases efficiency, avoiding frictions allow high productivity firms to create more vacancies. The second reason decreases efficiency, more firms choose to outsource than the Planner would prefer. In the economy without outsourcers, efficient spread requires worker bargaining power η to be 0, while efficient entry requires it to be α. As $\alpha \neq 0$ in general, the decentralized equilibrium is always inefficient. With outsourcers, efficient spread also requires η to be 0, but now the mix of hiring firms and outsourcers means efficient entry is no longer attainable.

4.3 Decentralizing Planner's Solutions Through Transfers

We just showed that the decentralized equilibrium is inefficient. From the NLSY, we also know that outsourced jobs are worse than traditional jobs. Concerned governments may choose to tax outsourcing firms to discourage too many firms outsourcing and to restore efficiency. 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 and 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

[33] It is easy to show that $\eta = \alpha$ does not achieve efficient entry for total entry by both hiring and outsourcing firms. This discrepancy comes because outsourcers must create $\frac{1}{q(\theta)}$ vacancies for each outsourcing vacancy to meet demand.

negative) and $\tilde{\tau}$ be the transfer to outsourcers. In Proposition 3 below, I show that this is sufficient to decentralize the Planner's solution.

Proposition 3. *The Planner can decentralize her solution through the following tax and transfer schedule*

- *Per vacancy transfers for firms following*

$$\tau(y) = \begin{cases} \eta c[v^P(y); y] - T & \forall\, y \leq \hat{y}^P \\ 0 & \forall\, y \geq \hat{y}^P. \end{cases}$$

- *Per vacancy transfers for outsourcers following* $\tilde{\tau} = \eta\tilde{c} - T$.
- *Lump sum transfers on workers to balance the government budget.*

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 Planner needs to ensure the right amount of firm and outsourcer entry and that firms make the correct outsourcing decision. Outsourcing firms make efficient decisions conditional on prices, so pay 0 taxes. 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 vacancies. 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 $\alpha = \eta$. In this case, $T = \alpha[(1-\pi^P)\int_{\underline{y}}^{\hat{y}^P} c[v^P(x); x] dF^P(x) + \pi^P \tilde{c}]$ is the match elasticity times the average marginal benefit of 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 already make efficient choices.[34]

[34]Workers make no decisions, so the lump sum transfers have no effect on the equilibrium outcome.

While my model is 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 opposes, they are also using it to avoid matching frictions, which the government supports. 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.

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 are occupations with 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 three features. First, it allows worker bargaining power η and exogenous position destruction δ to differ for firms and outsourcers. I denote outsourcer's values as $\tilde{\eta}$ and $\tilde{\delta}$. Separating η and $\tilde{\eta}$ allows me to better match the data on both wage levels and percent of workers outsourced.[35] 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 third addition is on-the-job search, workers can search on the job each period with probability ξ.[36] This allows me to match the job-to-job transitions I see in the

[35] I take bargaining power as exogenous in the model. One way different bargaining powers may arise 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 use generous benefits to attract core workers that must be extended to outsourceable workers. Outsourcing firms mainly hire outsourceable workers so are not as constrained by these laws.

[36] 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. 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

data.

All parameters and their values can be found in Appendix B. Each period in the model is equal to one week. 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 the 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 in the NLSY. I use a Cobb-Douglas matching function $M(s, v) = \phi s^{\alpha} v^{(1-\alpha)}$ where $s = u + (1-u)\xi[(1-\delta)(1-\zeta) + (1-\tilde{\delta})\zeta]$ is the total number of 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 Hall and Milgrom (2008) and Pissarides (2009), unemployment flow b equals 0.71 times the average log real weekly wage. 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 ζ. 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 regression (1) but without the indicator for outsourced.[37] I match the mean and

worker's outside option.

[37]I run the regression on the entire sample, take the residuals from my HO occupation sample, and re-scale them by the average log real weekly wage.

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 7: Calibration results.

standard deviation of both residual wage distributions.

