Three Essays on Macroeconomics with Search Frictions

by

Scott Spitze

(Under the Direction of Martin Gervais)

Abstract

This dissertation contains three essays on search frictions in macroeconomics. The first two study the effects of domestic outsourcing on workers and labor markets; the first empirically, the second theoretically. The third, written with Fan Liang, studies the theoretical value of new currencies with uncertain acceptance.

Chapters 1 and 2 study the effects of domestic outsourcing on workers and labor markets. In Chapter 1, I use self-reported outsourcing status from the NLSY 1979. Outsourced workers earn 7.1% less in total compensation, mainly because they have lower access to health insurance and retirement plans. These effects are heterogeneous by education: workers without a bachelor's degree earn 8.8% less, while workers with a bachelor's degree earn insignificantly more. Within occupations, outsourcing is positively correlated with employment. Outsourcing leads to a trade-off for workers without a bachelor's degree: jobs are lower quality but more plentiful. In Chapter 2, I examine this trade-off by developing a DMP-style model, in which firms endogenously choose to either hire workers from a frictional labor market or rent labor from outsourcers. High-productivity firms chose to outsource and expand: workers lose access to the highest-paying jobs but are more likely to be employed. Calibrations reveal outsourcing makes workers without a bachelor's degree worse off but workers with one better off.

Chapter 3 studies how new currencies with uncertain acceptance compete with existing currencies. Prices of new currencies reflect both their liquidity today and their expected future liquidity as more consumers and merchants accept them as means of payment. We adopt a New Monetarist framework with an emerging currency, cryptocurrency, competing with an existing currency, money. Seller's acceptance of cryptocurrency exogenously grows over time but this growth stops in a random period. Cryptocurrency prices increase in expected future acceptance and crash when acceptance growth stops, potentially to zero. We also study an environment in which a fraction of buyers are optimistic about the future of cryptocurrencies. Surprisingly, the presence of optimists has an ambiguous effect on prices.

Index words: Macroeconomics, Labor Economics, Monetry Economics, Search Frictions, Domestic Outsourcing, Cryptocurrencies

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by

Scott Spitze

B.A., University of Illinois at Urbana-Champaign, 2015
M.A., University of Iowa, 2018

A Dissertation Submitted to the Graduate Faculty of the
University of Georgia in Partial Fulfillment of the Requirements for the Degree

Doctor of Philosophy

Athens, Georgia

2022

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by

Scott Spitze

Major Professor: Martin Gervais

Committee: Roozbeh Hosseini
Ian Schmutte

Electronic Version Approved:

Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
May 2022

Acknowledgments

I would like to thank my chair Martin Gervais and committee members Roozbeh Hosseini and Ian Schmutte for the advice and guidance they have given me through this project. I would like to thank Fan Liang for her work as a co-author and her support as a friend.

This project was improved by the advice of Görkem Bostanci, Jonathan Chiu, Michael Choi, Lucas Herrenbrueck, Peter Newberry, Svetlana Pashchenko, Xinyi Peng, Alice Schoonbroodt, Pablo Troncoso and all participants at the 2018 Fall I-85 Macro Workshop, the Midwest Macroeconomics Meetings in Athens, GA, the Mini Conference on Search and Money at Madison, the 2020 Fall I-85 Macro Workshop, the SEA 2020 Conference, the NASMES 2021 Conference, the Federal Reserve Bank of St. Louis PhD. intern conference, University of Iowa internal seminars, and University of Georgia internal seminars.

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

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Chapter 1

The Equilibrium Effects of Domestic Outsourcing: Empirical Analysis

1.1 Introduction

This chapter studies the consequences of domestic outsourcing for workers and the labor markets they inhabit. Firms increasingly rely on domestic outsourcing to produce intermediate goods and services, for example tech companies Apple and Google purchase services from other firms for tasks such as janitorial work and hiring employees (Irwin, 2017; Wakabayashi, 2019).[1] Firms choose between producing inputs internally and purchasing them through markets, what economists think of as the boundary of the firm (Coase, 1937; Williamson, 1979). Since the 1980s, 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.

I study a type of domestic outsourcing known as contracting out. Contracted out workers are employed by outsourcers to provide services to client firms 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 work for only one firm at a time and often at the client's place of business. Commonly contracted-out jobs include security guards, electricians, and maids for workers without a bachelor's degree, and management analysts, administrative assistants, and database administrators for workers with a

[1] I find domestic outsourcing has increased in the United States, a result echoed in the literature centering on the U.S. and on other countries. For evidence by country, see Abraham and Taylor (1996); Dey et al. (2010); Katz and Krueger (2019a) for the United States; Goldschmidt and Schmieder (2017) for Germany; Berlingieri (2015); Bergeaud et al. (2021); Bilal and Lhuillier (2021) for France; Bertrand et al. (2021) for India; Kalleberg (2000) for the UK and Spain; Wooden (1999) for Australia.

bachelor's degree (see Tables 1.2 and 1.3). I focus on contracted-out workers for two reasons. First, they are hired by an outsourcer, unlike independent contractors, who work for themselves. Second, contracted-out jobs are expected to last many years, unlike temporary jobs which are fixed-term. For the rest of this paper, I use the terms "outsourced" and "contracted-out" interchangeably.

I use data from the National Longitudinal Survey of Youth 1979 (NLSY) from 2001 to 2016.[2] Since 2002, the survey asks questions about alternative job types for each job, including contracting out.[3] The NLSY provides a unique data combination for studying outsourcing in the United States: it has self-reported outsourcing status, so I can track outsourcing across all workers and occupations, and it has a panel data structure, so I can follow workers across time. The first feature is especially important for studying college educated workers, a group that has been understudied in past literature because of data limitations on outsourcing status. I use this data measure who is outsourced and how outsourcing affects worker outcomes.

I find outsourced workers are mostly similar to the rest of the population. From 2001 to 2016, 7.95% of workers are ever employed in a contracted-out job. This figure is a lower bound because my outsourcing measure starts about halfway into workers' careers. About 65% of these workers are male and they are more likely to be Black, but they have similar education profiles as the rest of the population (see Table 1.1).

On average, outsourced jobs are lower quality than traditional jobs where workers are hired directly by their employer. Compared to traditional workers, outsourced workers are 7.4 pp less likely to have access to health insurance and 7.2 pp less likely to have access to a retirement plan. When combined with insignificantly lower weekly wages, these losses mean outsourced workers earn 7.1% less in total compensation each week (see Table 1.5). These average negative effects mask heterogeneity by education. Workers without a bachelor's degree earn significantly lower wages in outsourced jobs and earn 8.8% less in total compensation each week. In contrast, workers with a bachelor's degree earn insignificantly higher wages and total compensation (see Table 1.6). There is even more heterogeneity for finer education categories, ranging from a 14.7% outsourcing penalty for workers with an associate's degree to a 25.0% outsourcing gain for workers with a postgraduate degree (see Table A3). Past work has found that high-productivity firms (which pay the highest wages) are the most likely to outsource (Goldschmidt and Schmieder, 2017; Drenik et al., 2020; Bilal and Lhuillier, 2021). Consistent with this story, I find that as more workers are employed in high-outsourcing occupations (defined below) the top of the wage distribution shifts left. Thus, outsourcing causes workers to lose access to the highest-paying jobs (see Figure 1.3).

Whereas outsourced jobs are lower quality than traditional jobs on average, outsourcing could still benefit workers in other ways. I study three potential benefits of outsourcing: changes in number of jobs available, differences in ease of finding outsourced jobs, and the quality of jobs found after outsourcing jobs. I find only the first one, more overall jobs, is relevant. Past literature has found outsourcing increases labor demand and overall employment (Bilal and Lhuillier, 2021; Bertrand et al., 2021). My results show that within occupations, increases in outsourcing correlate with increased employment share (see

[2]Over this time period, the NLSY surveys workers every two years. Data for 2001 was collected during the 2002 round of the survey.

[3]To my knowledge, no published research has used data from these questions.

Table 1.9). Moreover, job transitions might be different for outsourced jobs in ways that help or hurt workers. To study the length of job transitions and the quality of previous and subsequent jobs, I use the NLSY data to track the weeks workers start and stop working for employers. I find little evidence that outsourcing affects the number of weeks taken to find the current or subsequent job (see Table 1.10). These null results hold when breaking down by education, despite job quality being very different for the different education groups (see Table A13). Similarly, I find no effects of previous outsourcing status on current job quality (see Table 1.7). Thus, outsourcing neither helps workers find better jobs nor does it force them into worse jobs.

My work makes two contributions to the empirical literature on domestic outsourcing. First, I contribute to the literature on self-reported measures of outsourcing. This literature began with the CPS's Contingent Worker Supplement (CWS), which ran five times from 1995 to 2005 and again in 2017, and also includes Katz and Krueger (2019a), who ask about alternative jobs as part of the RAND American Life Panel in 2015. The NLSY questions I use come almost verbatim from the CWS. However, 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 1.1).

Second, I contribute to the literature on measuring outsourced job quality using panel data. The closest comparison is Dube and Kaplan (2010) (DK), and other papers include Goldschmidt and Schmieder (2017) and Drenik et al. (2020).[4] All of these papers focus on low-skilled workers because of data limitations in determining outsourcing status. They find outsourced workers suffer wage penalties, typically around 5–15%, and DK find these workers are less likely to receive health insurance. I find similar effects for workers without a bachelor's degree but potentially positive effects for workers with bachelor's degrees, especially those with postgraduate degrees. The heterogeneous effects show why it is important to encompass workers across the skill distribution when studying the effects of outsourcing. In Appendix A.1.5, I compare my measure of outsourcing using self-reported status and DK's measure of outsourcing using industry and occupation.

The rest of this chapter is organized as follows. Section 1.2 gives an overview of the NLSY data. Section 1.3 shows outsourcing trends over time and the demographics of outsourced workers. Section 1.4 compares the quality of outsourced jobs to traditional jobs. Section 1.5 shows how the right-tail of the wage distribution for occupations with high levels of outsourcing differ from other occupations. Section 1.6 relates outsourcing and employment within occupations. Section 1.7 studies the job transitions of outsourced workers. Section 1.8 concludes. Supplemental analysis is in Appendix A.1. For more information about how the data was cleaned, including a list of all variables used, see Appendix A.2.

[4] A paper related to Goldschmidt and Schmieder (2017) is Dorn et al. (2018), which uses a similar empirical strategy in the United States. As of this writing, this paper is still a work in progress.

1.2 Introduction to the NLSY 1979

The NLSY follows a nationally representative group of Americans born between 1957 and 1964 throughout their life. The 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: contracted-out, self-employed, independent contractor, temp worker, or on-call worker.[5,6] I classify a job as traditional if it is not reported as any other type.[7] My measure of outsourcing is all contracted-out jobs.[8] These jobs are the most comparable to traditional jobs in terms of wages, hours worked, and benefits.[9] The data ranges from January 2001 to October 2016; the first month is when my measure of outsourcing starts, the last month is when weekly job data becomes scarce as respondents complete the most recent wave of the survey.

My data set is made up of 8,154 workers in 26,184 jobs.[10] Most analysis is done at the job level: jobs with multiple observations across interviews use average or modal characteristics.[11] I also construct a weekly timeline of a worker's employer and labor market status, which I use in the calibration and in some supplemental analysis found in Appendix A.1. Throughout, I weight results based on NLSY supplied weights, which account for respondents' interview participation over time.

1.3 Who Is Outsourced?

In this section, I measure the prevalence of outsourcing and study the demographics of outsourced workers. Figure 1.1 shows the percent of employed workers in outsourced jobs each week. This measure has been increasing over the last two decades, starting at around 0.6% in 2001 and rising to over 2.5% in the

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[5] The NLSY 1997 asks the same job type questions after 2002. As of this writing, this data is not available to the public. According to contact with NLS User Services, they plan on releasing this data soon.

[6] Prior to 2021, this data was publicly available, but because these questions were asked in a separate part of the survey from where employer IDs are created, they could not be matched to job quality measures. Because of this, I am unaware of any published literature using this data. In 2021, the NLSY formally matched these two parts of the survey together, which is the match I use in this paper. For more details, see Appendix A.2.

[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. I assume these assignments are correct and label these jobs as traditional. For more, see `https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/employment/jobs-employers`.

[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?"

[9] See Appendix A.2 for summary statistics by job type. For more on how alternative jobs as a whole compare to traditional jobs, see Kass (2021).

[10] To see how this sample of jobs was obtained from the raw data, see Appendix A.2.

[11] Results are similar using job-interview observations.

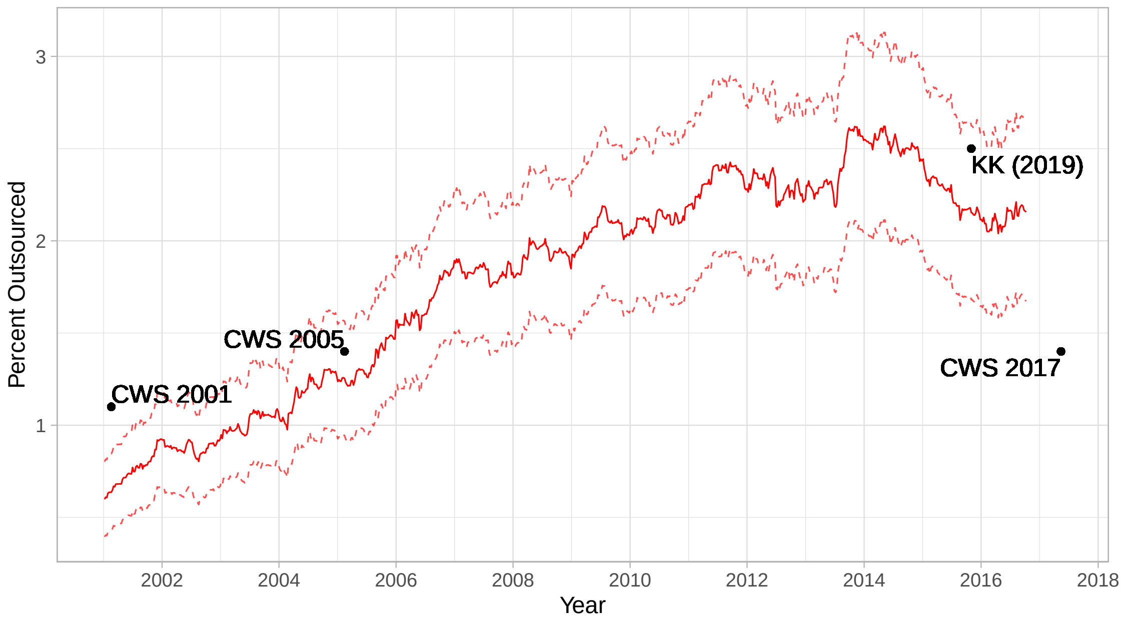

Figure 1.1: Percent of employed workers contracted-out each week in the NSLY. Solid line is the estimate each week, dashed lines are the 95% confidence interval. Point estimates come from Katz and Krueger (2019b) Table 1 compiling data from the Contingent Worker Supplement (CWS) and RAND American Life Panel using alternative weight 2 (Katz and Krueger (2019a)).

early 2010s before falling to 2.1% in 2016.[12] These findings are in line with the rest of the literature, which finds outsourcing is increasing in the United States.

The figure also compares my findings to past surveys from the CWS and Katz and Krueger (2019a) as reported in Katz and Krueger (2019b), Table 1. Both the NLSY and Katz and Krueger (2019a) alternative job questions were worded to closely mimic the CWS, but 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 Katz and Krueger (2019a) suggest 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. If repeated exposure to these questions makes it easier for workers to classify their own job type, then my results may show more contracting out. Katz and Krueger (2019a) show proxy respondents (i.e., spouses) make up about half of all CWS respondents and are about 2 pp less likely to report working in an alternative arrangement. Third, when the NLSY introduced the alternative job questions, the NLSY staff assumed 90% of previously held jobs were traditional (see Footnote 7). I assume that 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 those in the past

[12] Because the panel data follows only one cohort, we may worry the increase in outsourcing over time is due to age effects. In Appendix A.1.1, I show the increase in outsourcing holds even when holding age constant.

Table 1.1: Demographic Summary Statistics

Variable	Ever Outsourced	Never Outsourced
Female	0.353	0.493***
	(0.023)	(0.007)
Black	0.217	0.133***
	(0.015)	(0.003)
Hispanic	0.075	0.064
	(0.007)	(0.002)
Less High School	0.082	0.080
	(0.012)	(0.003)
High School	0.539	0.518
Diploma	(0.024)	(0.007)
Associate's	0.108	0.095
Degree	(0.015)	(0.004)
Bachelor's	0.163	0.174
Degree	(0.019)	(0.005)
Postgraduate	0.059	0.080*
Degree	(0.011)	(0.004)
Observations	648	7,506

Note: Demographic statistics for those who ever work in outsourced jobs versus those that never do. Observations are weighted at the person level. Stars represent significance difference at the .10 level (*), .05 level (**), and .01 level (***).

literature. While my measure of outsourcing is significantly below that of the 2001 CWS and significantly above that of the 2017 CWS, both the measures of outsourcing in the 2005 CWS and Katz and Krueger (2019a) are within my confidence interval. Note that Katz and Krueger (2019a)'s level of contracting out is more than 1 pp greater than the one found by CWS 2017, despite the fact they are only measured a year and a half apart. My measure of outsourcing is closer to Katz and Krueger (2019a), both of which find contracting out has increased since 2001.

Who works in outsourced jobs? In Table 1.1, I look at demographics based on worker job histories. The table divides workers between *ever outsourced* and *never outsourced*. Overall, 7.95% of workers are ever outsourced in the sample. My measure of outsourcing starts when workers are aged 37–44, well into their careers, so it is lower bound for workers ever experiencing outsourcing, especially as most job transitions occur when workers are young (Gervais et al., 2016). *Ever outsourced* workers are significantly more likely to be Black and male. Almost half of the never outsourced are women, but only about a third of the *ever outsourced* are. While *ever outsourced* workers are slightly more likely to have a high school diploma or associate's degree and slightly less likely to have a bachelor's degree or postgraduate degree, only the share

Table 1.2: Most Commonly Outsourced Jobs for Workers without Bachelor's Degree

Rank	Occupation
1.	Security guards and gaming surveillance officers
2.	Driver/sales workers and truck drivers
3.	First-line supervisors/managers of construction trades and extraction workers
4.	Electricians
5.	Construction laborers
6.	Welding, soldering, and brazing workers
7.	Insurance claims and policy processing clerks
8.	Maids and housekeeping cleaners
9.	General and operations managers
10.	Carpenters

Note: The ten most common outsourced jobs for workers without a bachelor's degree. Amount of outsourcing is measured as the number of weeks workers report "contracted-out" as their job type.

with postgraduate degrees is significantly different. In general, *ever outsourced* workers have similar levels of education to the rest of the population.[13]

Which occupations are outsourced workers employed in? Tables 1.2 and 1.3 show the occupations with the most weeks worked by outsourced workers without and with a bachelor's degree. Outsourced workers without a bachelor's degree are often in construction jobs, such as electricians and carpenters. This list also includes groups often studied in other papers: security guards, truck drivers, and maids. For workers with college degrees, many of the occupations relate to administrative work, such as secretaries; technology, such as computer support specialists; or a combination of the two, such as database administrators.

1.4 Quality of Outsourced Jobs

From the demographic comparisons above, it is clear outsourced workers are similar to the rest of the population, but what about outsourced jobs? I now compare the quality of outsourced jobs to that of traditional jobs. First, I compare summary statistics, and then I use worker- and occupation-fixed-effect regressions to examine if the comparison changes after controlling for potential underlying differences. I show how quality effects depend on workers' education level.

I start with summary statistics. Table 1.4 compares outsourced jobs to traditional jobs. Workers earn higher wages and work longer hours in outsourced jobs.[14] Moreover, outsourced workers are twice as

[13]In Appendix A.1.2, I use monthly CPS data from 2001 to 2016 to see how these results generalize to the rest of the population. I conclude that the NLSY cohort is a reasonable proxy for the rest of the population and the NLSY sample captures this cohort well.

[14]All wages are in logs of real 2016 dollars. I drop wages of people making less than $3.00 (Federal minimum wage in 2002 was $5.15, which is equivalent to about $6.60 in 2016) or more than $500 in real hourly wages or working 0 hours or more than 80 hours per week. I classify workers as part time if they work less than 35 hours a week.

Table 1.3: Most Commonly Outsourced Jobs for Workers with Bachelor's Degree

Rank	Occupation
1.	Managers, all other
2.	Management analysts
3.	Secretaries and administrative assistants
4.	Computer and information systems managers
5.	Computer support specialists
6.	Other teachers and instructors
7.	Database administrators
8.	Bill and account collectors
9.	Network systems and data communications analysts
10.	Marketing and sales managers

Note: The ten most common outsourced jobs for workers with a bachelor's degree. Amount of outsourcing is measured as the number of weeks workers report "contracted-out" as their job type.

likely to be unionized.[15] This finding contrasts Goldschmidt and Schmieder (2017) and Dube and Kaplan (2010), who find outsourced workers are less likely to be unionized. These differences may be due to the population of workers studied. In Tables A6 and A7 of Appendix A.1.5, I find janitors and security guards, the workers studied by Dube and Kaplan (2010), are less or equally likely to be unionized.

Broadening the analysis to other measures of job quality, outsourced jobs do not perform so well. The average tenure in outsourced jobs is 2 years, which is less than half the average tenure of traditional jobs, which is 5.25 years. More importantly, traditional workers are significantly more likely to have access to every measured benefit. This includes a 4-7 pp gap for access to any benefits and for major benefits of interest such as health insurance and retirement plans. To get a measure of overall job quality, I impute total compensation based on a worker's weekly wages and access to health insurance and retirement plans through the worker's employer. I derive the value of these plans in relation to wages using the National Compensation Survey (NCS), as detailed in Appendix A.2.3. My imputation suggests that outsourced worker's higher wages are more valuable than their fewer benefits, and that total compensation in outsourced jobs is higher. However, the NLSY asks workers to rank their job satisfaction from 1 to best to 4 for worst; and traditional workers are more satisfied with their jobs. From summary statistics alone, it is not clear whether outsourced jobs are better or worse than traditional ones.

Outsourced jobs are roughly similar to traditional jobs and are held by people with similar levels of education. Are they still comparable after controlling for observables? To find out, I run regressions on various measures of job quality: log real weekly wages, access to health insurance and retirement benefits, and log real total compensation. Equation (1.1) shows the main specification for person i in job j and

[15] Higher rates of unionization could arise because union workers are more likely to be outsourced, rather than outsourced workers being more likely to be unionized. In Table A12 from Appendix A.1.6, I show workers are more likely to be unionized in their current outsourced job than in their previous job. In an unpublished analysis (details available upon request), I find this is because workers who move from traditional jobs to outsourced jobs more than double their rate of unionization.

Table 1.4: Job Summary Statistics

	Outsourced	Traditional
Log Real	2.98	2.91***
Hourly Wage	(0.04)	(0.01)
Log Real	6.60	6.48***
Weekly Wage	(0.05)	(0.01)
Hours Worked	40.48	39.01***
Weekly	(0.59)	(0.16)
Part Time	0.18	0.22**
	(0.02)	(0.00)
Tenure	115.21	273.54***
(Weeks)	(5.88)	(3.54)
Union	0.10	0.05***
	(0.01)	(0.00)
Any Benefits[a]	0.72	0.79***
	(0.02)	(0.00)
Health	0.64	0.68**
Insurance[a]	(0.02)	(0.01)
Retirement	0.51	0.58***
Plan[a]	(0.02)	(0.01)
Subsidized	0.05	0.07*
Childcare[a]	(0.01)	(0.00)
Dental	0.56	0.60**
Insurance[a]	(0.02)	(0.01)
Flex	0.37	0.45***
Schedule[a]	(0.02)	(0.00)
Life	0.54	0.58**
Insurance[a]	(0.02)	(0.01)
Maternity	0.46	0.57***
Leave[a]	(0.02)	(0.01)
Profit	0.16	0.20***
Sharing[a]	(0.01)	(0.00)
Training[a]	0.29	0.41***
	(0.02)	(0.01)
Log Real	6.74	6.63***
Total Compensation[b]	(0.05)	(0.01)
Job Satisfaction	1.89	1.82**
(Lower Better)	(0.04)	(0.01)
Observations	741	19,967

Note: Summary statistics of jobs in the NLSY for 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 (***).