6 Results

Calibration results are in Table 7. First, I check calibrated wage distributions for hired and outsourced workers. Figure 4 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 good job of matching the wage distribution, although average wages for both hired and outsourced workers is too high. For the worker flow and percent outsourced moments, the model is very close to the data. I 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

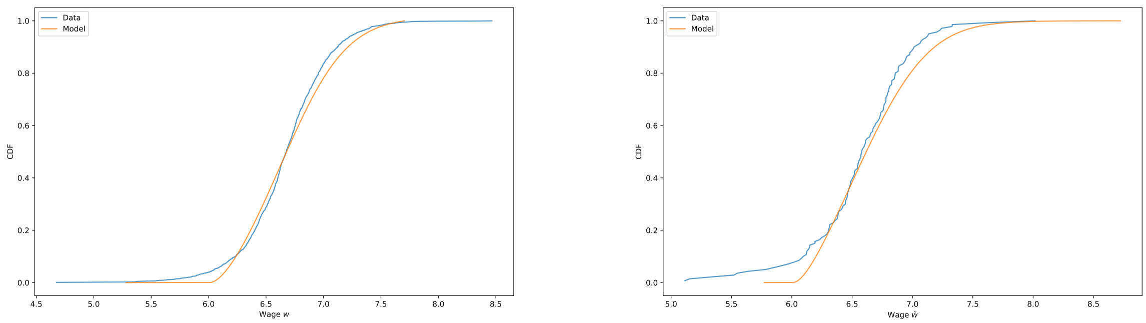

Figure 4: Distribution of log real weekly wage residuals versus distribution of weekly wages at in calibrated model. Left figure compares traditional jobs is data to hired workers in model. Right figure compares outsourced jobs in data to outsourced jobs in model.

model slightly overestimates the probability outsourced workers find new jobs, but matches these moments well.

To show how outsourcing affects worker welfare, I run a simulation of the model without outsourcers. Table 8 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%. While outsourcing increases the number of jobs available, the low quality of these jobs decreases overall welfare. Figure 5 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 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.

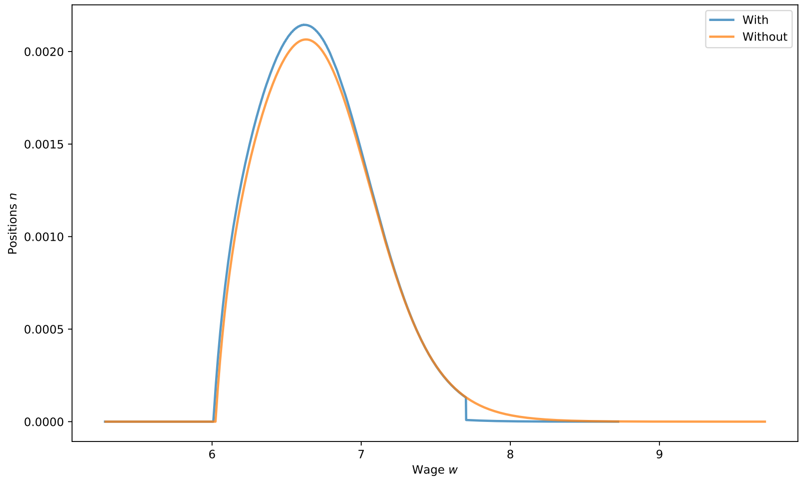

Figure 5: Distribution of workers by wages using parameters from calibrated model with and without outsourcers.

7 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. A lower bound of 10% of men ever work in outsourcing jobs, and these men are similar demographically to the rest of the population. Outsourced jobs are lower quality, outsourced workers earn lower wages and receive fewer benefits. These quality drops are in line with previous work but shows these quality drops are true for all workers, not just low-skilled ones. I find that outsourcing with occupations is associated with increases in employment. To my knowledge, I am the first show that outsourced workers transition between jobs in similar ways to traditional workers, so workers are not compensated for worse jobs with a higher job finding probability.

Using stylized facts from the literature and my data, I build a model of domestic outsourcing's effects on labor markets. The model is simple but captures the main reason firms

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

Table 8: Percent change in model outcomes when outsourcing is eliminated.

choose to outsource, to lower costs by lowering workers' share of production surplus and avoiding matching frictions. Outsourcing has ambiguous effects on worker welfare. On one hand, outsourcing lowers the average job quality, on the other, it increases the amount of jobs available. After calibrating the model to match NLSY data, I find the overall effect is negative, workers would be better off if all 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, there is not much work on what exactly makes some occupations more outsourceable than others. I leave these questions to future work.

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Appendices

A Supplemental Data Analysis

This section contains supplemental data analysis to complement the main data analysis in Section 3. Subsection A.1 shows robustness results for outsourcing over time. Subsection A.2 shows demographics of workers in and out of HO occupations from the CPS. Subsection A.3 shows robustness results for job quality. Subsection A.4 shows the job quality of other alternative job types. Subsection A.5 compares to the results of Dube and Kaplan (2010). Subsection A.6 supplements job transition data. Subsection A.7 shows how PBS workers relate to outsourcing.

A.1 Outsourcing Over Time Robustness

One weakness of my data is that I only see one cohort and contracting out may be increasing in age. The upper left figure in Figure A1 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. The bottom figure plots percent outsourced each year by birth cohort and shows that most of the dip in later years is a cohort effect. 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 the top right figure, which measures percent outsourced each week only for workers age 43-47, where the age plot shows approximately no change in percent outsourced.[38] This figure shows a similar increase in outsourcing over time. While age might have some effect on my data, the underlying increase in outsourcing is real.

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

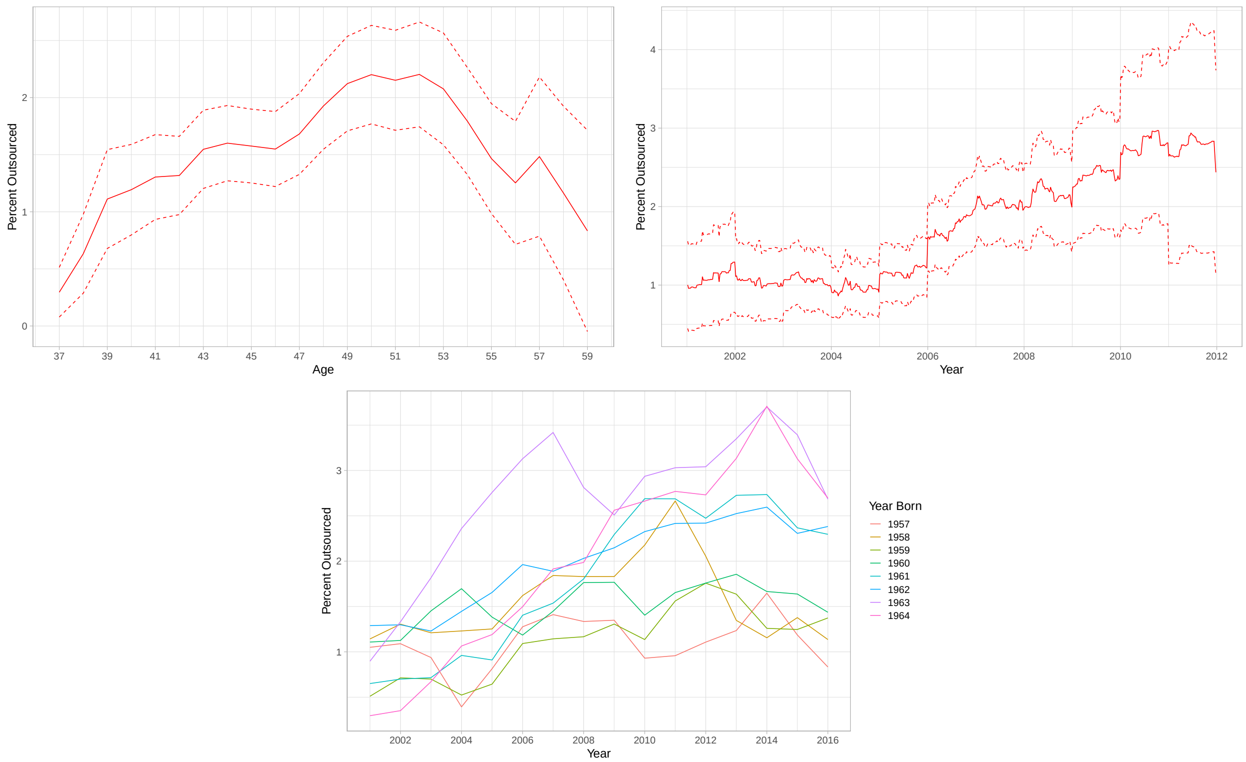

Figure A1: Outsourcing by age and over time. Top left shows percent of employed men and women outsourced by age. Top right shows percent of employed men and women age 43-47 outsourced each week. Bottom shows percent of employed men and women outsourced each year by year born.

A.2 Demographics in the CPS

In this subsection, I compare men in and out of HO occupations in the CPS. Table A1 shows the results: the left two columns shows all men age 18-65, the right two show 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.[39] Comparing the NLSY to the CPS within the NLSY cohort using Table 1, the CPS has less Black respondents and more Hispanic respondents. 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

[39]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.

	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 A1: 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 ***.

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.