[a] Benefits measure if worker reports access to benefit through employer.

[b] Total compensation is imputed using log real weekly wages and access to health insurance and retirement plans. The value of these benefits is calculated using data from the NCS. See Appendix A.2.3 for more details.

occupation k

$$Y_{ijk} = \beta_0 \; outsourced_{ij} + \beta_1 X_{ij} + \alpha_i + \psi_k + \epsilon_{ijk}. \tag{1.1}$$

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.[16] All standard errors are clustered by demographic sample, which the NLSY used when creating the data set to ensure it was nationally representative.

The results, reported in Table 1.5, show outsourced jobs are worse than traditional jobs. In summary statistics, outsourced jobs pay higher weekly wages, but these regressions find outsourced jobs have insignificantly lower wages: outsourced workers earn 4.2 log points per week less than traditional workers.[17] The more significant effects are for access to benefits, outsourced workers are 7.4 pp and 7.2 pp less likely to have access to health insurance and retirement plans, respectively. My imputation of total compensation, which combines all three measures, suggests outsourced workers earn 7.1 log points less each week.[18,19]

My results are mostly in line with past literature. Goldschmidt and Schmieder (2017) find workers in food service, cleaning, security, logistics occupations in Germany make about 4–15 log points per day less. Dube and Kaplan (2010) find outsourced security guards and janitors in the United States make about 7–11 log points per hour less and are 5–15 pp less likely to receive health insurance. I find similar benefits effects but smaller wage effects. This difference may be due to the population of workers studied. Their samples are restricted to occupations with relatively low education requirements, while mine contains all workers. To see how much education level affects the outsourcing penalty, I replace the $outsourced$ term in equation (1.1) with the interaction $outsourced \times bachelor$, where $bachelor$ measures if the worker has a bachelor's degree.[20] The results, shown in Table 1.6, show stark differences in outcomes by education. Outsourcing jobs are much lower quality for workers without a bachelor's degree. Their weekly wages are a significant 6.6 log points lower, an effect more in line with previous literature. While their benefit penalties are slightly smaller, their overall compensation is a significant 8.8 log points lower. For workers with a bachelor's degree, the effects are more mixed. Their weekly wages are an insignificant 8.5 log points higher, and despite their larger benefits penalties, their total compensation is insignificantly higher too. Outsourcing jobs are of similar quality, perhaps even of higher quality, for workers with a bachelor's

[16] Other controls are a quartic in age and job tenure, union status, region of country, if in a MSA, and marital status. I also include fixed effects for years job started and ended.

[17] This discrepancy suggests outsourced workers are positively rather than negatively selected for productivity. I provide more evidence for this assertion in Appendix A.1.3.

[18] In Table A2 from Appendix A.1.3, I run similar regressions for log real hourly wages, hours worked, part-time status, and access to any benefits. The results are insignificant for the first three measures. For access to any benefits, the results are similar to those for health insurance and retirement.

[19] In Appendix A.1.4, I compare contracted-out jobs to independent contractor, temp, self-employed, and on-call jobs. Many of these other job types have significantly lower earnings and all are much less likely to have access to benefits. Regressions show these discrepancies persist after controlling for observables.

[20] When constructing worker education, I assign workers their modal education over the entire period, so measured education does not change in the sample. Because worker fixed effects will capture any education effects, I do not include a $bachelor$ term in the regression.

Table 1.5: Quality of Outsourced Jobs

	Log Real Weekly Wages	Health Insurance[a]	Retirement Plan[a]	Log Real Total Compensation[b]
Outsourced	−0.042	−0.074***	−0.072***	−0.071**
	(0.026)	(0.021)	(0.015)	(0.026)
R^2	0.77	0.65	0.65	0.77
Observations	18,976	21,364	21,184	18,720

Note: Regressions of worker outsourcing status on job outcomes. Data comes from the NLSY. All regressions include controls for job type (traditional job is default), worker and occupation fixed effects, a quartic in age, dummies for year started and ended job, union status, dummies for region, whether in an MSA or central city, and marital status. All observations are at the person-job level,, where jobs observed more than once use average or modal characteristics. All regressions are weighted at the person level and all standard errors are clustered by demographic sample. Stars represent significance at the .10 level (*), .05 level (**), and .01 level (***).
[a] Benefits measure if worker reports access to benefit through employer.
[b] Total compensation is imputed using log real weekly wages and access to health insurance and retirement plans. The value of these benefits is calculated using data from the NCS. See Appendix A.2.3 for more details.

Table 1.6: Quality of Outsourced Jobs by Bachelor's Degree Attainment

	Log Real Weekly Wages	Health Insurance[a]	Retirement Plan[a]	Log Real Total Compensation[b]
No Bachelor's ×	−0.066**	−0.069**	−0.068***	−0.088***
Outsourced	(0.023)	(0.024)	(0.012)	(0.023)
Bachelor's ×	0.085	−0.094*	−0.093*	0.030
Outsourced	(0.094)	(0.049)	(0.050)	(0.114)
R^2	0.77	0.65	0.65	0.77
Observations	17,922	20,193	20,018	17,673

Note: Regressions of worker outsourcing status by bachelor's degree attainment on job outcomes. Data comes from the NLSY. Regressions control for bachelor's attainment multiplied by job type (default is traditional). Regressions also include worker and occupation fixed effects, a quartic in age and job tenure, and year started and ended job, union status, dummies for region, whether in an MSA or central city, and marital status. All observations are at the person-job level, where jobs observed more than once use average or modal characteristics. All regressions are weighted at the person level, and all standard errors are clustered by demographic sample. Stars represent significance at the .10 level (*), .05 level (**), and .01 level (***).
[a] Benefits measure if worker reports access to benefit through employer.
[b] Total compensation is imputed using log real weekly wages and access to health insurance and retirement plans. The value of these benefits is calculated using data from the NCS. See Appendix A.2.3 for more details.

degree. These differences in total compensation by bachelor's attainment is something I will address in the calibration.[21]

[21] In Table A3 in Appendix A.1.3, I show results from a regression that breaks education into five categories: less than high school diploma, high school diploma, associate's degree, bachelor's degree, and postgraduate degree. The most negatively affected workers are those with a high school diploma or associate's degree; these workers have 8.3 and 14.7 log point lower total compensation, respectively. At the other end of the spectrum, workers with a postgraduate degree have 25.0 log point higher total compensation.

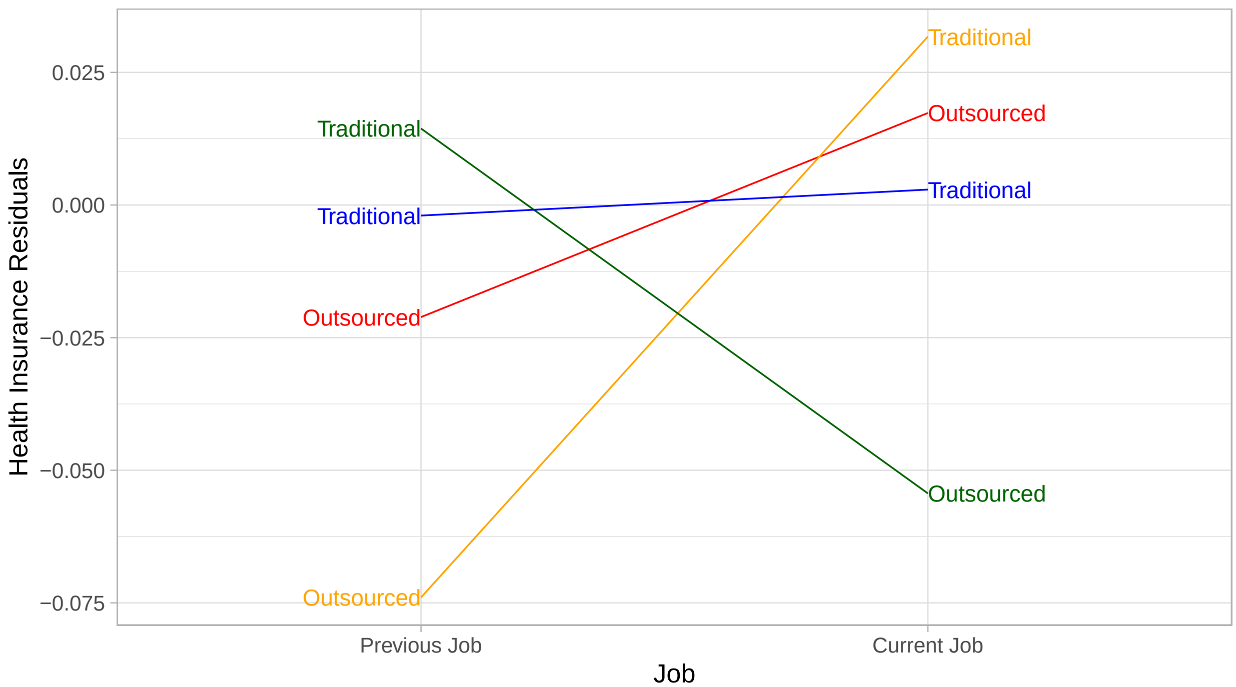

Figure 1.2: Mean access to health insurance residuals at previous and current job by current and previous job type. Residuals come from a regression similar to the one described in Table 1.5 but without the variable *outsourced*, which indicated if a job was outsourced (see Footnote 16).

These regressions use worker fixed effects, so the outsourcing effect is estimated by workers moving in and out of outsourced jobs. The key identifying assumption is that job quality can be divided into worker specific and job-type specific components. Endogenous job transitions could break this assumption, so I perform several robustness checks as diagnostic tests of key assumptions.[22] The first, in the spirit of Card et al. (2013), compares residual outcomes based on current and previous outsourcing status. As an example, I report results for receiving health insurance, but other outcomes are similar. I run regression (1.1) for receiving health insurance but without the variable *outsourced* to differentiate outsourced from traditional jobs. In Figure 1.2, I plot average residuals from these regressions by current and previous job types. Workers who go from traditional to outsourced jobs are about 7 pp less likely to have access to health insurance, whereas workers who go from outsourced to traditional jobs are 10 pp more likely to have access.[23]

The second robustness check, inspired by Gibbons and Katz (1992), is to regress current job quality on previous job type. For the sub-sample of jobs with information on previous job type, I run the original

[22]I report robustness checks only for the baseline regression without interactions by education. Adding education interactions shows similar results (details available upon request).

[23]In Appendix A.1.3, I perform similar exercises using unconditional health insurance access and for log real total compensation, with similar results.

Table 1.7: Effect of Previous Job Type on Current Job Quality

	Log Real Weekly Wages	Health Insurance[a]	Retirement Plan[a]	Log Real Total Compensation[b]
Outsourced	−0.031	−0.094***	−0.076***	−0.057
Current	(0.033)	(0.026)	(0.016)	(0.034)
R^2	0.85	0.71	0.70	0.85
Observations	8,730	9,844	9,739	8,569
Outsourced	−0.019	0.027	0.028	−0.001
Previous	(0.047)	(0.033)	(0.035)	(0.053)
R^2	0.84	0.66	0.65	0.83
Observations	8,733	9,846	9,739	8,573

Note: Regressions of worker outsourcing status on job outcomes in the NLSY. All regressions include controls for job type (traditional job is default) in current (top regressions) or previous (bottom regressions) 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, and marital status. All observations are at the person-job level, where jobs observed more than once use average or modal characteristics. All regressions are weighted at the person level, and all standard errors are clustered by demographic sample. Stars represent significance at the .10 level (*), .05 level (**), and .01 level (***).

[a] Benefits measure if worker reports access to benefit through employer.

[b] Log real total compensation imputed using year, occupation, log real weekly wage, access to health insurance and retirement benefits.

regression to confirm that this sub-sample is the same. Results on the top half of Table 1.7 (compare to the full sample in Table 1.5) confirm it is. The bottom half shows the results when previous job types are used instead. The effect on weekly earnings is almost exactly the same although both are insignificant. The effects on access to benefits go from significantly negative to insignificantly positive, consistent with the story that outsourced workers are positively selected. The net effect for total compensation is zero. These results confirm that past job type has little effect on current job quality.[24] These robustness checks suggest that my key identifying assumptions on the separability between worker specific and job-type specific quality components are reasonable.

Although I use a different measure of outsourcing, most of my results for workers with less than a bachelor's degree are similar to those from past literature. The most direct comparison is to Dube and Kaplan (2010) (DK), who study security guards and janitors in the monthly CPS. Without a direct measure of outsourcing, the authors 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 be applied only to a few occupations, it has the benefit of using commonly available data rather than less common self-reported measures. If industry-occupation

[24] Similar exercises confirm results for other the alternative measures of job quality and for specifications interacting outsourcing status both with bachelor's degree attainment and with more detailed education breakdowns (details available upon request).

Table 1.8: Job Type Classification Comparison to Dube and Kaplan 2010 for Security Guards

	Industry-Occupation (Dube and Kaplan)		
Self-Reported	Outsourced	Not Outsourced	Total
Contracted-Out (This Paper)	43	11	54
Independent Contractor	9	5	14
Temp Worker	2	3	5
On-Call Worker	12	4	16
Self-Employed	5	0	5
Traditional Employee	92	111	203
Total	163	134	297

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

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, I compare my measure of outsourcing to DK's for janitors and security guards. While I leave the full details to Appendix A.1.5, here I briefly compare how the methods measure outsourcing. Table 1.8 shows how security guards report their job type compared to their industry. Of the 54 contracted-out security guards in the survey, 11 would not be considered outsourced by DK's method, while of the 203 who are classified as traditional (workers who did not report an alternative job type), 92 would be considered outsourced. In Appendix A.1.5, I show similar discrepancies for janitors and using data from the six waves of the CWS. I also show how another common industry measurement of outsourcing, defining workers in professional business service industries as outsourced, differs from mine. This suggests that self-reported measures of outsourcing and self-reported industry-occupation are fundamentally different measures of outsourcing.

1.5 Wage Distributions

Most of the past literature on outsourcing has found that more productive firms are more likely to outsource and pay higher wages, even to outsourceable workers (Goldschmidt and Schmieder, 2017; Drenik et al., 2020; Bilal and Lhuillier, 2021). Given these facts, increases in outsourcing should lead to a "missing" right tail of the wage distribution as high-paying firms shift from hiring to outsourcing. In this section, I test this hypothesis empirically using workers in high-outsourcing (HO) occupations, occupations with higher than average levels of outsourcing (3.48%). To increase sample size, I use CPS data from January 2001 to October 2016, the same period as that of the NLSY data.[25]

[25] Similar results are found using NLSY data.

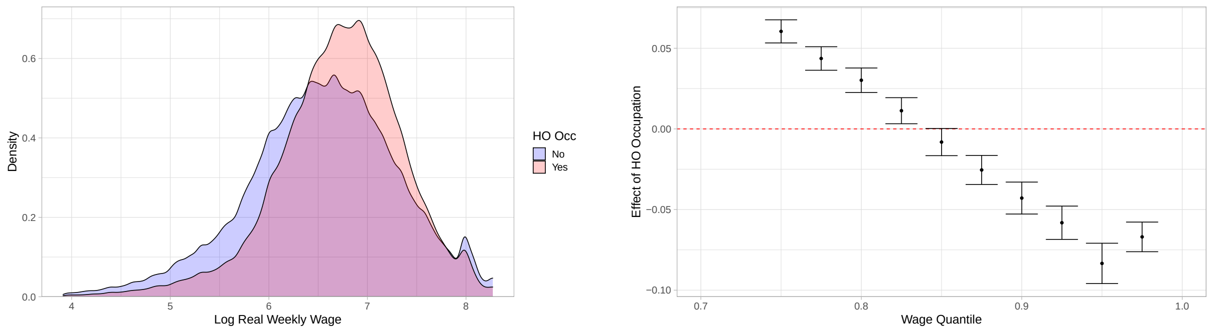

Figure 1.3: Distribution of log real weekly wages in the monthly CPS by whether worker is in a high-outsourcing (HO) occupation or not. HO occupations are occupations with more than twice the average outsourcing rate in the NLSY (3.48%). Data is from January 2001 to October 2016 for workers aged 18-65. Left panel shows raw data by occupation type. Right panel shows coefficients from unconditional quantile regressions (UQR) of high-outsourcing (HO) occupation on log real weekly wages at every every 2.5th quantile from 75 to 97.5.Regression for the τ quantile suggests that, holding all else equal, transitioning from an economy with no workers in HO occupations to all workers in HO occupations will shift the τ quantile of the wage distribution that amount. Regressions control for a quartic in age, gender, race, union status, marital status, and education, use monthly fixed effects, and are weighted by CPS earning weights.

The left panel of Figure 1.3 shows the raw weekly wage distribution for workers in and out of HO occupations. Of particular interest is the right tail of the distributions. While HO occupations appear to have higher average weekly wages, they have fewer workers earning log wages above 8 (about $3,000) each week. The raw data suggests that the missing right tail hypothesis is plausible.

To see if the missing right tail hypothesis holds after controlling for observables, I run unconditional quantile regressions, which show the impact of changing the distribution of explanatory variables on the marginal quantiles of the outcome variable Firpo et al. (2009). In my case, they show how increasing the percent of workers in HO occupations will affect the τ quantile of the wage distribution. In contrast, a standard (conditional) quantile regressions measures how the τ quantile workers' wage would change if they transitioned into a HO occupation. I run an unconditional quantile regression for every 2.5th quantile from 75 to 97.5. The outcome is log real weekly wage, and the main explanatory variable is *HO occupation*.[26]

The right panel of Figure 1.3 shows the regression results by quantile. For quantiles above 85, the coefficient on HO occupation is negative, which means more workers in HO occupations shift these quantiles of the wage distribution to the left. This result suggests that these occupations have missing right tails. When high-productivity firms outsource, workers lose access to the highest-paying jobs.

[26] I control for a quartic in age, gender, race, union status, marital status, and education and use monthly fixed effects. Regressions are weighted by CPS earning weights.

Table 1.9: Effects of Outsourcing Level within Occupation on Worker Share

	NLSY 79	CPS	CPS (NLSY 79 Cohort)
Outsourced Percent	0.00020*	0.00033***	0.00038**
	(0.00011)	(0.00013)	(0.00016)
R^2	0.98	0.94	0.92
Observations	73,356	68,109	57,988

Note: 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 female, 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. Stars represent significant difference from 0 at the .10 level (*), .05 level (**), and .01 level (***).

1.6 Employment Effects

If the ability to outsource increases the value of labor for a firm, then their demand for labor will increase. Bilal and Lhuillier (2021) find outsourcing firms increase production, while Bertrand et al. (2021) show that regions of India with more outsourcing have higher employment. In this section, I show evidence of similar effects of outsourcing in the US: increases in outsourcing within an occupation are correlated with a larger share of employment. I find this increase both in NLSY and CPS data.

Regression (1.2) details the specification. For occupation k in month t

$$Y_{kt} = \beta_0 \; outsourced_{kt} + \beta_1 X_{kt} + \psi_k + \omega_t + \epsilon_{kt}. \tag{1.2}$$

The outcome Y is the share of workers employed in the occupation. The main independent variable is $outsourced$, which measures the share of workers outsourced within the occupation each month. I also include occupation and week fixed effects ψ and ω and other occupation level controls X.[27] The result is shown in the first column of Table 1.9. A 1 pp increase in outsourcing within an occupation is associated with a significant 0.00020 pp increase in employment. The mean occupation makes up about .24% of total employment, so this result implies a 0.083% increase in employment in the average occupation.

We might worry 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 run the regression for workers age 18–65 and for workers in the NLSY cohort. The results are in the second and third column of Table 1.9. The association for the full sample is significant and larger than the NLSY results at 0.00033. The results are stronger when I restrict

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

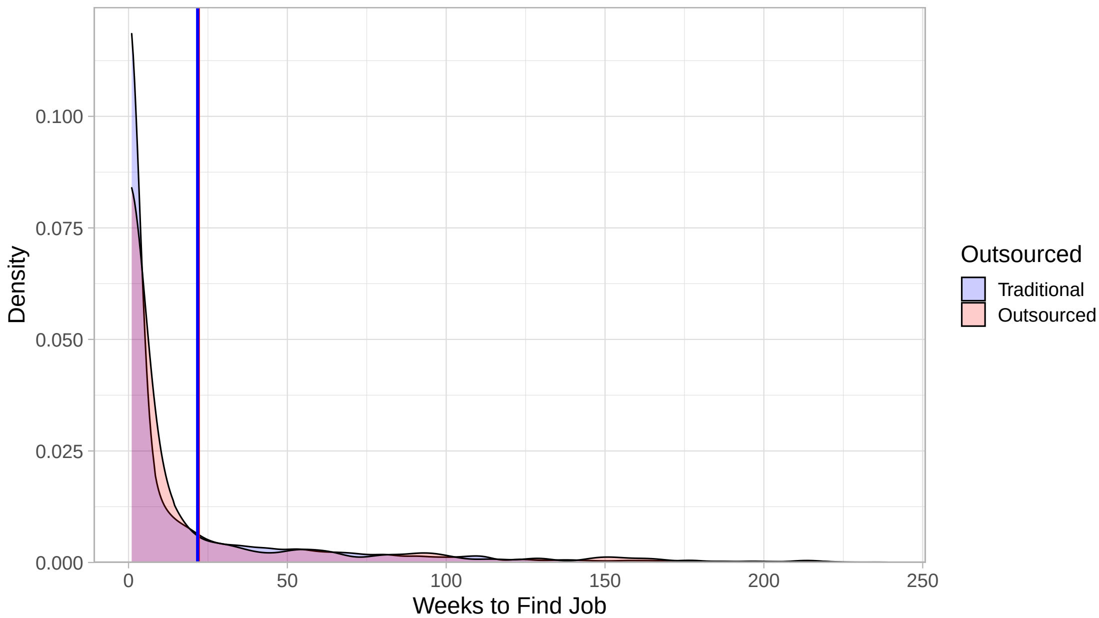

Figure 1.4: Weeks between previous job and current job for currently outsourced and currently traditional workers. Vertical lines are average weeks for outsourced and traditional workers. Figure excludes the longest 5% of transitions.

the sample to the NLSY cohort, where the coefficient of interest becomes 0.00038. This could be because, as in Katz and Krueger (2019a), older workers are more likely to be contracted-out, or because there are underlying contracting out patterns that differ by age. These regressions prove the positive correlation between outsourcing and employment.

1.7 Job Transitions

In this section, I study how outsourcing affects how workers transition between jobs. The main question I will answer is whether workers take longer to transition into or out of outsourced jobs. 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 stop weeks.[28] This timeline allows me to study how many weeks workers take to find jobs.[29]

I start with summary statistics. Figure 1.4 shows the distribution of weeks between the previous and current job for traditional and outsourced workers. The solid line shows the mean of each distribution.

[28] Table A12 from Appendix A.1.6 shows summary statistics for previous, current, and next job for current outsourced and traditional jobs.

[29] More details on how I link job histories can be found in Appendix A.2.

Table 1.10: Weeks to Find Current Job Regressions

Variables	Weeks to Job	Weeks to Job (> 1)	Job-Job Transition
Outsourced	−0.48	0.11	−0.01
Current	(3.49)	(7.04)	(0.03)
Outsourced	−12.07***	−15.00	0.04
Previous	(3.66)	(9.75)	(0.04)
R^2	0.73	0.83	0.59
Obs	9,615	5,197	9,476

Note: Regressions of outsourced at current and previous job on weeks to find current job (both overall and conditional on the transition 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) and fixed effects for occupation. Regressions contain a dummy for year current job began, and the following demographic variables: a quartic in age, dummies for region, whether in an MSA or central city, and marital status. 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 significance at the .10 level (*), .05 level (**), and .01 level (***).