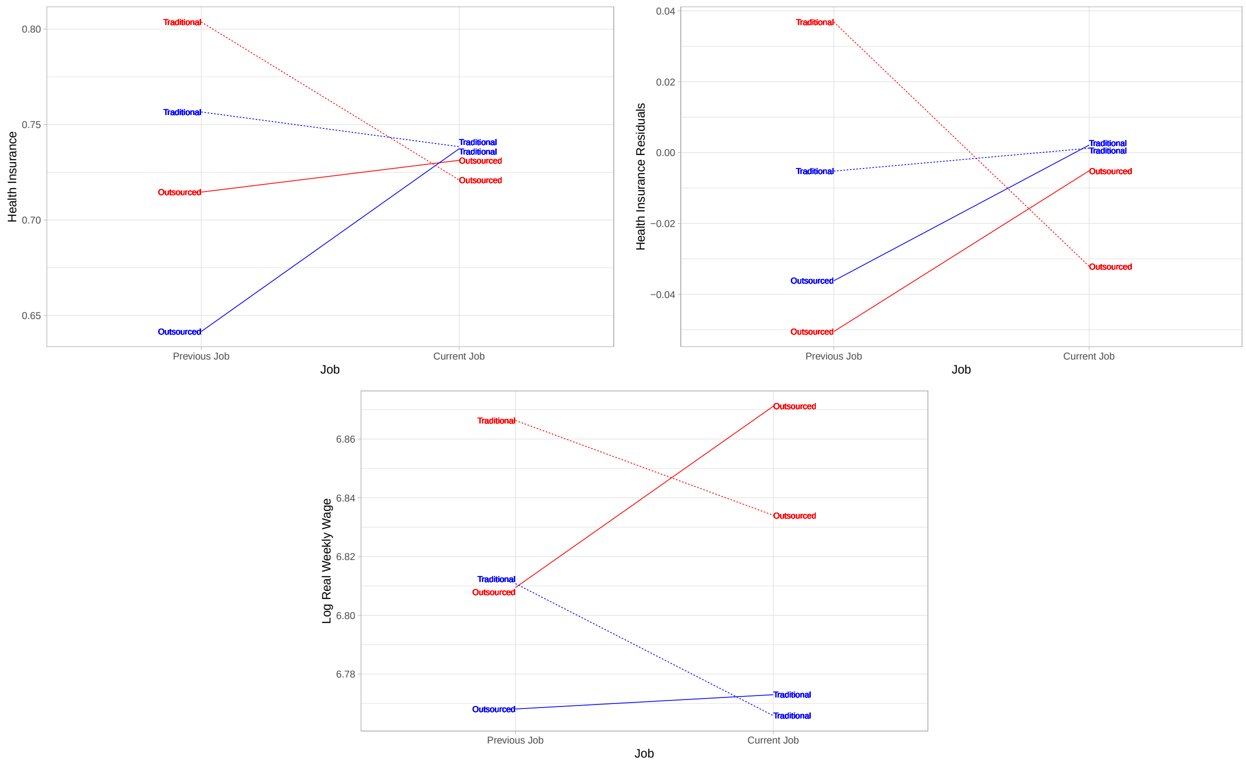

Figure A2: Job quality at previous and next job. Top left shows percent of workers receiving health insurance at previous and current job by current and previous job type. Top right shows mean chance of receiving health insurance residuals at previous and current job by current and previous job type. Residuals come from a regression similar to the one described in Table 3 but without the variable *outsourced*, which indicated if a job was outsourced (see Footnote 15). Bottom figure shows mean log real weekly wages at previous and current job by current and previous job type.

A.3 Job Quality Robustness

In the main text, following the spirit of Card et al. (2013), I plotted residual log weekly wages by previous and current outsourcing status. Here, I repeat similar exercises for wage levels and for health insurance levels and residuals. The results are in Figure A2. The level measures reinforce what the 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. The residual plots show traditional jobs are better than outsourced jobs both at previous and current jobs. My health insurance residuals show a much bigger drop for

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 A2: 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 ***.

traditional to outsourced workers than the gain for outsourced to traditional, but otherwise the patterns are similar to those for weekly wages.

Next, inspired by Gibbons and Katz (1992), I regress current job quality on previous job type. First, I rerun my original regression with current job type on the sub-sample of jobs with information on previous job type to confirm that this sub-sample is the same. Results on the left half of Table A2 show this is the case. The right half shows the results when previous job types are used instead. All of the outcomes for which currently outsourcing has a significant effect are now small and insignificant.[40] These results are consistent with a job search model where workers accept any better offer the receive. Because outsourced workers have worse jobs, the next jobs they accept will be slightly worse on average too.