Traditional jobs are more likely to be found quickly, but the distributions and means are similar for both job types. In Table A12, I show the average weeks between jobs are statistically indistinguishable between outsourced and traditional jobs. I also show the rate of job-to-job transitions, defined as a transition where the new job is reported the week after the old job ends, is statistically indistinguishable between these job types.

To see if this lack of differences holds after controlling for observables, I run regression (1.3). 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

$$Y_{iabjk} = \beta_0 \; outsourced_a + \beta_1 \; outsourced_j + \beta_2 X_{ia} + \beta_3 X_{ij} + \alpha_i + \psi_b + \psi'_k + \gamma_t + \epsilon_{iabjk}. \quad (1.3)$$

Once again, the main parameter of interest is $outcourced$, 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', respectively. Other previous and current job characteristics and current demographic characteristics are in X.[30]

Table 1.10 shows these results. For all outcomes, the effect of the current job being outsourced is near zero and statistically insignificant. Workers potentially find their next job quicker if they were previously outsourced, but there seems to be no effect on their likelihood of job-to-job transition. On average,

[30]Controls mostly come from current period: dummies for year, a quartic in age, dummies for region, whether in an MSA or central city, and marital status. Also control for current and previous job type (default is traditional). Standard errors are clustered at the demographic sampling group.

outsourced jobs have the same rate of job finding and job-to-job flows as traditional jobs.[31] I conclude that workers are not compensated for lower job quality with faster job finding rates.

1.8 Conclusion

Contracting out is an increasingly important phenomenon in the U.S. economy, I find the share of contracted out workers has about doubled from less than 1% in 2000 to more than 2% in 2016. Outsourced workers are employed in low-skilled occupations such as security guards and truck drivers and high-skilled occupations such as management analysts and computer support specialists. Outsourcing is a phenomenon experienced by workers across the education spectrum.

Outsourced workers are worse off compared to those in traditional jobs. They are about 7 pp less likely to have access to health insurance and retirement plans, leading to 7.1% less in total compensation each week. For workers without a bachelor's degree, these penalties are even larger; with significantly lower wages and access to benefits, their total compensation is 8.8% less. I find no evidence for potential compensating differentials such fewer weeks to find the job or higher quality future jobs. For workers with a bachelor's degree, the effects of outsourcing are more mixed and potentially positive for workers with a post-graduate degree.

The fact that these jobs are lower quality on average, however, does not guarantee that workers are worse off because of outsourcing. I find a positive relationship between outsourcing and employment within occupations. If outsourcing is causing firms to demand more labor, an increase in employment could still make workers better off overall. On the other hand, another negative of outsourcing for workers are the jobs that are no longer available. Past literature has found that high-productivity firms are more likely to outsource, and I find that occupations with high levels of outsourcing have fewer workers earning the highest wages in the economy. This suggests that outsourcing jobs are replacing the highest-paying jobs. To formally examine how workers should value the trade-offs of outsourcing, Chapter 2 will build a theoretical model of outsourcing and match it to the NLSY data.

[31] Table A13 in Appendix A.1.6 shows results from the same regression interacting job type with bachelor's attainment. Current outsourced jobs have no significant effects for workers with and without bachelor's degrees, even though outsourced jobs are significantly worse for workers without a bachelor's degree.

Chapter 2

The Equilibrium Effects of Domestic Outsourcing: Theoretical Analysis

2.1 Introduction

This chapter takes the empirical results from Chapter 1 and attempts to develop a theory for how domestic outsourcing affects workers and labor markets and measure how these effects are playing out in the U.S. economy. In the previous chapter, we learned that outsourcing comes with a trade-off for workers, especially those without a bachelor's degree. Outsourced jobs are lower quality, but outsourcing leads to higher labor demand and increased employment. To study these trade-offs, I develop a labor search model of domestic outsourcing. 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 renting 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. For outsourcers to exist in equilibrium, they must have some comparative advantage over firms hiring directly. I capture this comparative advantages in a reduced-form way through lower vacancy costs.

The model is able to capture three facts from my empirical findings and from past literature: the differences in compensation at outsourcers versus traditional firms, the productivity of firms that outsource, and the effects of outsourcing on employment.

1. In the data, I find outsourcing penalties for workers without a bachelor's degree and benefits for workers with one. In the model, the average wage at hiring firms can be higher or lower than the average wage at outsourcers.

2. Other papers show more productive firms are more likely to outsource (Goldschmidt and Schmieder, 2017; Drenik et al., 2020; Bilal and Lhuillier, 2021). In the model, outsourcing allows firms to

avoid search frictions and bargaining with workers, both of which are more valuable to high-productivity firms. High-productivity firms outsource; low-productivity firms hire. Furthermore, high-productivity (and high-wage) firms switching from hiring to outsourcing causes a "missing" right tail of the wage distribution. In the data, I find this missing right tail in the wage distribution for occupations with high levels of outsourcing.

3. Bilal and Lhuillier (2021) find outsourcing increases firm production and labor demand, while Bertrand et al. (2021) find outsourcing increases employment. I also find a positive correlation between outsourcing and employment share within occupations. In the model, increases in outsourcing lead to increased production and employment.

To study how outsourcing affects workers, I analytically solve for wages and vacancy creation. There are three key effects of outsourcing that determine how worker welfare changes: the decrease in wages at outsourcers compared to client firms, the total increase in jobs available, and the difference in wages at hiring firms versus outsourcers. First, workers are paid less by the outsourcer than they would be if they were hired by client firms. When workers and firms bargain directly, the surplus depends on the firm's productivity. When workers bargain with outsourcers, the surplus depends on the payment received from the firm, which is less than the firm's productivity. This effect always lowers worker welfare. Second, outsourcing increases the number of jobs available. Outsourcing firms respond to increased surplus by expanding production and demanding more labor. Outsourcers act as a multiplier on this demand increase because they must create multiple vacancies to ensure a worker for each client vacancy. This effect always increases worker welfare. Third, the increase in vacancies from outsourcers makes it harder to find workers, so hiring firms shrink. In other words, some of the new outsourcer jobs replace hiring firm jobs. This effect can increase or decrease worker welfare, depending on which jobs have higher wages.

The model also allows us to study how outsourcing affects labor market efficiency. To study efficiency, I solve the problem of a planner choosing firm and outsourcer vacancies subject to matching frictions. It is well known that the underlying model results in inefficient outcomes. Efficiency requires the right total number of vacancies and the right relative number of vacancies by different-productivity firms. In general, too many low-productivity firms enter the labor market and crowd out more productive firms. Outsourcing has ambiguous effects on labor market efficiency. Outsourcing improves efficiency on the intensive margin. Because the price of outsourcing does not depend on firm productivity, whereas worker wages do, outsourcing firms make more efficient entry choices than do hiring firms. Outsourcing worsens efficiency on the extensive margin. The planner values outsourcing because it avoids matching frictions for firms. Firms have an additional benefit from outsourcing: it allows them to avoid bargaining with the worker. As a result, for most parameter values, firms value outsourcing more than the planner does and too many firms choose to outsource. These competing effects can lead to higher or lower total welfare when outsourcing is added to the economy.

To study the quantitative effects of outsourcing on worker welfare, total welfare, and efficiency, I calibrate a more detailed version of the basic model. I perform two separate calibrations, one for workers without a bachelor's degree and one for workers with a bachelor's degree, to reflect the differences in relative job quality. The calibration matches moments for workers ever in high-outsourcing occupations, which are occupations with more than twice the average level of outsourcing (3.48%), because they are the most likely to experience equilibrium effects. I match the model to the data on residual compensation distributions, the percent of jobs that are outsourced, the rate of worker job-to-job transitions, and the unemployment rate. To show how outsourcing affects the economy, I simulate the model with and without outsourcing. The calibration captures the trade-offs of outsourcing for workers without a bachelor's degree: unemployment falls and total production rises but average wages (conditional on working) fall. The overall effect of outsourcing is negative. Specifically, workers welfare is 0.03% lower with outsourcing, even as total welfare increases by 0.02% and efficiency improves. For workers with a bachelor's degree, the effects of outsourcing are more uniformly positive: worker welfare, total welfare, and efficiency all increase.

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 workers' labor in frictionless markets. As a result, both have similar implications: more productive firms outsource and less productive ones hire, and outsourcing increases employment. The advantages of my model are that it easily allows for outsourced worker wages to be above or below hired worker wages, and it makes clear the effects of outsourcing on labor market efficiency. My baseline model allows outsourced wages to be higher or lower than wages at traditional jobs, and I use my model to explore why wages may be lower in outsourced jobs for workers without a bachelor's degree but higher in outsourced jobs for workers with one. In their baseline model, outsourced workers always earn reservation wages. My underlying search framework has a well-understood planner's problem, and I use my model to study the efficiency gains and losses from outsourcing.[1] Overall, these models are complementary, showing that the shared approach to outsourcing within a labor market has implications robust to how workers search for jobs.

For outsourcers to exist in an economy, they must have a comparative advantage in providing labor compared to firms hiring directly. My model captures these comparative advantages in a reduced-form way, through lower vacancy costs. This allows me to focus on how the presence of outsourcing affects labor markets and worker outcomes. Potential microfoundations for these comparative advantages have been explored in other works, with the most notable example being Grossman and Helpman (2002). While I study outsourcing with a frictional labor market and frictionless outsourcing market, they study outsourcing with a frictionless labor market and frictional outsourcing market, showing how property rights, hold-up issues, and asset specificity affect the comparative advantage of outsourcing. Other potential microfoundations include: limited management attention (Berlingieri, 2015), firing costs (Bostanci, 2021; Bertrand et al., 2021), and protection of trade secrets (Bostanci, 2021). Another potential microfoundation that has not been modeled is the cost of benefits. In the United States, firms have tax incentives to extend benefits to most workers (Perun, 2010); however, when workers are outsourced, these tax incentives no

[1] I do not claim that these things cannot be studied in their framework. Bilal and Lhuillier (2021) show their model can result in higher wages at the outsourcer than at firms under alternative assumptions. While they do not do so in their paper, the planner's problem can be analyzed in their framework.

longer apply. Over the last 40 years, benefit costs have increased (Gu, 2018), and outsourcing has too. I find the main penalty for outsourced jobs is lower access to benefits. Incorporating some of these details into models of outsourcing is a promising area for future work.

The rest of this chapter is organized as follows. Section 2.2 details the baseline model, shows it's predictions, and solves the Planner's version of the problem. Section 2.3 covers how the model is calibrated to match NLSY data. Section 2.4 compares the calibrated economy to a counterfactual without outsourcing to study how it affects worker welfare, overall welfare, and efficiency. Section 2.5 concludes.

2.2 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).[2] Both are built upon a standard DMP search model where workers randomly search for jobs and bargain with their employers over wages. 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 renting labor from outsourcers in a Walrasian market. Without outsourcing, my model collapses to LS. I present a basic version of the model to fix ideas. When calibrating I will match the full model covered in Appendix B.3. All proofs are in Appendix B.1.

The basic model matches many facts about outsourcing from my empirical work discussed above and from past research. I focus on three key empirical regularities in particular. The first is the difference in job quality for outsourced versus traditional workers. In Table 1.6 in Chapter 1, I show outsourced jobs are significantly worse for workers without a bachelor's degree but insignificantly better for workers with one. The second is that high-productivity firms outsource (Goldschmidt and Schmieder, 2017; Drenik et al., 2020; Bilal and Lhuillier, 2021). The third is that outsourcing increases employment (Bilal and Lhuillier, 2021; Bertrand et al., 2021). The model can capture all these outcomes: wages can be higher or lower in outsourced jobs, high-productivity firms outsource and low-productivity firms hire, and outsourcing increases employment.

2.2.1 Model Environment

First, I introduce the model environment. I model a labor market of one occupation, such as security guards or database administrators. 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 by factor $\beta = (1+r)^{-1}$. All analysis is of the steady state.

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 size n and must decide how many vacancies v to create. Vacancies cost $C(v; y)$ with marginal cost $c(v; y) \equiv C_v(v; y)$, and these costs are increasing $c(v; y) > 0$ and convex $c_v(v; y) \geq 0$.

[2] For more details, see Ljungqvist and Sargent (2004) pg. 953.

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 with market tightness θ (defined below) where they randomly meet workers with probability $q(\theta)$. These workers are called traditional because they are hired directly by the firm. Traditional workers earn 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 market clearing price p firms pay to outsourcers to rent each worker. Whether it hires or outsources, the firm exogenously loses δ fraction of its workers each period and so must continuously create new vacancies to remain the same size in steady state.

I conjecture, and later prove, firms below some endogenous productivity $\hat{y}$ only hire (hiring firms), while those above it only outsource (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 $F(y) = \int_{\underline{y}}^{y} \frac{v(x)}{v}dx$. Similarly, hiring and outsourcing sizes 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.[3] They fill their vacancies in the same way hiring firms do, by entering the labor market where they randomly meet workers with probability $q(\theta)$. Outsourced workers earn wages $\tilde{w}$ determined by Nash bargaining. Outsourcers exogenously lose their worker with probability δ each period. I use $\tilde{n}$ and $\tilde{v}$ to denote the size of the outsourcing sector and total number of outsourcer 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 of outsourcing p clears the outsourcing market, $\tilde{n} = \hat{n}$.

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.[4] Workers have bargaining power η with their employer and Nash bargain over wages $w(y)$ with the firm and $\tilde{w}$ with the outsourcer each period. Workers lose their job with probability δ.

[3]The fact that outsourcers have single workers and linear vacancy costs, while firms have multiple workers and convex vacancy costs, simplifies the analysis but is not important to the underlying results, as can be shown in the full model in Appendix B.3. The baseline model also implicitly assumes that workers are equally productive whether they are employed by firms or outsourcers. This assumption can also be relaxed.

[4]This matching process assumes workers cannot choose to apply for outsourcing versus traditional jobs. This assumption ensures workers find outsourcing jobs at the same rate as traditional jobs, which is true in the data. If workers could choose which jobs to apply for, they would apply only to lower-quality jobs if they were easier to find (e.g., Menzio and Shi (2010)).

2.2.2 Firm, Outsourcer, and Worker Value Functions

In this section, I specify value functions for firms, outsourcers, and workers. We will need the following assumption to ensure positive demand for outsourcing, and thus the existence of an indifferent firm $\hat{y}$.

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 $q(\theta) < 1$.

I 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

$$\begin{aligned} J(n;y) &= n[y - w(y)] + \max_v \{-C(v;y) + \beta J(n_+;y)\} \\ \text{s.t. } n_+ &= (1-\delta)n + q(\theta)v. \end{aligned} \tag{2.1}$$

An outsourcing firm has value

$$\begin{aligned} \hat{J}(n;y) &= n(y-p) + \max_v \left\{-C(v;y) + \beta \hat{J}(n_+;y)\right\} \\ \text{s.t. } n_+ &= (1-\delta)n + v. \end{aligned} \tag{2.2}$$

And an outsourcer with and without a worker has values

$$O = p - \tilde{w} + \beta(1-\delta)O_+ \tag{2.3}$$
$$V = -\tilde{c} + \beta q(\theta) O_+, \tag{2.4}$$

where I have used the fact that free entry implies $V_+ = 0$. For hiring firms, each worker gives per period profit $y - w(y)$, while for outsourcing firms, each gives per period profit $y - p$.[5] 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 of vacancies filled, which is $q(\theta)$ if hiring or 1 if outsourcing. For the outsourcer, a worker produces per period profits $p - \tilde{w}$. 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 firms and the outsourcer solve

$$c[v(y);y] \geq \beta q(\theta) J_n(n_+;y) \tag{2.5}$$
$$c[\hat{v}(y);y] \geq \beta \hat{J}_n(\hat{n}_+;y) \tag{2.6}$$
$$\tilde{c} \geq \beta q(\theta) O_+, \tag{2.7}$$

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

which are binding if $v(y) > 0$, $\hat{v}(y) > 0$, or $\tilde{v} > 0$, respectively. These are the free entry conditions: the LHS is the marginal costs of creating a vacancy, the RHS is the marginal benefit.[6]

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

$$J_n(n; y) = \frac{(1+r)[y - w(y)]}{r+\delta} \tag{2.8}$$

$$\hat{J}_n(n; y) = \frac{(1+r)(y-p)}{r+\delta} \tag{2.9}$$

$$O = \frac{(1+r)(p-\tilde{w})}{r+\delta}. \tag{2.10}$$

The value of each worker is the present value of the stream of per period profits over the expected lifetime of the match. Combining the free entry and envelope conditions in (2.5)–(2.10) implies wages and prices must satisfy

$$w(y) = y - \frac{r+\delta}{q(\theta)} c[v(y); y] \tag{2.11}$$

$$p = y - (r+\delta)c[\hat{v}(y); y] \tag{2.12}$$

$$\tilde{w} = p - \frac{r+\delta}{q(\theta)}\tilde{c}. \tag{2.13}$$

The wage or price that firms are willing to pay workers or 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 and then spreads its losses over the life of the match. Its ability to do so depends on the chance the firm meets a worker, which is increasing in $q(\theta)$; how it values the future, which is decreasing in r; and the expected length of the match, which is decreasing in δ. As each of these increases, the firm is better able to amortize and can fund more vacancy creation for a given wage or 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 is

$$W(y) = w(y) + \beta\Big\{\delta U_+ + (1-\delta)W_+(y)\Big\} \tag{2.14}$$

$$\widetilde{W} = \tilde{w} + \beta\Big\{\delta U_+ + (1-\delta)\widetilde{W}_+\Big\} \tag{2.15}$$

$$U = b + \beta\left\{\ell(\theta)\left[(1-\pi)\int_{\underline{y}}^{\hat{y}} W_+(x)dF(x) + \pi\tilde{W}_+\right] + [1-\ell(\theta)]U_+\right\}. \tag{2.16}$$

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

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, where workers have bargaining power η. Because firms have a measure of workers, workers and firms bargain over the marginal value of the match using Stole-Zwiebel bargaining (Stole and Zwiebel, 1996; Brügemann et al., 2019). Workers and outsourcers bargain over the total value of the match because outsourcers have only one worker. Firms and outsourcers bargain after paying vacancy costs, so their outside option is zero, while workers' outside option is unemployment. As a result, the bargaining games solve $\eta J_n(n;y) = (1-\eta)[W(y) - U]$ and $\eta O = (1-\eta)[\tilde{W} - U]$. Using these bargaining rules and the free entry conditions in (2.6) and (2.7) to solve for $W(y) - U$ and $\tilde{W} - U$, we rewrite the value of unemployment in (2.16) as

$$\frac{r}{1+r}U = b + \Gamma, \tag{2.17}$$

where

$$\begin{aligned}\Gamma &\equiv \theta\frac{\eta}{1-\eta}\left[(1-\pi)\int_{\underline{y}}^{\hat{y}} c[v(x);x]dF(x) + \pi\tilde{c}\right] \\ &= \frac{1}{u}\frac{\eta}{1-\eta}\left[\int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + \tilde{v}\tilde{c}\right]\end{aligned} \tag{2.18}$$

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 vacancies created by firms $c[v(x);x]$ and outsourcers $\tilde{c}$, which equals their marginal benefit of creating a vacancy due to free entry. The third is the relative probability of meeting a particular firm or outsourcer, which is the number of vacancies per unemployed worker for each firm $\frac{v(y)}{u}$ or outsourcer $\frac{\tilde{v}}{u}$.

2.2.3 Model Outcomes

In this subsection, I show the outcomes of the model and how they match my three empirical facts, prove that $\hat{y}$ exists and characterizes firms' outsourcing decisions, and define an equilibrium. We can use the value of unemployment in (2.17), the value of working for a firm and outsourcer in steady state in (2.14) and (2.15), the firm's and outsourcer's envelope condition in (2.9) and (2.10), and the bargaining rules to show firm and outsourcer wages solve

$$w(y) = \eta y + (1-\eta)(b+\Gamma) \tag{2.19}$$

$$\tilde{w} = \eta p + (1-\eta)(b+\Gamma), \tag{2.20}$$

Each period, the worker gets his share η of revenue and must be compensated by the firm for forgoing unemployment. As in the data, more productive firms pay higher wages. In the empirical section, I found outsourced workers without a bachelor's degree earned less than traditional workers, while workers with a bachelor's earned more. In the model, this comparison depends on whether average hiring firm productivity is higher or lower than the price of outsourcing, $\int_{\underline{y}}^{\hat{y}} xn(x)dx \lessgtr p$. Either sign of this relationship can be true, depending on parameters. In this way, the model can help justify why some groups of workers are paid less in outsourced jobs and others are paid more.

While the model is ambiguous about the average wages of traditional versus outsourced workers, it has more to say about the right tail of the wage distribution. To see why, imagine the following thought experiment, inspired by Goldschmidt and Schmieder (2017) who study workers whose jobs are outsourced: a worker starts employed at a firm and becomes employed by the outsourcer with his former employer as the client. In the language of my model, Goldschmidt and Schmieder (2017) study workers employed at a firm $y \geq \hat{y}$ who transition to outsourced jobs. For these workers, wages change from $w(y)$ to $\tilde{w}$. The difference in these wages is proportional to $y - p$, and because the firm chooses to outsource, it must be making positive per period profits, so $y > p$, and the workers' wages must fall. This is what Goldschmidt and Schmieder (2017) find in their analysis of low-skilled workers and Bilal and Lhuillier (2021) find in their analysis of all workers. Because of this mechanism, the model predicts that outsourcing will lead to a "missing" right tail of the wage distribution as high-paying firms shift from hiring to outsourcing. In the empirical section above, I find evidence of this missing right tail in high-outsourcing occupations (see Figure 1.3 in Chapter 1).

The total surplus of each match equals firm or outsourcer revenue minus the worker's home production. Knowing wages helps us solve for how this surplus is split. For hiring firms and outsourcers, we set the wage equation in (2.11) and (2.13) equal to the wage equation in (2.19) and (2.20) to show the net production of each match equals

$$y - b = \Gamma + \frac{r + \delta}{(1 - \eta)q(\theta)} c[v(y); y] \tag{2.21}$$

$$p - b = \Gamma + \frac{r + \delta}{(1 - \eta)q(\theta)} \tilde{c}. \tag{2.22}$$

In each case, production is split between compensating the worker for forgoing search and amortizing the firm's or outsourcer's vacancy costs. These equations highlight another obstacle to firms' and outsourcers' amortizing ability previously hidden in the wages they pay: firms bear the entire cost of vacancy creation but get only fraction $1 - \eta$ of net production. As firms' bargaining power increases, they can better amortize their costs and create more vacancies at a given productivity. We can use outsourcing production from (2.22) and the price the firm is willing to pay to outsource in (2.12) to show the net production for outsourcing firms is

$$y - b = \Gamma + (r + \delta) \left(c[\hat{v}(y); y] + \frac{\tilde{c}}{(1 - \eta)q(\theta)} \right). \tag{2.23}$$

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

The effects of outsourcing on workers are ambiguous. On one hand, outsourcing means high-productivity firms no longer hire workers. These high-quality vacancies are replaced by outsourcing vacancies, which have lower wages. On the other hand, outsourcing increases firm profitability. Because of free entry, firms respond by creating more vacancies than they would if hiring. On top of this increase, outsourcers must create $\frac{1}{q(\theta)} > 1$ vacancies for each outsourcing firm vacancy to match demand. An increase in vacancies increases market tightness θ and lowers firm match probability $q(\theta)$. As suggested by the hiring firm's free entry condition in (2.5), hiring firms respond by decreasing vacancies, dampening this effect. Nevertheless, the overall effect is more vacancies created. With more jobs available, outsourcing will increase employment, just as has been shown in past literature and is suggested by my analysis. In general, the effects of outsourcing on workers' welfare depends on underlying parameters. I cover this trade-off in more detail using calibration results in Section 2.4.

I previously conjectured that there exists some endogenous $\hat{y}$ below which firms only hire and above which firms only outsource. Proposition 1 proves this claim.