[40]Hours worked becomes significantly negative, but this was not significant for the currently outsourcing regression so I interpret this as noise.

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 A3: 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 or modal 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 ***.

A.4 Other Job Types

This section shows the characteristics of jobs other than outsourced and traditional workers. These are independent contractors, temp workers, self-employed, and on-call jobs. Self-employed, on-call, and temp workers all earn lower hourly wages. All job types work fewer

	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 A4: 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 ***.

hours each week and are more likely to work part-time. The self-employed have tenures similar to traditional workers while temp worker's mean tenure is about a year. All 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, the self-employed and independent contractors are more satisfied (although the difference is not significant for independent contractors) 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.

My main regressions showed that outsourced jobs are significantly worse than traditional jobs. What happens when we expand the comparison to all jobs? To find out, I rerun regression (1) for log real weekly wages in three batches. Results are in Table A4. The first regression excludes all job types besides outsourcing, this compares contracted out jobs to all other job types. This regression implies there is no difference in wages for contracted out jobs. The second regression adds independent contracts and self-employed. Outsourced jobs are still not significantly worse than other job types. The final batch is the full regression with all job types. These regressions show that, while contracted out jobs have lower wages than traditional jobs, they have similar wages to all non-contracted out jobs on average. They also show that other job types have significant wage penalties, earning 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, any benefits, or health insurance. For job satisfaction, self-employed workers are significantly more satisfied than traditional workers while all other job types are statistically indistinguishable. The results in this section justifies my use of contracted out workers to measure outsourcing, while these jobs are slightly worse than traditional jobs, they are much more similar than other job types.

A.5 Comparing to Dube and Kaplan (2010)

This section compares my work to Dube and Kaplan (2010) (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 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

Variable	Self-Reported (This Paper) Outsourced	Not Outsourced	Industry-Occupation (Dube and Kaplan) Outsourced	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 A5: 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 ***.

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 A5 and Table A6. 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, they find 22% and 48% of janitors and security guards were outsourced from 1998-2000. Using their measure, I find 22% and 51% over my entire sample. 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.[41] 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 difference 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?

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

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	2.38	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 A6: 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 A7: 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.

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 A7 and Table 4 (In the main text). 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.[42] 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.[43] Industry-Occupation measures classify 17% of traditional janitors and 40% of

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

[43]When introducing these alternative job types in 2002, the NLSY assumed about 90% of existing jobs were traditional (see footnote 7). For janitors and security guards, 79 (30%) and 47 (35%) of 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 given self-reporting, most of the differences would still be present.

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 A8: 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.

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 are in Table A8 and Table A9. 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 aligns better 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.

A.6 Job Transitions Supplement

In this subsection, I supplement my work on job transitions. First, I report summary statistics of job transitions in Table A10, which compares all outsourced and traditional workers

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 A9: 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.

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.[44] 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.

In the main text, I focused on how long it took workers to transition between jobs. I measure three factors, weeks between jobs, weeks between jobs conditional on non-job-to-job transition (longer than one week), and percent of job-to-job transition (job transitions

[44] 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.

	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 A10: 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 ***.

that are one week). Job-to-job transitions 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. In the main text, I showed the distribution of transition times for currently outsourced and traditional workers and showed they were nearly identical. In Figure A3, I show this is also true for non-job-to-job transitions.

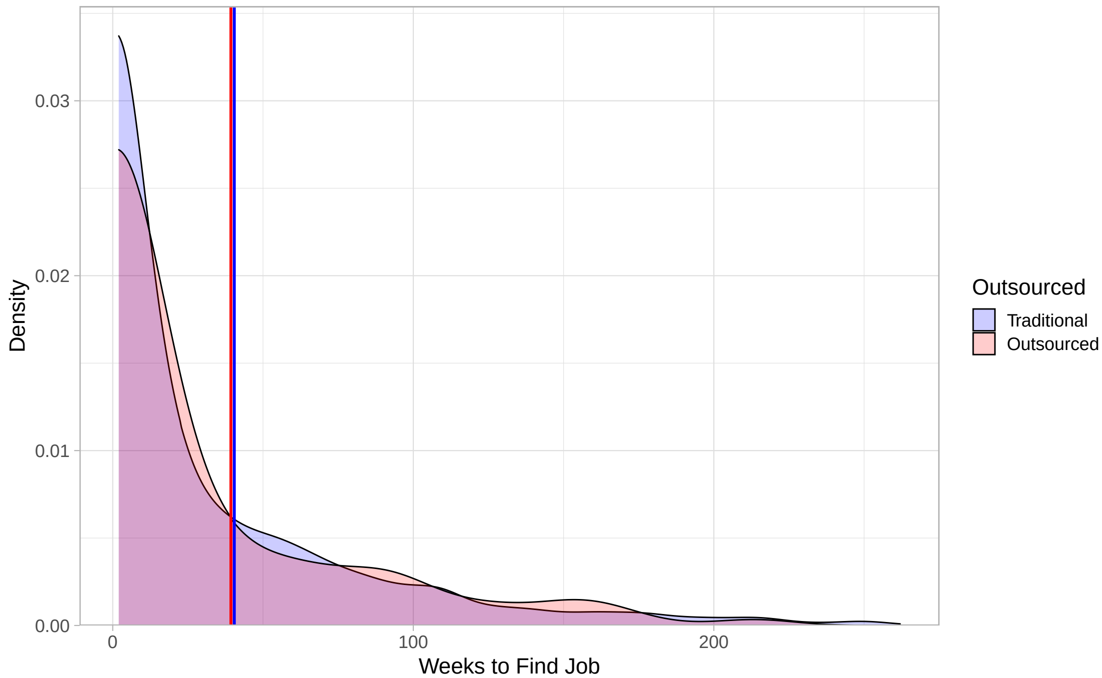

Figure A3: Weeks between previous job and current job excluding one week transitions for currently outsourced and currently traditional workers. Vertical lines are average weeks for outsourced and traditional. Graph excludes the top 1% longest transitions.

A.7 PBS Employment

In this subsection, I study the Professional and Business Services (PBS) industry and how it relates to outsourcing. The goal is to compare to past work by (Berlingieri, 2013) and (Bloom et al., 2018). They both 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 A11.[45] 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. 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

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

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 A11: 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.

be providing an intermediate good but working directly for their firm and would not be considered outsourced by my definition. Part of the discrepancy may be due to different samples.

To see how using PBS as a measure of outsourcing affects my employment results, I rerun the employment shares regression (3) but replace all job type information with percent of occupation employed in PBS industries. I run this regression in both the NLSY and the CPS. The results are in Table A12. These results suggest a similar relationship between employment share and PBS share as there is for outsourcing share, 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.[46]

[46] Berlingieri (2013) uses the BEA Annual Industry Accounts, which is a measure of economy-wide trade aggregates and Bloom et al. (2018) uses the Survey of Occupational Employment, which is a survey of firms.

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 A12: 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 ***.

B Calibration Details

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 A13: Calibration parameters.

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), we compare the benefit of hiring to the benefit of outsourcing

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

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 benefit of hiring increases at rate $\frac{(1-\eta)q(\theta)}{r+\delta}$, while the benefit of outsourcing increases at rate $\frac{1}{r+\delta}$. From Assumption 1, $(1 - \eta)q(\theta) < 1$, so the benefit of outsourcing is increasing faster. Define $y_{low} = b + \Gamma$, where $w(y_{low}) = y_{low}$ and $J_n(n; y_{low}) = 0$. As seen in the outsourcer surplus equation (25), the outsourcer must pay the worker his outside option and must be compensated for entering, implying $p \geq y_{low}$ and $\hat{J}_n(n; y_{low}) \leq 0$ (with strict inequalities 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 $y_{high} > y_{low}$, and both sides monotonically increase in y, these lines must cross exactly once where the firm is indifferent. I denote this point $\hat{y} \in [b + \Gamma, \infty)$, below which the LHS is greater and firms hire, and above which the RHS is greater and firms outsource. $\square$

C.2 Proof of Proposition 2

Proof. This is the proof of Proposition 2. 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 (34) and (35), 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 $y_{low} = b - \Gamma^P$. Under Assumption 2, $q(\theta^P) < 1$, 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 3

Proof. This is the proof of Proposition 3. 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 spread and total entry are efficient. To ensure efficient spread for firms of productivity z and $y \geq z$, compare decentralized spread in (38)-(40) to Planner's spread in (41)-(43) 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

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

$$\tau(y) - \tau(z) = 0 \quad \forall\, \hat{y}^P \leq z \leq y \tag{50}$$

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

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 help obtain the efficient spread between hiring and outsourcing firms.