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 and any firm with productivity above* $\hat{y}$ *strictly prefers to outsource.*[7]

The formal proof is in Appendix B.1.1, but I outline the logic here. Because the marginal cost of entry does not depend on whether the firm outsources or hires, we compare only the marginal benefits.[8] Using the free entry and envelope conditions of the firm from (2.5), (2.6), (2.8), and (2.9), 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 $\hat{y}$, both sides 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 avoiding matching frictions and guaranteeing access to workers. The second is avoiding bargaining with workers. More productive firms value both of these benefits more; their opportunity cost of not matching is higher, as are the wages they pay. In the model, high-productivity firms choose to outsource, which is consistent with past literature. 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 firm $\hat{y}$. This benefits the highest-productivity firms even more.

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 net production for hiring in (2.21) and outsourcing in (2.23) equal to show

$$[1 - (1 - \eta)q(\theta)]c[v(\hat{y}); \hat{y}] = \tilde{c}. \tag{2.24}$$

[7]While $\hat{y}$ is guaranteed to exist given Assumption 1, it is not guaranteed to be within the interval $[\underline{y}, \bar{y}]$. If it is below this interval, all firms will outsource, if it is above it, all firms will hire.

[8]This assumption would be satisfied if the main cost of creating vacancies is paying employees to attempt to fill them, and the effort needed to attempt to fill a vacancy is similar whether hiring or outsourcing. If the costs of creating vacancies were different, then this difference would be added to the comparison from my baseline case.

The term $1-(1-\eta)q(\theta)$ is the amortization ability of a hiring firm minus the amortization ability of an outsourcing firm divided by the amortization ability 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 the amortization gain from firm $\hat{y}$ outsourcing rather than hiring equals the amortization cost of the outsourcer. For firms and outsourcers to enter $(1-\eta)q(\theta) > 0$, so outsourcers need cheaper marginal vacancy costs to exist in equilibrium.[9] Cheaper vacancy costs is the reduced-form way the model captures outsourcers' comparative advantage in hiring workers. As $(1-\eta)q(\theta)$ approaches 1, firms have most of the bargaining power and are very likely to match with workers, so outsourcers must have a large comparative advantage (small $\tilde{c}$) to enter the market.

To calculate $\hat{y}$ more explicitly, we use their indifference between hiring and outsourcing along with firm free entry and envelope conditions in (2.5), (2.6), (2.8), and (2.9) and the wage and price equations in (2.19) and (2.22) to show

$$\hat{y} = b + \Gamma + \frac{r+\delta}{(1-\eta)q(\theta)[1-(1-\eta)q(\theta)]}\tilde{c}. \tag{2.25}$$

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 for the amortization gains of outsourcing. 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 for both firms and outsourcers, 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, I define equilibrium as follows

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

1. Given indifferent firm $\hat{y}$, market tightness θ, worker wages $w(y)$ and $\tilde{w}$, and outsourcing price p, firms less productive than $\hat{y}$ (hiring firms) choose $(v(y), n(y))$, firms more productive than $\hat{y}$ (outsourcing firms) choose $(\hat{v}(y), \hat{n}(y))$ and outsourcers choose $(\tilde{v}, \tilde{n})$ to satisfy their free entry and envelope conditions in (2.5)–(2.10).

2. Given market tightness θ, the distribution of vacancies in the labor market $(v(y), \tilde{v})$, and worker wages $w(y)$ and $\tilde{w}$, the value of search Γ satisfies (2.18).

3. Given market tightness θ and value of search Γ, firm $\hat{y}$ solves the indifference condition in (2.25).

[9] If $(1-\eta)q(\theta) = 0$, either firms and outsourcers get no rents from matching with workers or they cannot match with workers in the first place. In either case, neither can earn back vacancy costs, so no vacancies are created.

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

5. Given workers' value of search Γ, bargaining between firms and workers yields wages $w(y)$ in (2.19), and bargaining between outsourcers and workers yields wage $\tilde{w}$ in (2.20).

6. 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 size choices given market tightness, wages, and prices. These factors also determine the worker's value of search and the firms decision between hiring and outsourcing. In turn, these choices and the value of search must imply the same market tightness, wages, and prices.

2.2.4 Planner's Problem

As a result of search frictions, 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. However, in LS's model with heterogeneous productivity, Hosios rule is not enough. In general, low-productivity firms create too many vacancies, high-productivity firms create too few, and efficiency cannot be achieved. I now examine how outsourcing affects the efficiency of the economy. To do so, I first solve a planner's problem, showing that, under light assumptions, the planner also demands outsourcing. Outsourcing has an ambiguous effect on efficiency. It improves efficiency on the intensive margin: outsourcing firms make more efficient entry decisions. But it decreases efficiency on the extensive margin: firms make different choices between hiring and outsourcing than the planner. For typical parameters, too many firms outsource.

To study efficiency, we must first solve the planner's problem. The planner, facing search frictions, chooses vacancy creation for all firms and outsourcers. Outsourced workers can be used to fill any empty vacancy. There are two main differences between the planner's choices and the decentralized economy. The first is the planner does not bargain over wages. The second is she accounts for how vacancy creation affects firms, outsourcers, and workers through its effect on market tightness θ.

Let $\mathbb{n}$, $\hat{\mathbb{n}}$, $\mathbb{v}$, and $\hat{\mathbb{v}}$ be vectors of hiring size, outsourcing size, hiring vacancies, and outsourcing vacancies. Let $\tilde{n}$ and $\tilde{v}$ be outsourcer size and vacancies. Denote the planner's optimal choices with a superscript P, such as $n^P(y)$. I conjecture, and later prove, that the planner follows a cutoff strategy for hiring versus outsourcing, with $\hat{y}^P$ as the planner's optimal cutoff. Each period, the planner inherits $\{\mathbb{n}, \hat{\mathbb{n}}, \tilde{n}\}$ and chooses vacancies $\{\mathbb{v}, \hat{\mathbb{v}}, \tilde{v}\}$ to solve[10]

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

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

s.t.

$$n_{+}(y) = (1 - \delta)n(y) + q(\theta)v(y) \tag{2.26}$$

$$\hat{n}_{+}(y) = (1 - \delta)\hat{n}(y) + \hat{v}(y) \tag{2.27}$$

$$\tilde{n}_{+} = (1 - \delta)\tilde{n} + q(\theta)\tilde{v} \tag{2.28}$$

$$\int_{\hat{y}_{+}}^{\bar{y}} \hat{n}_{+}(x)dx = \tilde{n}_{+}. \tag{2.29}$$

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. We are interested in equilibria where the planner has positive demand for outsourcing and $\hat{y}^P$ exists. To ensure this criteria is fulfilled, we must assume the planner faces matching frictions.

Assumption 2. Not all vacancies match with workers $q(\theta^P) < 1$.

The planner values outsourcing for avoiding matching frictions; if these are not binding, her demand for outsourcing will be zero.

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

$$\Gamma^P = \frac{1}{u^P} \frac{\alpha}{1 - \alpha} \left\{ \int_{\underline{y}}^{\hat{y}^P} v^P(x) c[v^P(x); x]dx + \tilde{v}^P \tilde{c} \right\} \tag{2.30}$$

where $\alpha = -\frac{\theta^P q'(\theta^P)}{q(\theta^P)}$ is the elasticity of the matching function with respect to workers. Compare the planner's value of search with the worker's private value of search in (2.18). 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 relationship is the basis of the well-know Hosios rule.

I solve the planner's problem much like the decentralized problem. First I 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 the marginal cost of vacancy creation equal to the marginal benefit. To find the value of these vacancies, I next take the steady state envelope conditions for next period's hiring sizes $n_{+}(y)$, outsourcing

[10] 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 sizes $\tilde{v}^P(y)$ and $\tilde{n}^P(y)$ are zero for firms below $\hat{y}^P$, and outsourcing vacancies and sizes $v^P(y)$ 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.

sizes $\hat{n}_+(y)$, and outsourcer size $\tilde{n}_+$. Define ρ as the planner's (implicit) price of outsourcing.[11] Combining the free entry conditions and envelope conditions, we can see how the planner splits the net production of the match $y - b$ or $\rho - b$ for hiring firms, outsourcing firms, and outsourcers

$$y - b = \Gamma^P + \frac{r+\delta}{q(\theta^P)}\left(c[v^P(y); y] + \frac{\Gamma^P}{\theta^P}\right) \qquad \forall\, y \leq \hat{y} \tag{2.31}$$

$$y - b = \Gamma^P + (r+\delta)c[\hat{v}^P(y); y] + \frac{r+\delta}{q(\theta^P)}\left(\tilde{c} + \frac{\Gamma^P}{\theta^P}\right) \qquad \forall\, y \geq \hat{y} \tag{2.32}$$

$$\rho - b = \Gamma^P + \frac{r+\delta}{q(\theta^P)}\left(\tilde{c} + \frac{\Gamma^P}{\theta^P}\right). \tag{2.33}$$

Like the decentralized production splitting in (2.21)–(2.23), the planner splits production between compensating the worker for forgoing search and amortizing the cost of vacancy creation. The difference is that the planner does not worry about bargaining power but does worry about the cost 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 proves this claim.

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, and at productivities above she outsources.*

The proof, in Appendix B.1.2, is similar to the proof of the existence of $\hat{y}$ in Proposition 1. In the proof, I show the benefit of outsourcing minus the benefit of hiring is strictly increasing in productivity, is negative for low-productivity, and is positive for high-productivity. Low-productivity firms hire and high-productivity firms outsource, just like in the decentralized economy.

2.2.5 Efficiency of Equilibrium

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. My model adds a third efficiency concern, the firm's choice to hire or outsource. I will show how outsourcing affects each of these margins.

I 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 production

[11]When solving the planner's problem, $\beta\rho$ is the multiplier on the outsourcing market clearing condition in (2.29). The planner ensures tomorrow's outsourcing market clears today, so including β in the multiplier makes the planner's price ρ and the decentralized price p directly comparable.

$y - z$ in each case using equations (2.21) and (2.23)

$$y - z = \frac{r+\delta}{(1-\eta)q(\theta)}\big(c[v(y);y] - c[v(z);z]\big) \qquad \forall\, z \leq y \leq \hat{y} \tag{2.34}$$

$$y - z = (r+\delta)\big(c[\hat{v}(y);y] - c[\hat{v}(z);z]\big) \qquad \forall\, \hat{y} \leq z \leq y \tag{2.35}$$

$$y - z = (r+\delta)c[\hat{v}(y);y] - \frac{r+\delta}{(1-\eta)q(\theta)}\big(c[v(z);z] - \tilde{c}\big) \qquad \forall\, \hat{y} \leq z \leq y. \tag{2.36}$$

Similarly, we can use the planner's production equations (2.31) and (2.32) to show her optimal spreads solve

$$y - z = \frac{r+\delta}{q(\theta^P)}\big(c[v^P(y);y] - c[v^P(z);z]\big) \qquad \forall\, z \leq y \leq \hat{y}^P \tag{2.37}$$

$$y - z = (r+\delta)\big(c[v^P(y);y] - c[v^P(z);z]\big) \qquad \forall\, \hat{y}^P \leq z \leq y \tag{2.38}$$

$$y - z = (r+\delta)c[v^P(y);y] - \frac{r+\delta}{q(\theta^P)}\big(c[v^P(z);z] - \tilde{c}\big) \qquad \forall\, \hat{y}^P \leq z \leq y. \tag{2.39}$$

How efficient is the decentralized spread of vacancies? I start with hiring firms. Comparing the decentralized spread in (2.34) to the planner's spread in (2.37), 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 efficient only when worker bargaining power η is zero; otherwise the decentralized spread is too small. Low-productivity firms create too many vacancies, and high-productivity firms create too few. This result echoes LS, and the intuition is the same. If workers have some bargaining power, firms pay the entire cost of vacancy creation but receive only some of the benefits. This wedge 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.

Second, I turn to outsourcing firms, who will make more efficient choices. In fact, the decentralized spread in (2.35) is exactly the same as the planner's spread in (2.38). This equivalence 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, it shows how outsourcing can improve overall efficiency by reducing the frictions between workers and the most productive firms.

Last, I look at the spread between hiring and outsourcing firms. Both the decentralized spread in (2.36) and the planner's spread in (2.39) account for the outsourcer vacancy that must be created for firms to outsource. Again, if market tightness is optimal, the decentralized spread is efficient only when worker bargaining power η is zero. 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 outsourcing firms.

Next, I study total firm entry: whether firms create the right number of vacancies overall. To do so, we integrate over firm net production for hiring firms and outsourcing firms weighted by vacancy creation.

We first solve for decentralized entry. For hiring firms $y \leq \hat{y}$ and outsourcing firms $y \geq \hat{y}$ we integrate over production equations (2.21) and (2.23) to show

$$\int_{\underline{y}}^{\hat{y}} (x-b)v(x)dx = \frac{r+\delta+\eta(1-\pi)\theta q(\theta)}{(1-\eta)q(\theta)} \int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + \frac{\eta(1-\pi)\theta}{1-\eta}\tilde{v}\tilde{c} \tag{2.40}$$

$$\int_{\hat{y}}^{\bar{y}} (x-b)\hat{v}(x)dx = \frac{\eta\pi\theta q(\theta)}{1-\eta} \int_{\underline{y}}^{\hat{y}} v(x)c[v(x);x]dx + (r+\delta)\int_{\hat{y}}^{\bar{y}} \hat{v}(x)c[\hat{v}(x);x]dx + \frac{r+\delta+\eta\pi\theta q(\theta)}{1-\eta}\tilde{v}\tilde{c}, \tag{2.41}$$

Similarly, we integrate over the planner's production equations in (2.31) and (2.32) to show

$$\int_{\underline{y}}^{\hat{y}^P} (x-b)v^P(x)dx = \frac{(r+\delta)(1-\alpha\pi^P)+\alpha(1-\pi^P)\theta^P q(\theta^P)}{(1-\alpha)q(\theta^P)} \int_{\underline{y}}^{\hat{y}^P} v^P(x)c[v^P(x);x]dx + \frac{[r+\delta+\theta^P q(\theta^P)]\alpha(1-\pi^P)}{(1-\alpha)q(\theta^P)}\tilde{v}^P\tilde{c} \tag{2.42}$$

$$\int_{\hat{y}^P}^{\bar{y}} (x-b)\hat{v}^P(x)dx = \frac{[r+\delta+\theta^P q(\theta^P)]\alpha\pi^P}{1-\alpha} \int_{\underline{y}}^{\hat{y}^P} v(x)c[v(x);x]dx + (r+\delta)\int_{\hat{y}}^{\bar{y}} \hat{v}(x)c[\hat{v}(x);x]dx + \frac{(r+\delta)[1-\alpha(1-\pi^P)]+\alpha\pi^P\theta^P q(\theta^P)}{1-\alpha}\tilde{v}\tilde{c}. \tag{2.43}$$

To get the intuition behind decentralized hiring firm entry in (2.40), 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 (2.18). When other firms and outsourcers enter, they increase the worker's value of search and thus the worker's outside option. Firms must pay their share $1-\pi$ of this increase. Compare the decentralized choice of entry to the planner's choice of entry in (2.42). 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, Hosios rule setting $\eta = \alpha$ is enough to make total entry efficient because firms internalize the effect they have on workers and other vacancies. In my setting, firms properly account for how they affect other firms but not for how they affect outsourcers. When there is outsourcing (i.e., $\pi > 0$), $\eta = \alpha$ does not achieve efficient entry.

There is a similar logic for outsourcing firm entry in (2.41) and (2.43). Decentralized outsourcing firms account for their own amortization ability. Because of the Walrasian market, their entry rule is the same as the planner's. By paying p to outsource, they also implicitly account for the outsourcer's decision. Outsourcers' decisions are inefficient in the same way hiring firms' are: they fail to account for their effect on other vacancies. For outsourcing firms, $\eta = \alpha$ does not achieve efficient entry either.

Finally, I study the choice between hiring and outsourcing. To do so, I find the planner's choice of productivity cutoff $\hat{y}^P$ and compare it to the decentralized choice $\hat{y}$. To calculate $\hat{y}^P$, we solve the hiring production in (2.31) for $c[v(\hat{y}); \hat{y}]$ and plug it into the outsourcing production in (2.32) to show

$$\hat{y}^P = b + \Gamma^P + \frac{r+\delta}{q(\theta^P)[1-q(\theta^P)]}\tilde{c} + \frac{r+\delta}{\theta^P q(\theta^P)}\Gamma^P. \tag{2.44}$$

Comparing $\hat{y}^P$ to the decentralized indifferent firm in (2.25), the similarities are apparent. Both account for the worker's outside option. 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 firm minus the amortization ability of an outsourcing firm divided by the amortization ability of an outsourcer. Compared to the decentralized ratio in (2.24), when $q(\theta^P) > (1-\eta)q(\theta)$, the planner values outsourcing less. For most parameter values, workers have some bargaining power $\eta < 1$, and the planner prefers higher $q(\theta)$ because they account for congestion effects. Thus, for typical parameters, such as in the calibration below, $\hat{y}$ will be too small and too many firms will choose to outsource.

Outsourcing improves efficiency on the intensive margin: the entry decisions of firms. Hiring firms are about as efficient as before. Their spread of vacancies is just as efficient, while their total entry is less efficient because they do not account for outsourcers. This second discrepancy is small, however, when outsourcers are a small part of the economy. Outsourcing firms, on the other hand, make much more efficient decisions. Their spread of vacancies is exactly as the planner would choose, while their entry is different only because outsourcer entry is inefficient. But outsourcing decreases efficiency on the extensive margin: the hiring versus outsourcing decisions of firms. The planner values outsourcing for avoiding matching frictions. Firms do, too, but they also value avoiding bargaining with workers. For typical parameter values, this means too many firms choose to outsource and there is too much outsourcing in the economy. The overall effect on efficiency is ambiguous. Unfortunately, there is no easy way to see which effect dominates analytically. Instead, I will return to this question numerically in Section 2.4.

In the empirical section, I showed that outsourced jobs are lower quality than traditional jobs for workers without a bachelor's degree. In this section, I showed that the economy with outsourcing is generally inefficient and usually results in too many firms choosing to outsource. Concerned governments might wonder if penalizing outsourcing firms can improve outcomes for workers or overall. This question is studied in Appendix B.2. I ask if a planner with the power to subsidize and tax firm and outsourcer vacancy creation, along with the ability to make lump-sum transfers to and from workers to balance the budget, can achieve the optimal allocation. For simplicity, I abstract from incentive compatibility issues and assume the planner knows firm productivity. The planner is able to decentralize the optimal solution. The key insight is that, because outsourcing firms face Walrasian markets, they make efficient choices conditional on prices and should not be taxed. To get the right price of outsourcing, the planner instead taxes (or subsidizes) outsourcers. To ensure the right firms hire rather than outsource, the planner subsidizes hiring for firms close to $\hat{y}$. The main takeaway is that while outsourcing has some negative externalities for workers, it also leads to efficiency gains if used correctly. The best way to achieve these gains while correcting externalities is to tax outsourcers when hiring workers, not the relationship between outsourcers and firms.

2.3 Calibration

From the baseline model, we can see that outsourcing comes with trade-offs for workers and for labor market efficiency. For workers, outsourcing leads to a "missing" right tail of the wage distribution as workers lose access to the highest-paying jobs, but it also means more overall jobs available. For labor market efficiency, outsourcing increases efficiency on the intensive margin as outsourcing firms make more efficient entry decisions but decreases efficiency on the extensive margin as the wrong number of firms outsource. I will now calibrate to measure the size of these trade-offs.

The model I calibrate, detailed in Appendix B.3, takes the baseline model in Section 2.2 and adds three features. First, it allows exogenous job destruction rates to differ for firms δ and outsourcers $\tilde{\delta}$. 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 $\tilde{C}(\tilde{v}; o)$. Firms now rent effective labor from outsourcers, each unit costing p. The distribution of outsourcer productivity 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.[12] This addition allows me to match the job-to-job transitions I see in the data.

The calibrated model is affect by outsourcing in many of the same ways as the baseline model. It is still the case that high-productivity firms outsource while low-productivity firms hire. Outsourced workers still make less per unit of productivity than they do at client firms, although if outsourcer productivity o is high enough, they could earn higher wages. Outsourcing firms still expand production, still act on a multiplier on this expansion, and hiring firms still shrink as a result. The effects of outsourcing on efficiency are harder to show analytically, but are similar numerically, as will be seen below.

I calibrate the model twice, once for workers without a bachelor's degree and once for workers with one. I do this because the different job quality effects by education (see Table 1.6) suggest different underlying parameters. When explaining the calibration and results, I first focus on workers without a bachelor's degree, who are more negatively affected by outsourcing. For both calibrations, I limit the sample to workers ever in high-outsourcing (HO) occupations, which are occupations with outsourcing levels greater than 3.48%. I study these workers because they are the most likely to experience the equilibrium effects of outsourcing. Appendix B.4 contains additional results for workers without a bachelor's degree, and Appendix B.5 contains additional results for workers with a bachelor's degree.

I now briefly discuss the calibration strategy for each parameter. All parameters and their values can be found in Table D1 of Appendix B.4 for workers without a bachelor's degree and Table E2 of Appendix B.5 for workers with a bachelor's degree. Each period in the model is equal to one week. I choose β and r such that the yearly interest rate is 5%. The job loss probabilities of hiring firms and outsourcers δ and $\tilde{\delta}$ are set

[12] For simplicity, I assume firms cannot observe any outside offers from other firms, and so a worker's outside option is always unemployment benefit U.

to match the rate traditional and outsourced workers' exit to non-employment. I use a Cobb-Douglas matching function $M(s,v) = \phi s^{\alpha} v^{(1-\alpha)}$ where $s = u + (1-u)\xi[(1-\delta)(1-\zeta) + (1-\tilde{\delta})\zeta]$ is the total number of workers searching for a job. I take matching elasticity $\alpha = 0.5$ from Petrongolo and Pissarides (2001) and calibrate match efficiency ϕ and probability of on-the-job search ξ within the model. Following Hosios Rule, I set worker bargaining power $\eta = \alpha$. Workers' home production b is calibrated within the model. 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. Most of the parameters chosen outside of the model are the same as the calibration without bachelor' degree, except for the exogenous firing rates and the ranges of firm and outsourcer productivity. Unsurprisingly, workers with bachelor's degrees are much less likely to lose their jobs to unemployment in the data and this is reflected in lower job loss probabilities δ and $\tilde{\delta}$.

As mentioned above, I calibrate ϕ, ξ, b, 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 unemployment rate and the job finding rate of employed workers. I set b, c_0, c_1, $\tilde{c}_0$, and $\tilde{c}_1$ to match log total compensation distributions and the percent of employed workers in outsourcing jobs ζ. Total compensation is used to capture outsourcing's combined effects on weekly wages and access to health insurance and retirement benefits. Because compensation is measured in logs, we can interpret the calibration results as agents with log preferences bargaining over the level of compensation. The model represents a labor market with homogeneous workers in one occupation, while the data comes from heterogeneous workers in many occupations. Instead of matching compensation distributions directly, I match compensation residuals.[13] I match the 25th and 75th percentile of the compensation distribution for both traditional and outsourced workers.

2.4 Results

Calibration parameters for workers without a bachelor's degree are in Table D1 of Appendix B.4. The only parameter that needs explanation is home production b. In the data, mean weekly total compensation is about \$600, and the calibrated b of 2.67 implies a home production value of \$14, which is very low. The model needs this low b to match the wide-ranging compensation distribution: the 75th compensation percentile is about 1.8 times the 25th percentile.[14] Because one of the benefits of outsourcing is that it increases the demand for labor (and thus decreases unemployment), a low b will tend to overestimate the benefits of outsourcing for workers. In Table 2.2 below, I show that because the value of searching for a job is high, the welfare of unemployed workers is within 10% of the average traditional worker despite their much lower flow pay-offs (see Footnote 15). I take this as evidence that any bias small.

Calibration parameters for workers with a bachelor's degree are in Table E2 of Appendix B.5. Compared to parameters for workers without a degree, the vacancy costs for firms and outsourcers are lower,

[13]Residual total compensation comes from a regression similar to Equation 1.1 but without the term *outsourced*. The regression can distinguish if a worker is in an outsourced or traditional job, but cannot separate the two. I run the regression on the entire sample and then take the residuals from the HO occupation sample. Residuals are recentered at the mean total compensation by bachelor's degree attainment.

[14]See Hornstein et al. (2011) on the difficulty of matching wage dispersion using only search frictions.

Table 2.1: Calibration results for workers without a bachelor's degree who ever work in a high-outsourcing occupation. All compensation residuals are recentered at mean total compensation for workers without a bachelor's degree.

Moment	Model	Data
Targeted		
25th Percentile Compensation Residual, Traditional	6.12	6.18
75th Percentile Compensation Residual, Traditional	6.74	6.64
25th Percentile Compensation Residual, Outsourced	6.05	6.14
75th Percentile Compensation Residual, Outsourced	6.64	6.58
Weekly EE Rate	0.0019	0.0019
Unemployment Rate	0.086	0.086
Fraction Outsourced	0.064	0.064
Untargeted		
Mean Compensation Residual, Traditional	6.46	6.41
St. Dev. Compensation Residual, Traditional	0.43	0.42
Mean Compensation Residual, Outsourced	6.38	6.32
St. Dev. Compensation Residual, Outsourced	0.42	0.42
Difference in Mean Compensation Residuals	0.080	0.085
Fraction Outsourced, Newly Employed	0.076	0.076

but so are the matching efficiency ϕ and the probability of on the job search ξ. As shown in the matched moments in Table E3 of Appendix B.5, the former effect dominates the latter. The unemployment rate is much lower and job-to-job transition rate is a bit higher. The calibration needs a low value of home production b for similar reasons to workers without bachelor's degrees. Because worker's value of search is very high, the value of home production must be even lower to match the data.

Calibration results for workers without a bachelor's degree are in Table 2.1. I start by discussing the compensation distributions. The calibration slightly underestimates the 25th percentile and overestimates the 75th percentile. The table shows the untargeted moments of mean compensation, variance of compensation, and differences in compensation between traditional and outsourced workers. Figure D1 in Appendix B.4 shows the model's CDF of compensation for traditional and outsourced workers compared to the data. Both are evidence that the model, combined with a simple vacancy cost function, gives a good approximation for the overall compensation distribution. Worker flows, unemployment, and share outsourced are the same as in the data. A key outcome of the model is π, the share of vacancies from outsourcers. With random search, this is equivalent to the share of newly employed in outsourced jobs. The calibration matches this perfectly, despite not targeting it directly. The assumptions of random search, on-the-job search, and different exogenous firing rates allow the model to match the relative number of newly hired outsourced workers to the number of outsourced workers overall.

Calibration results for workers with a bachelor's degree are in Table E3 of Appendix B.5. For targeted moments, the calibration does about as well as the one for workers without a bachelor's degree. It does less well for untargeted moments. Specifically, the calibration does not match the standard deviation of compensation for traditional workers or the share of new workers in outsourcing jobs. As seen in the CDF of compensation in the model compared to the data in Figure E3 of Appendix B.5, the main reason the model struggles with compensation variance is that the model fails to capture the long left tail for traditional workers. According to the model, many of these jobs have utility below unemployment and should not exist in equilibrium. In the model, the share of outsourced among the newly employed should equal the share of vacancies from outsourcers, π. While the calibration for workers without a bachelor's matched the data almost perfectly, the result here is very different. Because outsourced workers are equally likely to be exogenously fired but have better jobs on average, the model needs fewer newly employed outsourced workers than the overall share of outsourced workers. In the data, the relationship is the opposite, there are many more newly outsourced workers than the overall average. One potential cause is if workers with bachelor's degrees can find jobs very quickly, then transitions that look job-to-job in the data (those only lasting one week) would be classified as exogenous firings with more granular data.

I use the calibrated model to answer two questions about the effects of outsourcing on labor markets. The first question asks if workers are hurt by or benefit from outsourcing. In my empirical work, I show that there is an outsourcing penalty for workers without a bachelor's degree (see Table 1.6), but I also show there is a positive relationship between outsourcing and employment (see Table 1.9). I use the model to study the trade-off between these two effects. The second question is how outsourcing impacts labor market efficiency. LS's model without outsourcing is in general inefficient. Outsourcing improves efficiency on the intensive margin, outsourcing firms make more efficient entry decisions; but decreases efficiency on the extensive margin, too many firms choose to outsource. I use the calibration to find which effect is larger. To perform this analysis, I compare the calibrated allocation to alternative simulations of the labor market. To find the effects of outsourcing on worker outcomes, I shut down the outsourcing market, which is equivalent to LS. To find the effects of outsourcing on efficiency, I compare the decentralized economy to the planner's choices with and without outsourcing.

I start by examining the effects of outsourcing on workers by comparing to a simulation without a market for outsourcing. Figure 2.1 shows the distribution of total compensation with and without outsourcing. It helps visualize the trade-off workers face when outsourcing is introduced to the economy. The compensation distribution with outsourcing (solid blue line) has greater area than the distribution without outsourcing (dashed purple line). When firms gain access to outsourcing, they increase their demand for labor and there are more jobs available, which is good for workers. On the downside, these job gains come from low- to middle-wage jobs. For high-wage jobs, outsourcing introduces a discrete drop, a missing right tail that emerges when high-productivity firms outsource instead of hire. This corresponds to the missing right tail discussed in Section 1.5. The overall impact of outsourcing on worker welfare depends on which effect is bigger.

The left two columns of Table 2.2 show the difference between the economy with and without outsourcers in more detail. In the first column, the top section characterizes the economy without outsourcing, while the bottom section characterizes the economy with it. The second column shows the percent difference between the two. Outsourcing adds some positives for workers: unemployment falls 1.65%

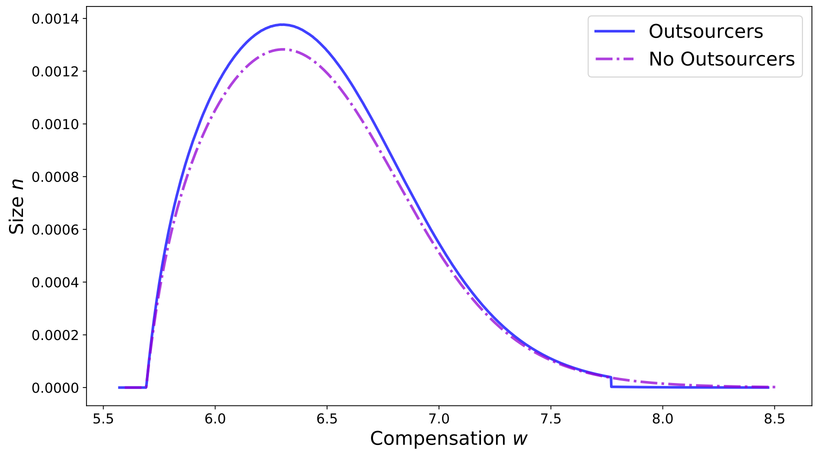

Figure 2.1: Distribution of worker compensation with and without outsourcers. Model parameters come from calibration for workers without a bachelor's degree.

and total production increases 0.50%. But it also has negatives: workers' share of production and average wages fall. The overall effect is negative, workers are 0.03% worse off under outsourcing.

Table 2.3 breaks down the welfare gains and losses from outsourcing for workers, firms, and outsourcers. For now I focus on workers, who I divide into three groups: unemployed, working at always hiring firms, and working either for the outsourcer (when the economy has outsourcers) or working for firms that will choose to outsource (when the economy has no outsourcers). For each of these groups, I show their share of the population, their average flow welfare, and their contribution to total welfare. First, I compare workers at firms above $\hat{y}$ when there is no outsourcing to outsourced workers when there is outsourcing. Firms above $\hat{y}$ pay the highest wages, while outsourcers pay below-average wages, so the average welfare of these workers falls. This is the type of transition studied in Goldschmidt and Schmieder (2017), who also find negative effects of outsourcing on worker's wages. On the other hand, outsourcing dramatically increases firms' demands for labor, such that the total welfare of outsourced workers is much more than the welfare of workers at high-productivity firms. This result makes it plausible that outsourcing could benefit workers despite the losses in compensation. This is not true here, however, because these gains are less than the losses for workers at firms less productive than $\hat{y}$, which always hire. While the average welfare in these jobs is almost identical, the number of jobs decreases 5 pp. The influx of outsourcing vacancies makes it harder for firms to hire workers, and hiring firms respond by decreasing their labor demand. There is also a slight decrease in the welfare of the unemployed, partially because

Table 2.2: Outcomes of four different variations of the model. Parameters come from calibration for workers without a bachelor's degree who ever work in a high-outsourcing occupation. The bottom left model is the baseline specification. The top left model uses the same parameters but does not allow outsourcing. The right two models are the planner's versions. For each model, I report levels for outcomes of interest. The bottom row shows the percent differences between the model with outsourcing and the model without outsourcing. The right column shows the percent differences between the planner's choices and the decentralized outcomes.

		Decentralized		Planner		
		Level		Level	$\Delta\%$ Decent.	
No Out	Unemployment Rate u	8.74		19.01	117.42	
	Worker Match Prob ℓ	4.69		1.92	−59.16	
	Firm Match Prob q	24.51		60.02	144.84	
	Total Production	6.70		7.17	7.00	
	Total Vacancy Costs	0.24		0.29	21.72	
	Worker's Share Production	91.46		–	–	
	Average Compensation | Working	6.46		–	–	
	Flow Worker Welfare	6.13		–	–	
	Flow Total Welfare	6.17		6.49	5.07	
	% Efficient Welfare	95.17		–	–	
		Level	$\Delta\%$ No Out	Level	$\Delta\%$ Decent.	$\Delta\%$ No Out
w/Out	Unemployment Rate u	8.60	−1.65	18.68	117.23	−1.73
	Worker Match Prob ℓ	4.81	2.48	1.96	−59.19	2.39
	Firm Match Prob q	23.92	−2.42	58.62	145.06	−2.34
	Price of Outsourcing p (ρ)	9.09	–	8.74	−3.83	–
	Indifferent Firm $\hat{y}$	9.50	–	10.24	7.81	–
	Percent of Jobs Outsourced	6.41	–	2.05	−68.08	–
	Total Production	6.73	0.50	7.18	6.65	0.17
	Total Vacancy Costs	0.26	5.93	0.30	16.90	1.74
	Worker's Share Production	90.98	−0.53	–	–	–
	Average Compensation | Working	6.45	−0.12	–	–	–
	Flow Worker Welfare	6.13	−0.03	–	–	–
	Flow Total Welfare	6.17	0.02	6.49	5.05	−0.00
	% Efficient Welfare	95.19	0.02	–	–	–

there are fewer unemployed workers and partially because their average welfare decreases as the value of searching for a job falls.[15] These changes result in the 0.03% fall in worker welfare seen in Table 2.2.

I now discuss the effects of outsourcing on firm and outsourcer welfare. Because the measures of firms and outsourcers are exogenously fixed and their vacancy cost functions are convex, firms and outsourcers

[15]One of the worries with the calibration is that the value of home production b is quite low. Because one of the workers' benefits of outsourcing is a decrease in unemployment, this will bias the results in favor of outsourcing. These results show unemployed worker welfare is less than .1 lower than average, a result of a high value of job search. This suggests that any bias on the difference in outcomes with and without outsourcing should be small.

Table 2.3: Comparing welfare flows of decentralized model with and without outsourcing. For workers, firms, and outsourcers, table reports share in certain categories, average welfare in these categories, and how much these categories add to total welfare. Parameters come from calibration for workers without a bachelor's degree who ever work in a high-outsourcing occupation.

	Counterfactual (No Outsourcers)			Baseline (w/Outsourcers)		
	Population	Average Welfare	Total Welfare	Population	Average Welfare	Total Welfare
Unemployed	0.087	6.041	0.528	0.086	6.041	0.520
Below $\hat{y}$	0.906	6.135	5.559	0.855	6.136	5.249
Above $\hat{y}$/Outsourcers	0.006	6.393	0.041	0.059	6.119	0.359
Workers			6.129			6.127
Below $\hat{y}$	0.728	0.059	0.043	0.728	0.056	0.041
Above $\hat{y}$	0.273	0.004	0.001	0.273	0.014	0.004
Firms			0.044			0.045
Outsourcers						0.002
Total			6.173			6.174

make profits on inframarginal workers. Without outsourcing, firms with productivity above $\hat{y}$ are not very profitable. Despite their high productivity, they pay high vacancy costs and wages, and so are small in size. When outsourcers enter the economy, these firms are much better off, and their average welfare more than triples. As discussed above, always-hiring firms face competition from outsourcers and profits fall. For workers, the increase in demand for labor does not make up for the lower job quality, and workers become worse off under outsourcing. Outsourcing firms both increase in size and make more inframarginal profits, so overall firm welfare increases. Outsourcers are obviously made better off when they are allowed to exist. Overall, outsourcing increases total welfare by 0.02%.[16]

To better understand these welfare gains, I now analyze how outsourcing affects efficiency. To set a baseline, I start with LS's model without outsourcers. Outcomes for the decentralized and planner's problem are shown in the top half of Table 2.2. When the planner creates vacancies, she internalizes the effects on the matching probability of workers and other firms. Efficiency requires both the right total number of vacancies and the right relative number of vacancies from firms of different productivities. As I show in Section 2.2, it is generally impossible for the decentralized economy to be efficient along both dimensions. As such, the decentralized economy is inefficient, even with Hosios rule imposed. The planner chooses to employ much fewer workers, and her unemployment rate is more than twice as high. Despite this fall in employment, she produces more and pays higher vacancy creation costs. These

[16] While it may seem that adding a more efficient technology, outsourcing, to the economy will always increase total welfare, this is not necessarily true. Firms make private decisions to outsource which have externalities on market tightness and worker wages. There are model parameters for which the benefits of outsourcing for outsourcing firms and outsourcers are less than the losses for hiring firms and workers. In these cases, total welfare decreases.

Table 2.4: Outcomes of four different variations of the model. Parameters come from calibration for workers with a bachelor's degree who ever work in a high-outsourcing occupation. The bottom left model is the baseline specification. The top left model uses the same parameters but does not allow outsourcing. The right two models are the planner's versions. For each model, I report levels for outcomes of interest. The bottom row shows the percent differences between the model with outsourcing and the model without outsourcing. The right column shows the percent differences between the planner's choices and the decentralized outcomes.

		Decentralized		Planner		
		Level		Level	$\Delta\%$ Decent.	
No Out	Unemployment Rate u	2.98		7.96	167.30	
	Worker Match Prob ℓ	9.20		3.27	−64.46	
	Firm Match Prob q	5.21		14.65	181.41	
	Total Production	7.21		7.59	5.32	
	Total Vacancy Costs	0.16		0.19	16.76	
	Worker's Share Production	94.30		–	–	
	Average Compensation | Working	6.97		–	–	
	Flow Worker Welfare	6.80		–	–	
	Flow Total Welfare	6.84		7.10	3.85	
	% Efficient Welfare	96.30		–	–	
		Level	$\Delta\%$ No Out	Level	$\Delta\%$ Decent.	$\Delta\%$ No Out
w/Out	Unemployment Rate u	2.98	−0.05	7.89	165.23	−0.82
	Worker Match Prob ℓ	9.17	−0.30	3.29	−64.15	0.57
	Firm Match Prob q	5.22	0.30	14.57	178.98	−0.57
	Price of Outsourcing p (ρ)	9.52	–	9.43	−0.94	–
	Indifferent Firm $\hat{y}$	9.60	–	9.70	1.04	–
	Percent of Jobs Outsourced	6.24	–	6.36	1.89	–
	Total Production	7.25	0.60	7.63	5.27	0.55
	Total Vacancy Costs	0.17	5.83	0.20	16.30	5.42
	Worker's Share Production	93.99	−0.33	–	–	–
	Average Compensation | Working	6.99	0.26	–	–	–
	Flow Worker Welfare	6.81	0.26	–	–	–
	Flow Total Welfare	6.86	0.31	7.12	3.78	0.25
	% Efficient Welfare	96.36	0.07	–	–	–

happen simultaneously because the planner creates fewer vacancies overall but more vacancies for highly productive firms. This can be seen in the distribution of firm size for the decentralized versus the planner's equilibrium in the top left plot of Figure D2 in Appendix B.4. In the decentralized economy, too many low-productivity firms enter, crowding out more productive firms and lowering total output.

How does outsourcing change the optimal allocation? The right three columns of Table 2.2 compare the planner's choices when outsourcing is and is not available. Outsourcing does not change the planner's choices much. The top right plot of Figure D2 compares the planner's distribution of firm sizes with and without outsourcing. For hiring firms, the planner's choices are very similar, but the planner does

Table 2.5: Comparing welfare flows of decentralized model with and without outsourcing. For workers, firms, and outsourcers, table reports share in certain categories, average welfare in these categories, and how much these categories add to total welfare. Parameters come from calibration for workers with a bachelor's degree who ever work in a high-outsourcing occupation.

	Counterfactual (No Outsourcers)			Baseline (w/Outsourcers)		
	Population	Average Welfare	Total Welfare	Population	Average Welfare	Total Welfare
Unemployed	0.030	6.708	0.200	0.030	6.725	0.200
Below $\hat{y}$	0.970	6.798	6.591	0.910	6.815	6.199
Above $\hat{y}$/Outsourcers	0.001	7.122	0.004	0.061	6.829	0.414
Workers			6.795			6.813
Below $\hat{y}$	0.720	0.061	0.044	0.720	0.057	0.041
Above $\hat{y}$	0.280	0.000	0.000	0.280	0.011	0.003
Firms			0.044			0.044
Outsourcers						0.003
Total			6.839			6.860

take advantage of outsourcing to increase the size of the most productive firms. As such, the planner increases employment, productivity, and vacancy costs. Therefore, outsourcing allows the planner to increase welfare by 0.01%.

How does outsourcing change the efficiency of the economy? Outcomes for the decentralized and planner's problem with outsourcing are shown in the bottom half of Table 2.2. In Section 2.2, I argued that outsourcing increases efficiency along the intensive margin but decreases efficiency along the extensive margin. This trade-off is made clear in the bottom left plot of Figure D2 in Appendix B.4, which compares the distribution of firm sizes for the decentralized and planner allocations. The decentralized outsourcing firm size is very close to what the planner would choose, while the hiring firm size distribution is shifted to the left of what the planner wants, just as in the LS economy. But when allowed to make their own outsourcing choices, too many firms choose to outsource; the planner's indifferent firm $\hat{y}^P$ is 80 log points more productive than the decentralized indifferent firm $\hat{y}$. The bottom right plot of Figure D2 compares the distributions of outsourcer size. The planner uses far fewer outsourcers, and the ones she uses are much more productive on average. While over 6% of positions are outsourced in the decentralized economy, the planner outsources fewer than 2% of jobs. To sustain more outsourcers, the price of outsourcing must be higher, which is why outsourcing firms are smaller than the planner prefers. Overall, the intensive margin efficiency gains dominate the extensive margin losses; outsourcing improves efficiency. The decentralized choices for employment, total production, and vacancy costs are all closer to the planner's choices with outsourcing than without it. The outsourcing economy captures 0.01% more of the efficient welfare than LS.

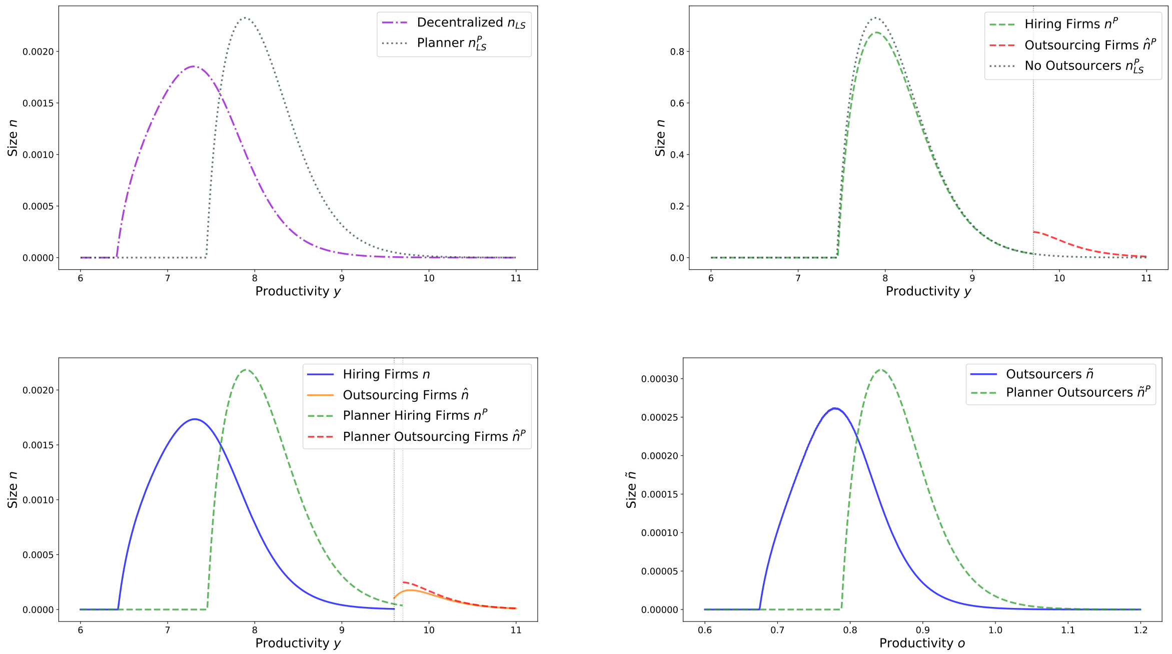

Figure 2.2: Distributions of firm and outsourcer size in decentralized versus the planner economy. Top left figure shows distributions of firm size in LS model without outsourcing. Top right figure shows the planner's distributions of firm size in an economy with and without outsourcing. Bottom figures show distributions of firm size (left) and outsourcer size (right) in my model with outsourcing. Model parameters come from calibration on workers with a bachelor's degree.

We now see how outsourcing affects the labor market for workers with a bachelor's degree. Table 2.4 compares the model with and without outsourcers for both the decentralized and planner's solutions. Once again, I start by comparing the two left columns which contain details on the decentralized economies. As before, outsourcing increase employment and production but decreases worker's share of production. Unlike in the case for workers without bachelor's degrees, average compensation increases, because outsourced jobs are better than traditional jobs on average. As a result, worker welfare increases rather than decreases.

Table 2.5 helps illuminate why worker welfare increases. As in the previous calibration, workers would still rather work directly for a firm rather than the outsourcer, but the increase in the number of jobs means total welfare of these workers increases. In the calibration for workers without a bachelor's, this influx of outsourcing jobs crowded out higher paying traditional jobs, so workers were worse off overall. Here there is still crowding out, but because outsourcing jobs are better, the trade-off is worth it. In fact, outsourcing increases the value of job search, so the average unemployed and traditional worker are made better off than before. The only losers of outsourcing are hiring firms, who are less likely to match because of tighter markets, must pay higher wages because of an increased outside option, and are more likely to lose workers to better paying outsourcers.

Just as outsourcing leads to better worker outcomes for workers with a bachelor's degree, it also leads to better efficiency outcomes. As shown in the right three columns of Table 2.4 and the top right plot of Figure 2.2, the planner is more reactive to the addition of outsourcing for these workers. She is much more willing to substitute hiring vacancies for outsourcing vacancies, so production and total welfare increase more. In the economy for workers without a bachelor's degree, there was a big difference between how much outsourcing the planner wants and how much outsourcing firms choose. The decentralized outsourcing share of employment sector is more than three times bigger than the planner wants. Here, the share of workers at outsourcers is too small. While slightly too many firms choose to outsource, the higher price of outsourcing means firms are not outsourcing as much as the planner wants them to. These off-setting effects means the outsourcing choices of firms are much closer to what the planner wants. As a result, the gains in total welfare from introducing outsourcing are higher.