To ensure efficient entry for hiring and outsourcing firms, compare decentralized entry in (44) and (45) 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 the spread and entry requirements. □

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. It allows 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 steady state 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 have 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 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 the 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 will hire any worker it meets. I also must assume Assumption 1 from the baseline model.

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 find first order and envelope conditions. These tell us how many vacancies firms and outsourcers will create given wages and prices. The intuition for all is similar to the baseline model

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

$$W(y) = w(y) + \beta \Bigg\{ \delta U + (1-\delta)\xi\ell(\theta) \left[(1-\pi) \int_{y}^{\hat{y}} W(x) dF(x) + \pi \int_{R(y)}^{\bar{o}} \tilde{W}(a) d\tilde{F}(a) \right] + (1-\delta)[1 - \xi\ell(\theta)D(y)]W(y) \Bigg\} \tag{56}$$

$$\tilde{W}(o) = \tilde{w}(o) + \beta \Bigg\{ \tilde{\delta} U + (1-\tilde{\delta})\xi\ell(\theta) \left[(1-\pi) \int_{\tilde{R}(o)}^{\hat{y}} W(x) dF(x) + \pi \int_{o}^{\bar{o}} \tilde{W}(a) d\tilde{F}(a) \right] + (1-\tilde{\delta})[1 - \xi\ell(\theta)\tilde{D}(o)]\tilde{W}(o) \Bigg\} \tag{57}$$

$$U = b + \beta \left\{ \ell(\theta) \left[(1-\pi) \int_{\underline{y}}^{\hat{y}} W(z) dF(z) + \pi \int_{\underline{o}}^{\bar{o}} \tilde{W}(a) d\tilde{F}(a) \right] + [1 - \ell(\theta)]U \right\}. \tag{58}$$

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, it is sufficient that $w(\hat{y}) \geq \tilde{w}(\bar{o})$ and $\delta \leq \tilde{\delta}$, with one of these inequalities strict. In the data, $w(\hat{y}) \approx \tilde{w}(\bar{o})$ and $\delta < \tilde{\delta}$, so this assumption holds.

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 and the first order conditions to solve for $W(y) - U$ and $\tilde{W}(o) - U$, we can write the value of search at a given job as

$$\begin{aligned}\Gamma(y, o) &\equiv \theta \left\{ \frac{\eta}{1-\eta}(1-\pi) \int_y^{\hat{y}} \frac{c[v(x); x]}{G(x)} dF(x) + \frac{\tilde{\eta}}{1-\tilde{\eta}} \pi \int_o^{\bar{o}} \frac{\tilde{c}[\tilde{v}(a); a]}{\tilde{G}(a)} d\tilde{F}(a) \right\} \\ &= \frac{1}{s} \left\{ \frac{\eta}{1-\eta} \int_y^{\hat{y}} \frac{v(x) c[v(x); x]}{G(x)} dx + \frac{\tilde{\eta}}{1-\tilde{\eta}} \int_o^{\bar{o}} \frac{\tilde{v}(a) \tilde{c}[\tilde{v}(a); a]}{\tilde{G}(a)} da \right\}. \end{aligned} \tag{59}$$

The intuition is the same as the baseline model, but now workers can search on the job. When they do so, they only accept jobs 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. The value of search while unemployed is $\Gamma^U \equiv \Gamma(\underline{y}, \underline{o})$.

To find the wage at a hiring firm or outsourcer we can use the value of unemployment, the value of working for a firm and outsourcer in steady state, the firm's and outsourcer's envelope condition, and the bargaining rules to solve

$$w(y) = \eta y + (1-\eta)\Big(b + \Gamma^U - (1-\delta)\xi\Gamma[y, R(y)]\Big) \tag{60}$$

$$\tilde{w}(o) = \tilde{\eta} op + (1-\tilde{\eta})\Big(b + \Gamma^U - (1-\tilde{\delta})\xi\Gamma[\tilde{R}(o), o]\Big). \tag{61}$$

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. Because outsourced worker's wages depend in part on firm productivity which can be great than 1, it is now possible for worker wages to increase if their position is outsourced, $\tilde{w}(\bar{o}) > w(\hat{y})$. It is still the case that wages will fall per unit of productivity, $\frac{\tilde{w}(\bar{o})}{\bar{o}} < w(\hat{y})$.