Policy makers face trade-offs when it comes to outsourcing for workers without a bachelor's degree. Workers are made worse off but total welfare and efficiency increase. For workers with a bachelor's degree, policy makers face no trade-off: all three of these measures rise together. One caveat to this result is that this calibration combined workers with only a bachelor's degree and with a post graduate degree. The results in Table A3 suggest that it is only the latter who's total compensation increases when outsourced. While I combine these workers together in this calibration because of small samples, it could be the case that workers with only a bachelor's degree have similar outcomes to workers without one.

2.5 Conclusion

Policy makers should take away two main lessons from this chapter and from Chapter 1. The first is that outsourcing hurts workers without a bachelor's degree. Their total compensation is 8.8 log points lower than that of workers in traditional jobs. Moreover, my calibration suggests the welfare of workers in high-outsourcing occupations is 0.03% lower compared to what it would be in an economy without outsourcing. The second lesson is that forbidding outsourcing is not an optimal response. Outsourcing improves efficiency and overall welfare. For workers with a bachelor's degree in high-outsourcing occupations, outsourcing increases welfare. Ideal policies should maximize the gains from outsourcing, which are lower market frictions for connecting workers to firms, while minimizing the losses, which are the rent seeking behavior by firms and outsourcers.

These results come with caveats that point to potential avenues for future work. First, I study a specific type of outsourcing, contracting out. These jobs are the most comparable to traditional jobs and distill the effects of being employed by one firm (the outsourcer) while performing tasks for another (the outsourcing firm). But firms have other ways to outsource domestically, namely by using independent contractors and temporary workers. Data on wages and access to benefits suggests these jobs are much worse than contracted-out jobs, but data on job satisfaction suggests that independent contractors earn compensating differentials. Studying these workers might require a slightly different framework than that of my current model.

Second, I take the outsourceability of tasks as given. My calibration focuses on occupations where outsourcing is prevalent and does not allow workers to switch into or out of these occupations. In reality, firms choose which position to outsource and workers choose their occupation knowing the share of jobs that are outsourceable. Outsourced workers come from across the education distribution, but perhaps their occupations share characteristics that make them easier to purchase outside the firm. Knowing how firms make these decisions, and how workers react, is key to understanding the future of outsourcing.

Third, the model captures the comparative advantages of outsourcers in a reduced-form way: lower vacancy costs. This allows me to capture the first-order effects of outsourcing on worker welfare, total welfare, and overall efficiency. However, it is not helpful for explaining why outsourcing has been increasing over time or if we should expect it to increase in the future. It also excludes second-order effects that are especially important for optimal policies. Combining microfoundations for outsourcing with realistic labor market dynamics is a key next step for understanding the implications of outsourcing. Besides past microfoundations for outsourcing (Grossman and Helpman, 2002; Berlingieri, 2015; Bostanci, 2021), my work suggests access to benefits might be an important driver of outsourcing behavior, at least in the United States.

Chapter 3

Currency Competition with Uncertain Acceptance: The Case of Cryptocurrencies (with Fan Liang)

3.1 Introduction

Since the creation of Bitcoin by Nakamoto in 2008, cryptocurrencies, cash-like electronic payment systems issued by private entities, have substantially grown in popularity.[1] Users are drawn to these currencies partly for transaction motives – low transaction fees (especially for international transactions), fixed currency supply schedules, and anonymous/pseudonymous transactions – but also for speculative reasons. Because most cryptocurrencies are fiat assets, their long run viability depends on their transaction (liquidity) value; this paper focuses on transaction motives. Specifically, we study how current seller acceptance and beliefs about future firm acceptance affect cryptocurrency prices. When sellers start accepting these currencies as means of payment, the transaction value of cryptocurrencies increase and prior beliefs about the usefulness of cryptocurrency as a means of payment are (partially) justified.[2] However, seller adoption takes time, some sellers are willing to accept cryptocurrency sooner than others. Because cryptocurrency prices depend on potential future acceptance, events that hurt beliefs about the growth of seller acceptance, such as China's outlawing of Bitcoin exchanges or the US's disapproval of Facebook's proposed cryptocurrency Libra, can have large effects on prices even if they have small effects on current acceptance.

This paper answers the following questions: How do beliefs about cryptocurrency acceptance affect prices? How important is expected acceptance compared to current acceptance? When do people

[1] An overview of what cryptocurrencies are and their benefits and downsides can be found in Böhme et al. (2015) or Berentsen et al. (2018). Dwyer (2015) gives an overview of virtual currency with a focus on Bitcoin.

[2] One example of cryptocurrency used to buy goods is when KFC Canada introduced a "Bitcoin Bucket" of fried chicken and waffle fries in 2018. A short list of companies that accept cryptocurrencies as payments include tech companies like Microsoft, but also non-tech firms such as Expedia and Subway.

adopt or abandon cryptocurrency? How does the presence of cryptocurrency affect welfare? How do heterogeneous beliefs about future acceptance affect current prices?

Our paper examines competition between two currencies: an emerging currency, cryptocurrency, and an existing currency, money, that differ in acceptance rate and currency stock growth rate. Money is universally accepted but inferior at preserving value because its stock grows at a faster rate. Currently, cryptocurrency competes with some local currencies, like Venezuela Bolivar, that are experiencing hyperinflation.[3] To study the liquidity value of these currencies, we adopt a Lagos and Wright (2005) (LW) framework where assets are used to overcome trading frictions.[4] Our main contribution is to study how changes in future currency acceptance affect prices today.

Inspired by Zeira (1999), we add informational dynamics to study cryptocurrency markets' booms and crashes. Cryptocurrency is accepted by a fraction of sellers, but this fraction exogenously increases over time.[5] Agents expect the acceptance rate of cryptocurrency to follow a known growth path until a random termination date, after which cryptocurrency acceptance will stay constant forever. Upon reaching the termination date, the world enters steady state and real balances stay constant; the environment is the same as a standard LW. Each period, after choosing their currency portfolios, agents observe the acceptance rate and update their beliefs about the termination date. Because today's cryptocurrency price depends on tomorrow's price, while acceptance rate is growing, cryptocurrency price exceeds steady state value. However, when agents realize that acceptance growth had stopped, the price of cryptocurrency immediately crashes to its steady state value. Like Zeira, cryptocurrency crashes occur even if buyers are rational and have correct beliefs about the termination date. Unlike Zeira, our assets are intrinsically valueless, so prices can potentially crash to zero if not enough sellers accept cryptocurrency.

Because our economy has a random finite termination date, we can use backwards induction to find a well-defined solution for prices and quantities traded each period. We find that the potential for growth in cryptocurrency acceptance raises expected future prices, which in turn lowers expected cryptocurrency inflation. Lower expected inflation means higher cryptocurrency prices today and makes holding cryptocurrency worthwhile for buyers even when acceptance is low and cryptocurrency would not be valued if acceptance growth was stagnant. This means cryptocurrency growth have a large effect on prices even when current acceptance is low. Higher demand for cryptocurrency crowds out demand for money, so money prices are below steady state levels and decrease in cryptocurrency acceptance. If buyers are more optimistic about future acceptance, cryptocurrency prices increase and money prices decrease. Once acceptance stops growing, cryptocurrency prices fall and money prices jump to steady state values. If acceptance is too low, buyers will abandon cryptocurrency. We also study total welfare in the setting of competing currencies. Total welfare is determined by trade between buyers and sellers which is increasing and concave in buyer's real balances. Because of this, agents are always worse off with higher money growth rate but may be better or worse off with higher cryptocurrency growth rate or acceptance rate.

[3]For more on usage of cryptocurrencies in Venezuela, see `https://www.nytimes.com/2019/02/23/opinion/sunday/venezuela-bitcoin-inflation-cryptocurrencies.html`.

[4]Or, more accurately, a Rocheteau and Wright (2005) framework, as we have permanent buyers and sellers. For more on the New Monetarist literature, see Lagos et al. (2017) and Williamson and Wright (2010).

[5]Appendix C.4 shows a model with endogenous cryptocurrency acceptance by sellers.

Intuitively, the presence of cryptocurrency crowds out money holdings, which can make buyers much worse off when they meet sellers who only accept money.

In Appendix C.4 we show how to derive this exogenous acceptance equilibrium in an environment where cryptocurrency acceptance is endogenous. In the endogenous acceptance model, sellers pay a heterogeneous fixed cost to permanently adopt the technology that allows them to accept cryptocurrency. These costs behave like acceptance in the exogenous model; they can potentially fall each period, but once they stop falling, they stay constant forever. Even without dynamics in cryptocurrency acceptance, LW models lead to multiple equilibria (Lester et al., 2012; Rocheteau and Wright, 2013). Because the decision to accept cryptocurrency depends on future values and future acceptance choices, the potential for many equilibrium paths means this problem is hard to define in general. By focusing on the case where acceptance can be treated as exogenous, we select an equilibrium that can be well characterized.

People have heterogeneous beliefs about future cryptocurrency acceptance and start adopting cryptocurrencies at different times.[6] We extend the model to parsimoniously capture this heterogeneity. In the extended model, a fraction of buyers we call normal buyers behave as in the baseline model, the rest are optimistic buyers we call hodlers who believe that acceptance of cryptocurrency will always grow.[7] While simplistic, this framework sheds light on how early adopters affect prices as well as cryptocurrency holdings of normal buyers. Hodlers' optimism causes them to hold more cryptocurrency and less money than normal buyers. At low levels of acceptance, they can crowd normal buyers out of the cryptocurrency market, but when cryptocurrency is accepted by enough sellers, normal buyers will start to use cryptocurrency. Interestingly, adding hodlers to the baseline model has an ambiguous effect on prices. The presence of hodlers can increase cryptocurrency prices because they are optimistic about its future and value it more today. But the price of cryptocurrency can be lower because currencies are valued for their marginal liquidity, and the marginal liquidity can be lower for both types compared to the baseline case. Hodlers may have large enough cryptocurrency real balances such that the marginal unit of cryptocurrency is worth less to them than to normal buyers in the baseline case. Normal buyers now replace some cryptocurrency holdings with money, which also decreases the value of the marginal unit of cryptocurrency compared to the baseline case. If both these effects are strong enough, cryptocurrency prices are lower.

Our model studies uncertain growth of cryptocurrency acceptance and the potential for crashes in the price of cryptocurrency. In this way, our paper is similar to Choi and Rocheteau (2019) which studies agents' decision to mine cryptocurrency or participate in trade. They also generate booms and crashes in prices, but their crashes can occur even with perfect foresight and their prices always crash to zero.[8] We abstract from the mining process and our crash relies on informational dynamics, but we allow for post-crash cryptocurrency to still be useful with a positive price.

Our information dynamics are inspired by Zeira (1999), who models crashes in asset prices as the result of uncertain termination of economic growth, such as the end of productivity increases or population

[6] Athey et al. (2016) estimates that there are 27,474,538 entities using Bitcoin as of Nov. 2015.

[7] The word hodler, a corruption of the word holder, has come to stand for "Hold-On-for-Dear-Life-ER" or people who believe Bitcoin will keep rising in price.

[8] Other papers study cryptocurrency prices and crashes but do not consider liquidity, see Glaser et al. (2014); Cheah and Fry (2015); Weber (2013); Cheung et al. (2015); and Donier and Bouchaud (2015).

booms. We apply these dynamics to fiat rather than real assets, which are valued for their liquidity rather than their dividends. Because the value of fiat assets is mainly determined by beliefs, incomplete information has a greater effect on prices. For example, our prices can start positive then crash to zero when acceptance growth stops, which can never happen with real assets.

While this paper is motivated by cryptocurrency, our model applies just as well to any pair of competing fiat currencies, i.e. Mexican Pesos and US Dollars. As such, our paper relates to the dual currency literature. The paper closest to ours is Lester et al. (2012), who also study how an asset with more liquidity competes with an asset with higher returns, but they focus on endogenous acceptance of the higher return asset. Similarly, Zhang (2014) studies competing national currencies with endogenous acceptance of the other nation's currency. Both papers only study steady state equilibrium, while we focus on dynamics where acceptance changes gradually over time. We show how uncertainty of acceptance affects price and quantity traded. While we can endogenize acceptance in ways similar to these papers (see Appendix C.4), we focus on exogenous acceptance in the main body of the paper. Fernández-Villaverde and Sanches (2016) endogenize cryptocurrency creation by allowing entrepreneurs to create their own monies, while we take cryptocurrency issuance as exogenous. Schilling and Uhlig (2019) study an endowment economy with both money and cryptocurrency where acceptance is universal but with uncertain endowment, while our model addresses uncertain acceptance. Like Rocheteau and Wright (2013), we study how prices can change with expectations about future liquidity. Our model relies on seller acceptance of cryptocurrency changing over time while their model relies on changing beliefs about currency value.

The rest of this chapter is organized as follows. Section 2 overviews the baseline model: defining the model and equilibrium, examining steady state and comparative statics, introducing dynamics, and showing a numerical example. Section 3 shows the hodlers extension along with a numerical example and comparison to the baseline model. Section 4 concludes.

3.2 The Model

In this section, we describe the setup of our model and define equilibrium. We first derive steady state equilibrium conditions and show some useful comparative statics. Then we show how we recursively solve the model outside steady state. Finally, we show some numerical examples of the model to demonstrate booms and crashes.

3.2.1 The Environment

Our model builds on the money search framework of Lagos and Wright (2005) (LW). Time is infinite and discrete. Each period has two subperiods: a frictional decentralized market (DM) in the first subperiod and a frictionless centralized market (CM) in the second subperiod. In the CM, all agents receive lump-sum transfers, produce and consume a numeraire good, and choose their optimal portfolio of money and cryptocurrency. In the DM, buyers and sellers meet bilaterally and bargain over price and quantity if matched. Both CM and DM goods are non-storable. We assume anonymity in the DM to rule out the use of credit in trade. There are two types of fiat assets: government issued fiat money m and privately issued cryptocurrency c. Money supply M has growth rate $1+\gamma_m = \frac{M_{t+1}}{M_t}$ and cryptocurrency supply C has growth rate $1+\gamma_c = \frac{C_{t+1}}{C_t}$.

There is a unit measure of infinitely lived buyers and sellers. There are two types of sellers: crypto sellers have measure α and accept both money and cryptocurrency while money sellers have measure $1-\alpha$ and only accept money. The measure of crypto and money sellers evolves over time. After each CM, some money sellers are exogenously provided the technology to recognize cryptocurrency and thus become crypto sellers.[9] The measure of crypto sellers evolves following $\alpha_{t+1} = g(\alpha_t)$ where $g'(\cdot) > 1$ so $\alpha_{t+1} > \alpha_t$. After some unknown period $T \in \{0, 1, ..., \overline{T}\}$, the measure of crypto sellers stays constant and we assume the world reaches a monetary steady state with constant real balances, where $\overline{T} < \infty$ is the largest possible termination date.[10] The law of motion of α is

$$\alpha_t = \begin{cases} g(\alpha_{t-1}) & \text{if } t < T; \\ \alpha_T & \text{if } t \geq T. \end{cases}$$

Agents discover that growth stopped in period T when they reach the DM of period $T+1$ and learn α did not grow. Buyers have a common prior over date $F(T)$ with pdf $f(t)$. We use π_t to denote buyers' beliefs exiting the CM about α staying constant conditional on α's growth history. If $t > T$, buyers know that acceptance growth has stopped and $\pi_t = 1$. If $t \leq T$, buyers know that acceptance grew last period but are unsure whether it will grow this period, so

$$\pi_t = \mathbb{P}(\alpha_{t+1} = \alpha_t \,|\, \alpha_t > \alpha_{t-1}) = \mathbb{P}(t = T \,|\, t \leq T) = \frac{f(t)}{1 - F(t-1)}.$$

Because time is discrete, beliefs are not continuous. Define buyer's prior as $F(T) = \{\hat{\pi}_0, \hat{\pi}_1, ..., \hat{\pi}_{\overline{T}}\}$ where $\hat{\pi}_t \equiv \mathbb{P}(t = T)$. Then

$$\pi_t = \begin{cases} \frac{\hat{\pi}_t}{1 - \sum\limits_{\tau < t} \hat{\pi}_\tau} & \text{if } t \leq T \\ 1 & \text{if } t > T. \end{cases} \tag{3.1}$$

For now, we assume all agents have the same beliefs, an assumption we relax in Section 3.

The prices of money and cryptocurrency are denoted as ϕ and ψ respectively. In equilibrium, prices depend on currency stock (which only depends on time period t), acceptance rate α, and beliefs π; $\phi = \phi_t(\alpha, \pi)$ and $\psi = \psi_t(\alpha, \pi)$. Throughout the paper, we abuse notation and denote these as $\phi_{t,\alpha}$ and $\psi_{t,\alpha}$ while acceptance is still growing and $\overline{\phi}_{t,\alpha}$ and $\overline{\psi}_{t,\alpha}$ when acceptance has stopped growing and the economy is in steady state. When referring to individual real balances, we use $\omega = \phi m$ and $\upsilon = \psi c$. We

[9] As shown in Lester et al. (2012), endogenous acceptance allows multiple levels of seller acceptance due to different levels of coordination. Because we focus on dynamics, agents would need to form beliefs about future seller coordination. By keeping acceptance growth exogenous, we abstract from this issue. For a version of the model with endogenous acceptance, see Appendix C.4.

[10] As we show in Section 3.2.4, guaranteeing a termination date allows us to use backwards induction to solve for prices and quantities traded.

use effective wealth to denote the total real balances recognized by a seller, i.e. $\omega + \upsilon$ for crypto sellers and ω for money sellers.

3.2.2 Buyer's Problem

In the CM, a buyer facing acceptance rate α with initial portfolio (m, c) and belief π solves the following maximization problem

$$
\begin{aligned}
W(m, c, \alpha, \pi) = \max_{x,h,m',c'} & \left\{ x - s + \beta \mathbb{E}_\pi \big[V(m', c', \alpha', \pi') \big] \right\} \\
\text{s.t. } & x + \phi_\alpha m' + \psi_\alpha c' \leq s + \phi_\alpha m + \psi_\alpha c + \Omega^m + \Omega^c; \\
& x \geq 0; \;\; m' \geq 0; \;\; c' \geq 0.
\end{aligned}
$$

Buyers have linear utility of consumption x and disutility of working s.[11] Ω^m and Ω^c are the lump-sum transfer of currency by the government and private issuer respectively. At the end of the CM, buyers choose their asset portfolio for tomorrow (m', c') to maximize the continuation value V in the upcoming DM. Agents cannot short assets, so portfolio holdings are non-negative. Expectations about α' are taken over their current prior π and beliefs are updated as explained above.

In the DM, a buyer is matched with a seller with probability λ. Conditional on meeting a seller, the probability of meeting a crypto type seller is α while the probability of meeting a money type seller is $1 - \alpha$. The value of the DM is

$$
V(m, c, \alpha, \pi) = \lambda \left\{ \alpha V^{cs}(m, c, \alpha, \pi) + (1 - \alpha) V^{ms}(m, c, \alpha, \pi) \right\} + (1 - \lambda) W(m, c, \alpha, \pi)
$$

where V^j is the value of a buyer meeting a crypto or money seller $j \in \{cs, ms\}$. When a buyer meets with a seller, the terms of trade specify quantity q^j and payment d^j such that the buyer receives fraction θ of total surplus, i.e Kalai bargaining. They solve

$$
\begin{aligned}
V^j(m, c, \alpha, \pi) = \max_{q^j, d^j} & \left\{ u(q^j) - d^j \right\} + W(m, c, \alpha, \pi) \\
s.t. \;\; u(q^j) - d^j & = \frac{\theta}{1 - \theta} \big[d^j - h(q^j) \big]; \\
q^j \geq 0; \;\; d^j & \leq \begin{cases} \phi_\alpha m + \psi_\alpha c & \text{if } j = cs, \\ \phi_\alpha m & \text{if } j = ms. \end{cases}
\end{aligned}
\tag{3.2}
$$

Quantity of exchange must be non-negative and payment is constrained by effective wealth. Buyers' utility of consumption and sellers' disutility of production have the usual properties: $u' > 0,\ u'' < 0,\ u'(0) = \infty,\ h' > 0,\ h'' \geq 0$, and $h(0) = 0$.

We now define a few terms to simplify the problem. The efficient quantity traded in the DM is q^* which satisfies $u'(q^*) = h'(q^*)$. Suppose a buyer has effective wealth w. Let $q(w)$ be the quantity traded

[11] Wages from working are normalized to 1.

given the buyer's effective wealth, which solves equation (3.2), and $S(w)$ be the total trading surplus in the DM given effective wealth w, i.e. $S(w) \equiv u[q(w)] - h[q(w)]$. Finally, we define $\ell(w)$ as the liquidity premium which corresponds to the buyer's marginal gain of carrying one additional unit of effective wealth w into a DM meeting, i.e.

$$\ell(w) \equiv \theta S'(w) = \begin{cases} \theta \frac{u'[q(w)] - h'[q(w)]}{z'[q(w)]} & \text{if } q(w) < q^*; \\ 0 & \text{otherwise,} \end{cases}$$

where $z[q(w)] \equiv (1-\theta)u[q(w)] + \theta h[q(w)]$ is the transfer of wealth from buyers to sellers. By bringing more effective wealth into a match, buyers can increase their trading surplus by raising the total surplus. However, if a buyer can already purchase the efficient amount, the extra wealth is unspent and carried into the next CM. The opportunity cost of holding money and cryptocurrency can be defined as $i_\alpha^m = \frac{\phi_\alpha}{\beta \mathbb{E}_\pi[\phi'_{\alpha'}]} - 1$ and $i_\alpha^c = \frac{\psi_\alpha}{\beta \mathbb{E}_\pi[\psi'_{\alpha'}]} - 1$. Following LW, the assumption of linear utility in the CM makes W linear in (ω', υ'). Using these definitions, buyers' CM maximization problem becomes

$$\max_{m', c'} \Big\{ - i_\alpha^m \mathbb{E}_\pi[\phi'_{\alpha'}]m' - i_\alpha^c \mathbb{E}_\pi[\psi'_{\alpha'}]c' + \lambda\theta \mathbb{E}_\pi\big[\alpha S(\phi'_{\alpha'}m' + \psi'_{\alpha'}c') + (1-\alpha)S(\phi'_{\alpha'}m')\big]\Big\}. \tag{3.3}$$

The sellers' problem can be similarly defined. We assume sellers have the same beliefs as buyers. Because sellers do not consume in the DM, they have no incentive to carry a positive amount of real balances into the trade meeting. Sellers consume all their wealth and choose portfolio $(m', c') = (0, 0)$ in the CM and split $(1-\theta)$ of the total surplus in the DM. Hence, a sequential monetary equilibrium can be defined as follows

Definition 2. Let $\boldsymbol{q} = (q^{cs}, q^{ms})$ and $\boldsymbol{m} = (m, c)$. Given initial prior $\{\hat{\pi}_t\}_{t=1}^{\overline{T}}$, define a *sequential monetary equilibrium* as a set of quantities traded

$\big\{\{\boldsymbol{q}_t(\pi_t, \alpha_t)\}_{t \le T},\ \{\boldsymbol{q}_t(\pi_t, \alpha_T)\}_{t=T+1},\ \{\boldsymbol{q}_t(1, \alpha_T)\}_{t > T+1}\big\}_{t=0,\ T=0}^{\infty \quad \overline{T}}$ and real balances

$\big\{\{\boldsymbol{m}_t(\pi_t, \alpha_t)\}_{t \le T+1},\ \{\boldsymbol{m}_t(1, \alpha_T)\}_{t > T+1}\big\}_{t=0,\ T=0}^{\infty \quad \overline{T}}$ such that[12]

1. $\big\{\{\boldsymbol{q}_t(\pi_t, \alpha_t)\}_{t \le T},\ \{\boldsymbol{q}_t(\pi_t, \alpha_T)\}_{t=T+1},\ \{\boldsymbol{q}_t(1, \alpha_T)\}_{t > T+1}\big\}_{t=0,\ T=0}^{\infty \quad \overline{T}}$ solves the bargaining problem in (3.2);
2. $\big\{\{\boldsymbol{m}_t(\pi_t, \alpha_t)\}_{t \le T+1},\ \{\boldsymbol{m}_t(1, \alpha_T)\}_{t > T+1}\big\}_{t=0,\ T=0}^{\infty \quad \overline{T}}$ solves buyers' maximization problem in (3.3);
3. Beliefs update according to Bayes' rule in (3.1);
4. Currency markets clear.

[12]These sets take into account how quantities traded and real balances are different when acceptance is growing, in the period that agents realize acceptance stopped growing, and periods of known constant acceptance respectively.

For the rest of the paper, we focus on symmetric equilibrium where at least one currency is valued and aggregate real balances are stationary after agents learn acceptance has stopped growing.[13]

3.2.3 Steady State Analysis

We first analyze an economy in steady state with constant real balances, so acceptance α is known and constant and $\pi = 1$. Following LW, steady state allocations are tractable and well understood; this will allow us to study the economy outside steady state. We use upper bars to denote steady state prices. In steady state, the opportunity costs are proportional to currency growth rates, so $\bar{i}^m_\alpha = \frac{\bar{\phi}_\alpha}{\beta\bar{\phi}'_\alpha} - 1 = \frac{1+\gamma_m}{\beta} - 1$ and $\bar{i}^c_\alpha = \frac{\bar{\psi}_\alpha}{\beta\bar{\psi}'_\alpha} - 1 = \frac{1+\gamma_c}{\beta} - 1$. The buyer's maximization problem from (3.3) becomes

$$\max_{m',c'} \Big\{ - \bar{i}^m_\alpha \bar{\phi}'_\alpha m' - \bar{i}^c_\alpha \bar{\psi}'_\alpha c' + \lambda\theta \big[\alpha S(\bar{\phi}'_\alpha m' + \bar{\psi}'_\alpha c') + (1-\alpha) S(\bar{\phi}'_\alpha m')\big] \Big\}. \tag{3.4}$$

Using the definitions of opportunity costs and effective wealth and first order conditions, it is easy to show prices satisfy

$$\bar{\phi}_\alpha \geq \bar{\phi}'_\alpha \beta \big[1 + \alpha\lambda\ell(\bar{\phi}'_\alpha m' + \bar{\psi}'_\alpha c') + (1-\alpha)\lambda\ell(\bar{\phi}'_\alpha m')\big], \tag{3.5}$$
$$\bar{\psi}_\alpha \geq \bar{\psi}'_\alpha \beta \big[1 + \alpha\lambda\ell(\bar{\phi}'_\alpha m' + \bar{\psi}'_\alpha c')\big]. \tag{3.6}$$

If $m' > 0$ and $c' > 0$, each of the above conditions hold with equality. The steady state equilibrium prices of money and cryptocurrency only depend on currency growth rates, the discount factor, and acceptance rates.[14] Proposition 3 below establishes the conditions under which cryptocurrency and money will be held.

Proposition 3. *In steady state, there exists a stationary money-cryptocurrency equilibrium, i.e.* $m' > 0$ *and* $c' > 0$ *if and only if*

$$1 + \gamma_c < \alpha(1+\gamma_m) + (1-\alpha)\beta, \tag{3.7}$$
$$\frac{\gamma_m - \gamma_c}{\beta} < \lambda(1-\alpha)\frac{\theta}{1-\theta}. \tag{3.8}$$

Proof. See Appendix C.1. □

Figure 3.1 shows how equilibrium type changes with currency growth rate γ_m and acceptance rate α, holding cryptocurrency growth rate constant at a fixed γ_c. In the state space above Condition (3.7), cryptocurrency is valued in equilibrium while below it is not. The intuition behind this condition is the following. In meetings with crypto sellers, which happen with probability α, money and cryptocurrency

[13] In a proof similar to one from Rocheteau and Wright (2013), we can prove existence of equilibrium. Email authors for details.

[14] Because some sellers do not accept cryptocurrency, money and cryptocurrency are not perfect substitutes. This means we do not need to worry about exchange rate indeterminacy as in Kareken and Wallace (1981). See also Zhang (2014).

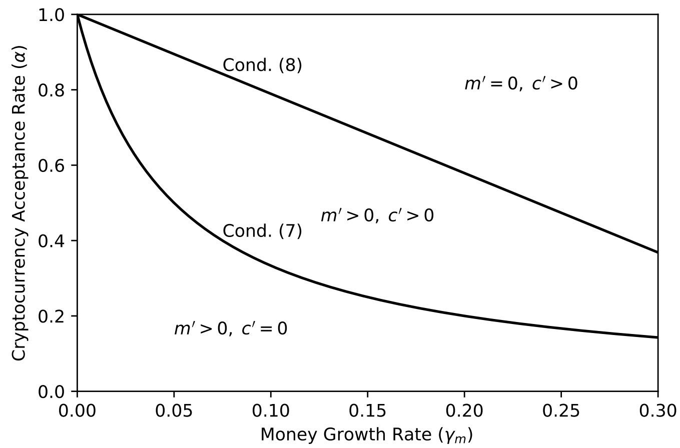

Figure 3.1: Type of equilibrium in steady state based on currency growth rate γ_m and cryptocurrency acceptance rate α, with cryptocurrency acceptance rate $\gamma_c = 0$.

are substitutes, so cryptocurrency could have a currency growth rate as high as that of money and still be valued. However, in meetings with money type sellers, which happen with probability $1 - \alpha$, cryptocurrency has no liquidity value and thus needs to have a return equal to the rate of time preference β for it to be held, i.e. satisfy the Friedman rule. Because buyers are risk neutral in the CM, the maximum growth rate that cryptocurrency can have and still be valued is the probability weighted average of these two types of meetings. As the money growth rate or acceptance rate increases, cryptocurrency becomes more valuable relative to money, hence it is more likely to be held.

In the state space below Condition (3.8), money is valued in equilibrium while above it is not. The intuition behind this condition is that the difference in opportunity cost between money and cryptocurrency (LHS) needs to be smaller than the benefit of trading with a money seller (RHS). The term $\frac{\theta}{1-\theta} = \ell(0)$ represents the liquidity value of a marginal unit of effective wealth when the buyer has none. As the money growth rate or acceptance rate increases, money becomes less valuable relative to cryptocurrency, hence it is less likely to be held. Figure 3.1 is for a fixed γ_c. From Conditions (3.7) and (3.8), it is clear that increasing γ_c will shift Condition (3.7) to the right and rotate Condition (3.8) clockwise. This makes cryptocurrency less likely to be valued.

We are also interested in characterizing total welfare in steady state. If we add up the value functions of all buyers and sellers starting from each DM, we get total welfare each period is

$$\mathcal{W}_\alpha = \lambda\big\{\alpha S(\bar{\phi}'_\alpha m' + \bar{\psi}'_\alpha c') + (1-\alpha)S(\bar{\phi}'_\alpha m')\big\}, \tag{3.9}$$

which is the expected trade amount in the DM. Note that trade surplus $S(\cdot)$ is increasing and concave in effective wealth, which has important implications for comparative statics as we will see below.

Table 3.1: Effects of steady state parameter changes on model outcomes.

χ	$\frac{\partial q^c}{\partial \chi}$	$\frac{\partial q^m}{\partial \chi}$	$\frac{\partial \bar{\phi}'}{\partial \chi}$	$\frac{\partial \bar{\psi}'}{\partial \chi}$	$\frac{\partial \mathcal{W}}{\partial \chi}$
γ^m	0	-	-	+	-
γ^c	-	+	+	-	?
α	+	-	-	+	?

In Table 3.1, we show how quantities traded, prices, and total welfare change with currency growth rates and cryptocurrency acceptance rate.[15] The first row examines how these factors are affected by increases in money growth rate γ_m. Increased growth rate means the currency loses value faster, so the price of money $\bar{\phi}'$ decreases and trade with money sellers q^m does too. Buyers substitute for lost money holdings by using more cryptocurrency, driving up the price $\bar{\psi}'$ and leaving trade with crypto sellers q^c unchanged. Lower trade with money sellers means less trade overall, so welfare decreases. The second row shows that increasing cryptocurrency growth rate γ_c has the opposite effect on quantities and prices, but now trade with crypto sellers decreases because money loses value faster (which must be true if cryptocurrency is valued). The third row shows the effects of increasing cryptocurrency acceptance α. This increases the liquidity value of cryptocurrency, so its price rises and buyers demand less money and more cryptocurrency. Lower money demand lowers its price and quantity traded with money sellers, but buyers still hold more liquidity overall and quantity traded with crypto sellers increases. Both cryptocurrency growth rate and acceptance rate have ambiguous effects on total welfare. On one hand, as cryptocurrency becomes more valuable as a currency (as γ_c decreases or α increases), trade with crypto sellers increases which increases welfare. On the other hand, it leads to less valuable money and trade with money sellers decreases, which lowers total welfare, especially because the total surplus function is concave. In Appendix C.2, we show that welfare effects of more valuable cryptocurrency tend to be negative when effective wealth is already high and cryptocurrency acceptance is very low, meaning the lower trade with money sellers is very costly.

From analyzing steady state, we have shown how currency acceptance mainly depends on currency stock growth rates and acceptance rate. As today's cryptocurrency acceptance increases, the price of cryptocurrency increases, and it's more likely to be valued. Because money and cryptocurrency are partial substitutes, money prices fall with rising cryptocurrency prices. This can have ambiguous effects on welfare, making cryptocurrency more valuable can have negative affects on total welfare. In the next section, we use this steady state knowledge to analyze our dynamic problem where acceptance is increasing over time.

[15] Calculations are provided in Appendix C.2.

3.2.4 Dynamics

Now we want to examine how the model behaves outside of steady state. We can characterize the equilibrium by starting in the steady state with the highest acceptance rate and working backwards. Figure 3.2 demonstrates a simple example with $T \in \{0, 1\}$, so $\overline{T} = 1$ is the largest possible termination date. In the DM of $t = 0$, α is revealed to be α_0 with probability π_0 or $\alpha_1 = g(\alpha_0) > \alpha_0$ with probability $1 - \pi_0$. If $\alpha = \alpha_0$ then $T = 0$, the world reached the low acceptance steady state, and $\alpha = \alpha_0$ forever. If $\alpha = \alpha_1$, then $T = 1$, growth will stop after $t = 1$, and α_1 stays constant forever. We call this the high acceptance steady state.

We want to solve the ex ante price in period 0, where the future is known to be either a high or a low acceptance steady state. The opportunity cost of money and cryptocurrency are $i^m_{\alpha_0} = \frac{\phi_{0,\alpha_0}}{\beta[\pi_0\bar{\phi}_{1,\alpha_0}+(1-\pi_0)\bar{\phi}_{1,\alpha_1}]} - 1$ and $i^c_{\alpha_0} = \frac{\psi_{0,\alpha_0}}{\beta[\pi_0\bar{\psi}_{1,\alpha_0}+(1-\pi_0)\bar{\psi}_{1,\alpha_1}]} - 1$. Buyers solve the following problem

$$
\begin{aligned}
\max_{m_1,c_1} \Big\{ &- i^m_{\alpha_0}\big[\pi_0\bar{\phi}_{1,\alpha_0} + (1-\pi_0)\bar{\phi}_{1,\alpha_1}\big]m_1 - i^c_{\alpha_0}\big[\pi_0\bar{\psi}_{1,\alpha_0} + (1-\pi_0)\bar{\psi}_{1,\alpha_1}\big]c_1 \\
&+ \lambda\theta\Big[\pi_0\big[\alpha_0 S(\bar{\phi}_{1,\alpha_0}m_1 + \psi_{1,\alpha_0}c_1) + (1-\alpha_0)S(\bar{\phi}_{1,\alpha_0}m_1)\big] \\
&\qquad + (1-\pi_0)\big[\alpha_1 S(\bar{\phi}_{1,\alpha_1}m_1 + \psi_{1,\alpha_1}c_1) + (1-\alpha_1)S(\bar{\phi}_{1,\alpha_1}m_1)\big]\Big]\Big\},
\end{aligned}
\tag{3.10}
$$

which implies prices satisfy

$$
\begin{aligned}
\phi_{0,\alpha_0} \geq &\beta\Big\{\pi_0\bar{\phi}_{1,\alpha_0}\big[1 + \alpha_0\lambda\ell(\bar{\phi}_{1,\alpha_0}m_1 + \psi_{1,\alpha_0}c_1) + (1-\alpha_0)\lambda\ell(\bar{\phi}_{1,\alpha_0}m_1)\big] \\
&+ (1-\pi_0)\bar{\phi}_{1,\alpha_1}\big[1 + \alpha_1\lambda\ell(\bar{\phi}_{1,\alpha_1}m_1 + \bar{\psi}_{1,\alpha_1}c_1) + (1-\alpha_1)\lambda\ell(\bar{\phi}_{1,\alpha_1}m_1)\big]\Big\}
\end{aligned}
\tag{3.11}
$$

$$
\begin{aligned}
\psi_{0,\alpha_0} \geq &\beta\Big\{\pi_0\bar{\psi}_{1,\alpha_0}\big[1 + \alpha_0\lambda\ell(\bar{\phi}_{1,\alpha_0}m_1 + \bar{\psi}_{1,\alpha_0}c_1)\big] \\
&+ (1-\pi_0)\bar{\psi}_{1,\alpha_1}\big[1 + \alpha_1\lambda\ell(\bar{\phi}_{1,\alpha_1}m_1 + \psi_{1,\alpha_1}c_1)\big]\Big\},
\end{aligned}
\tag{3.12}
$$

with equality if each currency is held in equilibrium. Prices are probability weighted averages of low and high acceptance steady state prices. Because cryptocurrency prices increase in acceptance ($\bar{\psi}_{1,\alpha_0} < \bar{\psi}_{1,\alpha_1}$), ex ante price at period 0 will be higher than the period 0 steady state even though acceptance is the same, $\psi_{0,\alpha_0} > \bar{\psi}_{0,\alpha_0}$. Because money prices decrease in acceptance ($\bar{\phi}_{1,\alpha_0} > \bar{\phi}_{1,\alpha_1}$), ex ante prices will be lower when acceptance is growing compared to the period 0 steady state, $\phi_{0,\alpha_0} < \bar{\phi}_{0,\alpha_0}$. Cryptocurrency price in the low acceptance steady state is positive if Condition (3.7) is satisfied, otherwise it is zero. Even if this price is zero, prices may still be positive today if agents are optimistic enough about reaching the high acceptance steady state. Our model can generate short term positive prices of cryptocurrency even if fundamentals never allow for long-run viability of the currency.

For economies with longer potential growth $\overline{T} > 2$, we solve the model using backwards induction. Because period $\overline{T} + 1$ is always a steady state, we can solve for prices in period $\overline{T}$. Then in period $\overline{T} - 1$, tomorrow's acceptance either grows to this state or stays constant, either way prices are known, so this

$$
\begin{tikzcd}
\underline{t=0} & \underline{t=1} & \underline{t=2} \\
& \begin{matrix}\alpha_1 = g(\alpha_0)\\ \bar{\zeta}_{0,\alpha_1}\end{matrix} \arrow[r, "1"'] & \begin{matrix}\alpha_1\\ \bar{\zeta}_{1,\alpha_1}\end{matrix} \\
\begin{matrix}\alpha_0\\ \zeta_{0,\alpha_0}\end{matrix} \arrow[ur, "1-\pi_0"] \arrow[r, "\pi_0"'] & \begin{matrix}\alpha_0\\ \bar{\zeta}_{0,\alpha_0}\end{matrix} \arrow[r, "1"'] & \begin{matrix}\alpha_0\\ \bar{\zeta}_{1,\alpha_0}\end{matrix}
\end{tikzcd}
$$

Figure 3.2: Dynamics of acceptance rates α and real balances $\zeta \in \{\phi M, \psi C\}$.

period's prices can also be solved for. This continues to the initial date, giving us the potential path of prices. In the next subsection, we show a numerical example for a longer period of potential acceptance growth.

3.2.5 Numerical Example

We now show some numerical examples. For functional forms, we choose $u(q) = \frac{(q+b)^{1-\eta} - b^{1-\eta}}{1-\eta}$ and $h(q) = q$, where b is a small number to ensure a solution to the bargaining problem. We take $g(\alpha) = (1-\delta)\alpha + \delta\bar{\alpha}$, where $\bar{\alpha} \leq 1$ is some exogenous upper bound on the measure of crypto sellers; acceptance grows by a percentage δ of the distance between the maximum possible acceptance rate and current acceptance rate each period. We assume the buyers' prior is such that $\pi_t = \pi \ \forall \ t < \overline{T}$, so each period before $\overline{T}$ buyers have constant belief that growth will stop.[16]

The growth path of real balances of cryptocurrency and money are shown in the left and right panels of Figure 3.3.[17] The graphs compare real balances if acceptance grows to real balances if acceptance stops growing and the economy enters steady state with constant acceptance. The first x-axis measures time t, which moves linearly, while the second measures acceptance α, which grows according to $g(\cdot)$. For example, in the left panel, the solid yellow line represents the real balances of cryptocurrency while acceptance is still growing. As acceptance grows each period, real balances also grow. If growth stops, real balances crash to the steady state level of the dashed black line where they will stay forever. The dotted red line shows one potential path when $T = 20$. Before $t = 20$, real balances of cryptocurrency grow following the solid yellow line. At $t = 21$, agents realize acceptance has stopped growing, and the real balance immediately crashes to the steady state level where it stays forever.

[16] Parameters used are $b = 0.00001,\ \beta = 0.95,\ M_0 = 1,\ C_0 = 1,\ \gamma_m = 0.02,\ \gamma_c = 0,\ \eta = 0.3,\ \lambda = 0.5,\ \theta = 0.5\ \ \alpha_0 = 0,\ \alpha_g = 0.1,\ \pi = 0.1,\ \delta = 0.1,$ and $\overline{T} = 50$.

[17] We show total real balances rather than prices because inflation decreases prices over time, and we want to differentiate the change of prices due to inflation from the change of prices due to more cryptocurrency acceptance.

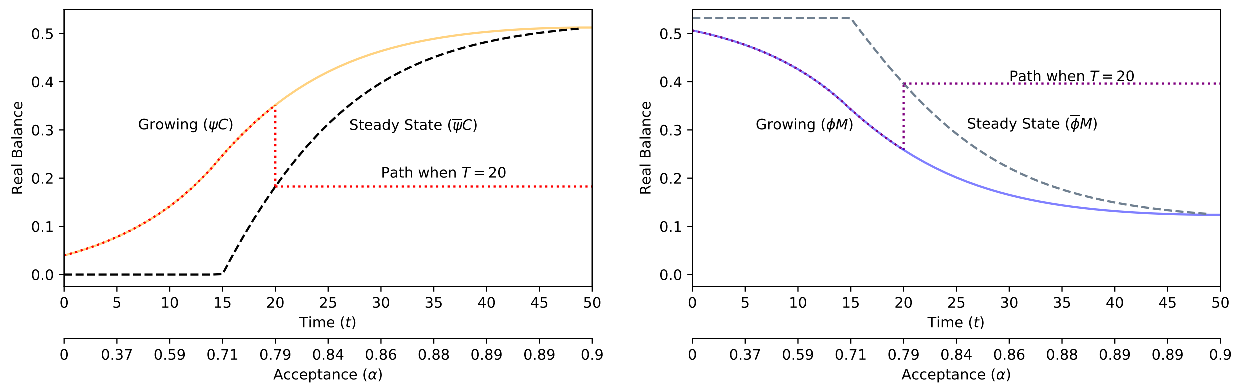

Figure 3.3: Total real balances of cryptocurrency (left) and money (right) while acceptance is still growing versus when it is not growing (steady state) and an example path when $T = 20$. The x-axis shows both time and acceptance rate.

For cryptocurrency, real balances during the growth phase are higher than the corresponding steady state. As we saw in the previous subsection, the possibility that prices will be higher if acceptance is still growing tomorrow lowers the cryptocurrency inflation rate buyers face and makes cryptocurrency more attractive today. Even though cryptocurrency will not be viable in steady state until period 16, where α is high enough to satisfy Condition 3.7 of Proposition 3, cryptocurrency will still have positive prices starting in period 0. Once acceptance stops growing, real balances crash to steady state value and stay constant thereafter. The increased demand for cryptocurrency decreases the demand for money, so its price is lower than it would be in steady state. When growth stops, the real balances of money increase.

To see how beliefs affect prices, Figure 3.4 shows how different priors $\pi \in \{0, .1, .2\}$ that acceptance growth will stop each period change price curves. We again show cryptocurrency real balances on the left and money real balances on the right. When $\pi = 0$, buyers believe acceptance will always grow until $\overline{T}$, so they believe there is no risk in holding cryptocurrency. As a result, real balances of cryptocurrency are much higher and real balances of money are much lower. By contrast, when $\pi = .2$, buyers are much more skeptical about the future of cryptocurrency but it still has positive prices for low acceptance. In general, cryptocurrency real balances monotonically decrease with π while money real balances monotonically increase. When all buyers are more optimistic, cryptocurrency prices increase; however, as we will show in the next section, when only some buyers are more optimistic, price changes are ambiguous.

In the above example, the long-run price of cryptocurrency is positive only if acceptance stops growing after period 16, which happens less than 20% of the time. Even though cryptocurrency's long-run viability is in doubt, people still value it because it facilitates transactions next period. The potential for future growth lowers expected cryptocurrency inflation, making in cheaper to use in transactions and worthwhile to hold. Through this mechanism, our model justifies holding cryptocurrency for transaction purposes

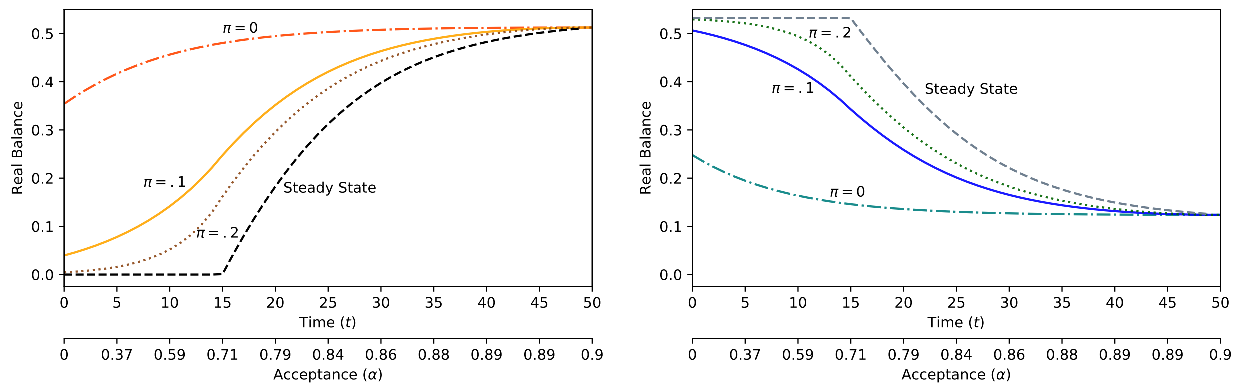

Figure 3.4: Total real balances of cryptocurrency (left) and money (right) for different priors $\pi = \{0, .1, .2\}$.

even when few sellers accept cryptocurrency today. But because acceptance growth may stop, our model can also generate crashes in prices, both to zero and positive values.