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 and outsourcer in steady state, the value of unemployment, and the fact that $D(y) = \tilde{D}[R(y)]$, we can show this comparison implies

$$\tilde{w}[R(y)] = \frac{X(y;\tilde{\delta})w(y) + (\tilde{\delta} - \delta)\left\{\xi\Gamma[y, R(y)] - [1 - \xi\ell(\theta)D(y)](b + \Gamma^U)\right\}}{X(y;\delta)}, \tag{62}$$

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 similarly define the outsourced worker's reservation wage.

I now 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 hired 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, the relevant comparison is

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

By Assumption D1, the marginal hiring firm offers better terms than all outsourcers (it already offers better terms than all other hiring firms). This implies that 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 (60) gives $(1-\eta)q(\theta) < 1$, which is true by Assumption 1. 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.[47]

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

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.

2. Given market tightness θ and bargained wages $w(y)$ and $\tilde{w}$, the value of unemployment U satisfies (58) and worker reservation values $(R(y), \tilde{R}(o))$ satisfy (62).

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 (60) and bargaining between the outsourcer and the worker gives wage $\tilde{w}(o)$ in (61).

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.

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

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.[48] My analysis focuses on 3 questionnaires within the sample: On Jobs (sometimes On Jobs New or On Employers), Employer Supplement, and Employer History Roster.[49] 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),[50] and new jobs not reported previously (here call NJ but NLSY calls NEWEMP).[51] 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

[48] 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`.

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

[50] 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.

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

are also asked if their job is non-traditional: contracted out, self-employed, an independent contractor, a temp worker, or an on-call worker.[52] 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.[53] I use this measure to find the 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.[54] 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[55]

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

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

[52] 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.

[53] 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.

[54] 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.

[55] 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

Subset	Number
In Employer History Roster and Employer Supplement	35,220
Only in Employer History Roster	+126
Only in Employer Supplement	+3
	35,349
Unmatched with On Jobs	-197
Conflicting Start or Stop Dates	-559
Missing/Conflicting Job Types	-1,753
Total	32,840

Table E1: 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	3,013	31,573	9.54
On Jobs with Information	1,652	30,696	5.38
On Jobs Outsourced	49	541	9.06

Table E2: 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.

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.[56] I have three main ways of matching On Jobs to Employer Supplement: start month, end month, and rank. Unfortunately, many jobs are missing one or more of these variables in the On Jobs section.[57] I therefore match several different ways, from highest to lowest quality, as follows:

1. Start and end month and job rank all match.

2. Start and end month both match.[58]

[56]It seems like the NLSY breaks ties this way, but I was unable to find how priority is determined explicitly.
[57]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.
[58]I prioritize start and end month matching over rank as rank is imputed and could be incorrect.

3. Start month and rank.[59]

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.[60]

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.[61] I also drop any conflicting start or end months between the data sets. Table E1 shows the number of observations added/subtracted at each step of the matching process from the Employer Supplement/Employer History Roster Side. Table E2 shows the match quality from the On Jobs side. Table E3 shows the number of matches by each quality.

[59] 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.

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

[61] 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.

Match Quality	Overall	Outsourced
1. Matched start date, end date, and rank	2,164	110
2. Matched start date and end date	205	12
3. Matched start date and rank	14,423	626
4. Matched end date and rank	6,076	48
5. Matched start date	107	6
6. Matched end date	1,064	14
7. Only unmatched job in year	7,406	58
8. Only unmatched job type in year	172	0
9. Matched rank	1,223	49
Total	32,840	923

Table E3: 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.

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 E4. 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 E6.[62] 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

[62]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.

union, and hourly wage. I use FRED's measure of CPI, CPIAUCSL, to make wages real in 2016 dollars.[63] 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.

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.[64] 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 E7. 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

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

[64] 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.

respondent received any benefits.[65]

I finally cover variables from the rest of the NLSY, which are listed in Table E8. 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 because the NLSY over-samples Hispanics, Blacks, and military members. I often cluster regressions using this 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.[66] 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. 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.[67] I then use job start and end weeks to match my job-year data set to my timeline data set.[68] 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.[69] I then link current jobs to the previous and next job. Finally,

[65]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.

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

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

[68]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.

[69]Because workers can be employed at multiple jobs simultaneously, overlapping jobs can look like job

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 (CWS) to compare to my measure of outsourcing. The variables I use for both analyses are in Table E9, for only the timeline are in Table E10, and for only the CWS are in Table E11. 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.[70] 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).

transitions even when no transition has occurred. Keeping only jobs with the same ranked start and end date drops these occurrences.

[70]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."

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.

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 E4: 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 E5: 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 E6: 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 E7: 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 E8: 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 E9: 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 E10: 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 E11: 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.