How does the presence of cryptocurrency affect welfare? Figure 3.5 shows total welfare from our numerical examples change with cryptocurrency acceptance both for steady state with the dashed black line and while acceptance is growing with the solid yellow line. As we saw in comparative statics there are two competing forces affecting steady state welfare. On one hand, cryptocurrency holds its value better than money does, so effective wealth in crypto meetings increase in acceptance. On the other hand, cryptocurrency holdings replace money, so effective wealth in money meetings is lower. Initial increases in acceptance make cryptocurrency valuable enough to hold even if many sellers do not accept it, lowering total welfare. When enough sellers accept cryptocurrency, the increase in total real balances are enough to increase total welfare. Adding dynamics means that cryptocurrency is worth more and that buyers hold cryptocurrency even when very few sellers accept it. It also means the value of buyer's cryptocurrency is uncertain; usually it is worth slightly more than what they purchased it for but it may be worth much less. When acceptance is low, these effects combine to make welfare much lower than the steady state case; as acceptance increases, they make welfare a little bit higher.

Overall, our numerical examples show how important dynamics can be: the potential for higher future acceptance means cryptocurrency can have positive price even when acceptance is very low. Potential for acceptance growth means cryptocurrency prices are above steady state while money prices are lower, and these effects grow stronger as buyers become more optimistic. When acceptance stops growing, prices immediately crash to steady state levels. The presence of dynamics has uncertain effects on total welfare; it initially is below steady state levels but increases above steady state as acceptance grows. In the next section, we will extend the model with heterogeneous beliefs and show how this changes the model's predictions.

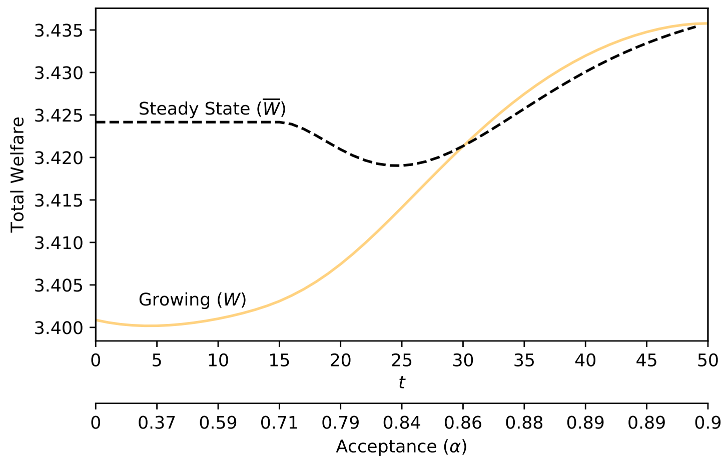

Figure 3.5: Total welfare starting in the DM of each period while acceptance is still growing versus when it is not growing (steady state). The x-axis shows both time and acceptance rate.

3.3 Hodlers Extension

Our baseline model assumed all buyers have the same beliefs, but some early adopters started valuing cryptocurrencies before others. We want to see how these optimistic agents affect currency values and normal buyers' portfolios. To do so, we model an extension where buyers' beliefs about acceptance growth are heterogeneous. We add optimistic buyers called hodlers (see Footnote 7) who have measure $1-\mu$ and *a priori* believe that α will always grow until $\overline{T}$.[18] We denote hodlers' asset holdings and beliefs with a tilde. A measure μ of buyers are normal buyers who behave exactly as in the baseline model. Both normal buyers and hodlers agree to disagree on their beliefs. Despite their different priors, once acceptance stops growing and the economy enters steady state, hodlers and buyers behave identically, as they now share the same beliefs. For simplicity, we assume sellers have the same beliefs as normal buyers.[19] In Appendix C.3, we define a sequential monetary equilibrium similar to the one in Definition 2.

We want to characterize how prices are determined with the addition of hodlers. To compare with the baseline model, we use the same scenario as the dynamics in Section 3.2.4 and study the problem in period 0. The normal buyers' problem and first order conditions are the exact same as in the baseline model (see Equations (3.11) and (3.12)), so we focus here on the hodlers' problem. In steady state, α is known, so the hodlers value function is given by Equation (3.4). Because hodlers have the same steady state values as

[18] Formally, their prior is $\tilde{f}(\overline{T})=1$.

[19] Because information arrives at the beginning of the DM, sellers learn no new information between receiving currency payments in the DM and selling back these currencies in the next CM. Because sellers have no liquidity needs, they will only hold cryptocurrency for speculative reasons. As such, our results hold as long as sellers are weakly less optimistic about cryptocurrency than hodlers.

normal buyers, we can solve their out-of-steady-state problem in a similar fashion. Before learning the termination date T, hodlers believe α is always growing, so their prior is $\tilde{\pi}_0 = 0$. After solving the hodlers' problem, prices satisfy:

$$\phi_{0,\alpha_0} \geq \bar{\phi}_{1,\alpha_1}\beta\left[1 + \alpha_1\lambda\ell(\tilde{\phi}_{1,\alpha_1}\tilde{m}_1 + \tilde{\psi}_{1,\alpha_1}\tilde{c}_1) + (1-\alpha_1)\lambda\ell(\tilde{\phi}_{1,\alpha_1}\tilde{m}_1)\right], \tag{3.13}$$

$$\psi_{0,\alpha_0} \geq \bar{\psi}_{1,\alpha_1}\beta\left[1 + \alpha_1\lambda\ell(\tilde{\phi}_{1,\alpha_1}\tilde{m}_1 + \tilde{\psi}_{1,\alpha_1}\tilde{c}_1)\right]. \tag{3.14}$$

If hodlers value money and cryptocurrency then each condition holds with equality. Notice that the above conditions are special cases of Equations (3.11) and (3.12) with $\pi_0 = 0$. Intuitively, hodlers are more optimistic about cryptocurrency's future and thus they value cryptocurrency more than regular buyers and hold more cryptocurrency. The opposite is true for money. Because prices are determined by marginal values, which decrease in effective wealth, it is still possible for both types to hold both currencies. In fact, the effect of adding holders on marginal valuation of both currencies is ambiguous, so it is possible for cryptocurrency prices to fall and money prices to rise from the baseline case. We will discuss this in detail in the next section.

Equilibrium in this simple example is characterized by market clearing conditions $\mu m + (1-\mu)\tilde{m} = M$ and $\mu c + (1-\mu)\tilde{c} = C$ plus the first order conditions from (3.11)-(3.12) and (3.13)-(3.14). For more general cases with more periods of potential growth, we can follow the same logic from Section 3.2.4 and use backwards induction to find each potential price sequence. We show a numerical example of such a case in the next section.

3.3.1 Numerical Example

To see how the model works, we use the same parameters as Footnote 16 but now add hodlers to the economy. We compare results with different fractions of normal buyers $\mu = \{.5,\ .99,\ 1\}$.[20] Real balances are shown in Figure 3.6 and asset holdings are shown in Figure 3.7. First we look at the left panel of Figure 3.6 concerning cryptocurrency real balances. The internal margin of hodler population works much like the internal margin of beliefs π from Figure 3.4; as we add hodlers to the economy, the average beliefs about acceptance growth become more optimistic and cryptocurrency price rises. The external margin of adding hodlers from the baseline is less certain. When acceptance is low, cryptocurrency prices are higher in the presence of hodlers because they are more optimistic about the future of cryptocurrency, which is especially important in determining prices when α and liquidity value are small. But as acceptance grows, adding only a few hodlers $\mu = .99$, leads to a lower price compared to the baseline case. When there are few hodlers, they hold lots of cryptocurrency, which lowers the liquidity premium of a marginal unit of cryptocurrency, lowering their marginal demand compared to the baseline case. Normal buyers have lower cryptocurrency real balances, but, as we will see in Figure 3.7 below, they get more liquidity from money which is valued in all meetings and has less competition from hodlers. Therefore, marginal demand for cryptocurrency decreases, lowering the price. As the proportion of hodlers increases, each

[20] Note that $\mu = 1$ is equivalent to the economy in Figure 3.3. Also note that an economy with only hodlers is equivalent to one where $\pi = 0$ in Figure 3.4.

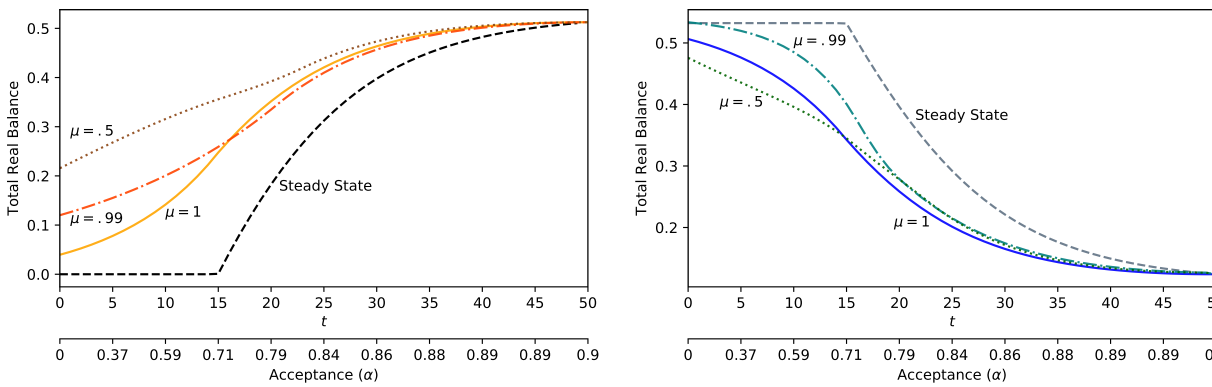

Figure 3.6: Total real balances of cryptocurrency (left) and money (right) for different populations of buyers and hodlers. For each line, μ is the measure of normal buyers and $1 - \mu$ is the measure of hodlers.

individual hodler holds less cryptocurrency so the marginal unit has a higher liquidity premium and hodler competition drives up prices. With enough hodlers, prices are always above the baseline case.

We now look at the right panel concerning money real balances. Again, the effect of adding hodlers is ambiguous. For low levels of acceptance, money prices are higher for smaller populations of hodlers and lower for larger populations of hodlers. There are two forces affecting money prices compared to the baseline case. The first is that normal buyers are crowed out of the cryptocurrency market (see left panel of Figure 3.7) and they replace this loss of liquidity by demanding more money. The second is that hodlers demand less money but because cryptocurrency still has low acceptance, they still have moderate demand for money (see right panel of Figure 3.7). With only a few hodlers in the economy, the first force dominates. With a lot of hodlers, the second force dominates.

As acceptance increases, the size of these two forces changes. While normal buyers are crowded out of the cryptocurrency market, their lost cryptocurrency liquidity increases with acceptance and their relative demand for money increases. When they begin to hold cryptocurrency, they still hold fewer real balances, either because cryptocurrency is worth less or because their holdings are very low. In either case, their demand for money is higher than the baseline case. As acceptance grows, cryptocurrency becomes more liquid and hodlers demand less money. But eventually normal buyers' beliefs converge to hodlers', so their allocations converge as well and hodlers hold more money. In our numerical example, the first effect dominates as acceptance increases, so money prices stay above the baseline case both with few and with many hodlers. But for other specifications, for example in an economy with only hodlers as is the case when $\pi = 0$ in Figure 3.4 above, money prices can be lower than the baseline case.

Our model shows that the interaction between agents with heterogeneous beliefs has a non-obvious effect on prices. While hodlers are more optimistic about the future of cryptocurrency and will hold more cryptocurrency than buyers, they may have negative effects on cryptocurrency prices. This occurs because their cryptocurrency holdings can be so large that their marginal demand is lower. Adding hodlers can

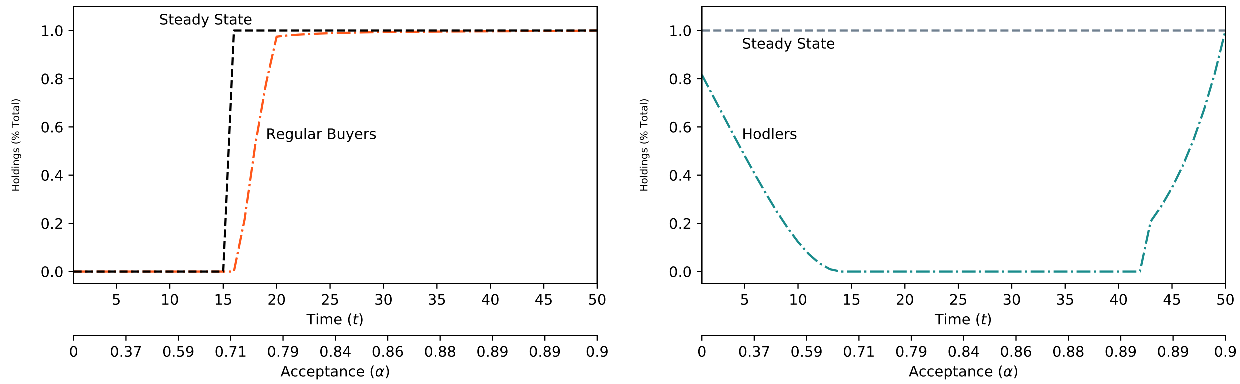

Figure 3.7: Cryptocurrency holdings for normal buyers (left) and money holding for hodlers (right) while acceptance is still growing versus when it is not growing (steady state) for $\mu = .99$. normal buyer holdings are for a measure $.1$ of buyers for ease of comparison.

increase money prices both in the short- and long-run. This extension shows how optimistic agents may crowd regular people out of cryptocurrency when acceptance is low and drive up cryptocurrency prices, but if optimist's predictions come true, normal people will start to use it as well when many sellers accept it. While this has clearly not happened yet globally, cryptocurrencies have been taken up in countries like Venezuela where money inflation is extreme.

3.4 Conclusion

Our model studies the transaction motive for holding cryptocurrency and relates uncertain acceptance of cryptocurrency to both high values of cryptocurrency today even when seller acceptance is low and crashes in price even when seller acceptance remains unchanged. Our crashes can occur even with rational agents with correct beliefs and can result in both positive and zero long-run prices. We show that in steady state, cryptocurrency prices rise with money growth rate and acceptance rate and fall with cryptocurrency growth rate. We use our steady state results to backwards induct prices when acceptance is growing and show the potential for growth increases the value of cryptocurrency today. This can result in positive short-run prices even when acceptance is low and positive prices are unlikely in the long-run. Additionally, we extend the baseline with heterogeneous beliefs about future seller acceptance. Optimistic agents value cryptocurrency more but surprisingly their presence may lead to lower cryptocurrency prices.

The main contribution of our paper is the focus on how future acceptance affects the value of currencies today. While our paper is inspired by cryptocurrency, it can be applied to a broader context of competing currencies, such as dollarization, where a widely accepted domestic currency faces competition from a more stable foreign currency. Our model is highly stylized. We assume one cycle of boom and bust; there is no potential for acceptance to grow once it has stopped. In reality, acceptance growth may start and stop, and prices will reflect this. Cryptocurrencies are not like many other fiat currencies, in that their supply and transaction fees depend on mining games, something we abstract from here.

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Appendix A

Appendices for Chapter 1

A.1 Supplemental Data Analysis

This section contains supplemental data analysis to complement the main data analysis in Section 1.2. Subsection A.1.1 shows robustness results for outsourcing over time. Subsection A.1.2 shows the demographics of workers in and out of HO occupations from the CPS. Subsection A.1.3 shows robustness results for job quality of contracted-out jobs. Subsection A.1.4 shows the job quality of other alternative job types. Subsection A.1.5 compares my measure of outsourcing to that of Dube and Kaplan (2010) and to defining outsourcing as workers in professional business services. Subsection A.1.6 presents supplemental job transition data.

A.1.1 Outsourcing Over Time Robustness

One weakness of the data is I only see one cohort and contracting out may be increasing in age. The upper left plot in Figure A1 shows percent of employed workers outsourced by age and gives potential reason to be concerned. Outsourcing increases then decreases in age in a pattern similar to the time trend. The bottom graph plots the percent outsourced each year by birth cohort and shows most of the dip in later years is a cohort effect. The older cohorts in the sample are less likely to be outsourced and the old age observations only come from these cohorts. To see if there is a time trend after accounting for age, I plot the percent outsourced each week only for workers age 43–47, where the age plot shows approximately no change in percent outsourced.[1] This graph, in the upper right, shows a similar increase in outsourcing over time to the measure for all ages. While age might have some effect in the data, the underlying increase in outsourcing is real.

[1] I perform a similar test for ages 49–53, with similar results.

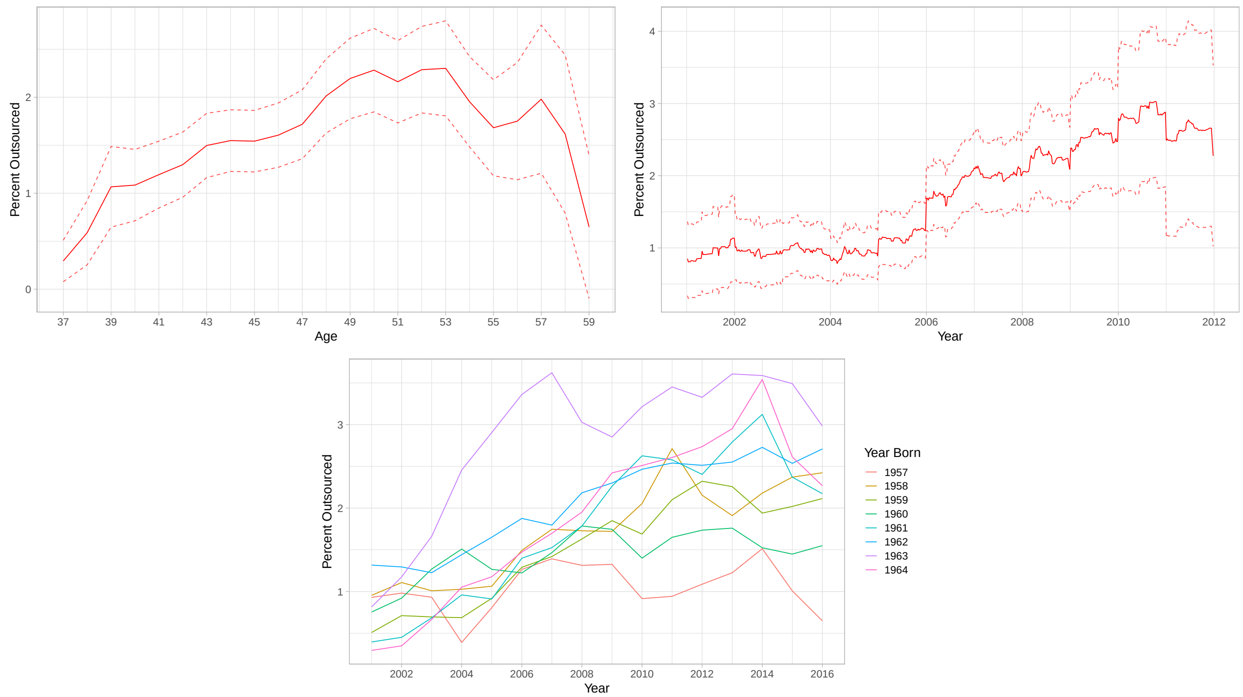

Figure A1: Outsourcing by age and over time. Top left shows percent of employed men and women outsourced by age. Top right shows percent of employed men and women age 43–47 outsourced each week. Bottom shows percent of employed men and women outsourced each year by year born.

A.1.2 Demographics in the CPS

In this subsection, I compare workers in and out of high-outsourcing (HO) occupations (occupations with more than 3.48% of weeks worked by outsourced workers) in the NLSY and CPS. The CPS data comes from the monthly survey from January 2001 to October 2016. To better compare to the CPS, I take the first week of every month as the NLSY observation. Table A1 shows the results: the left two columns shows the NLSY data, the middle two show for all CPS workers age 18–65, and the right two show the NLSY cohort (born between 1957 and 1964) in the CPS. Each sample shows around 12–14% of workers are in HO occupations at any given time.

I start by comparing the NLSY cohort in the NLSY and CPS. Unsurprisingly, the groups have similar ages. Both show large differences in the gender of HO workers, these occupations are only about 20% women. The NLSY has more Black and fewer Hispanic respondents. Education levels are similar in the two data sets. In Table 1.1, I compared *ever outsourced* to *never outsourced* workers and showed that only the percent with postgraduate degrees were significantly different. For HO occupations overall, education gaps are a bit larger. HO workers are significantly more likely to only have a high school diploma and less likely to have less than a high school diploma or a bachelor's degree or more. Despite this, there is still a large fraction of highly educated workers in HO occupations. The CPS sample is less likely to be single

Table A1: Summary Statistics of Workers in HO Occupations: NLSY vs CPS

	NLSY		CPS		CPS (NLSY Cohort)	
	HO Occ	Other Occ	HO Occ	Other Occ	HO Occ	Other Occ
Age	47.394	47.513***	40.768	40.180***	47.698	47.731***
	(0.1010)	(0.0393)	(0.0113)	(0.0044)	(0.0101)	(0.0039)
Female	0.235	0.507***	0.200	0.508***	0.209	0.517***
	(0.0146)	(0.0076)	(0.0004)	(0.0002)	(0.0008)	(0.0004)
Black	0.141	0.126***	0.117	0.123***	0.116	0.117
	(0.0084)	(0.0034)	(0.0003)	(0.0001)	(0.0007)	(0.0003)
Hispanic	0.061	0.062	0.170	0.145***	0.129	0.114***
	(0.0046)	(0.0021)	(0.0004)	(0.0001)	(0.0007)	(0.0003)
Less	0.077	0.062***	0.125	0.093***	0.112	0.083***
High School	(0.0087)	(0.0033)	(0.0003)	(0.0001)	(0.0006)	(0.0002)
High School	0.559	0.498***	0.550	0.481***	0.558	0.472***
	(0.0175)	(0.0076)	(0.0005)	(0.0002)	(0.0010)	(0.0004)
Associate's	0.094	0.097***	0.103	0.098***	0.111	0.109**
Degree	(0.0104)	(0.0045)	(0.0003)	(0.0001)	(0.0006)	(0.0002)
Bachelor's	0.163	0.195***	0.160	0.215***	0.156	0.216***
Degree	(0.0134)	(0.0062)	(0.0003)	(0.0001)	(0.0007)	(0.0003)
Postgraduate	0.056	0.094***	0.061	0.112***	0.064	0.119***
Degree	(0.0086)	(0.0048)	(0.0002)	(0.0001)	(0.0005)	(0.0002)
Single	0.131	0.127***	0.265	0.296***	0.115	0.118***
	(0.0106)	(0.0048)	(0.0004)	(0.0002)	(0.0006)	(0.0002)
Married	0.644	0.657***	0.593	0.560***	0.691	0.686***
	(0.0161)	(0.0070)	(0.0005)	(0.0002)	(0.0009)	(0.0004)
Log Real	6.900	6.746***	6.700	6.526***	6.854	6.709***
Weekly Wage	(0.0208)	(0.0118)	(0.0016)	(0.0007)	(0.0032)	(0.0015)
Part-Time	0.086	0.157***	0.156	0.221***	0.133	0.184***
	(0.0076)	(0.0042)	(0.0003)	(0.0001)	(0.0007)	(0.0003)
Union	0.061	0.070***	0.120	0.097***	0.144	0.116***
	(0.0079)	(0.0032)	(0.0006)	(0.0002)	(0.0014)	(0.0005)
Observations	155,994	964,507	1,492,906	10,861,964	328,311	2,245,653

Note: Summary statistics for workers in the NLSY and CPS. NLSY data uses job data from the first week of every month from January 2001 to October 2016. CPS data comes from the monthly January 2001 to October 2016 surveys for all employed workers 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 3.48% in the NLSY). Statstics are weighted at the person level. Stars represent significant difference from HO occupations within own sample at the .10 level (*), .05 level (**), and .01 level (***).

and more likely to be married, but in both HO workers are more likely to be single rather than married. For average job quality, both show HO jobs earn higher wages and are less likely to be part-time. Overall, the NLSY and CPS samples are similar and show similar differences between HO and non-HO workers and jobs.

I now briefly compare the overall CPS sample to the NLSY cohort. Many of the differences are those we expect to see from a younger-on-average group: more Hispanic and single, fewer married, lower wages, and less likely to be unionized. But the gender and education profiles are very similar, as are the differences between HO and non-HO occupations. The NLSY cohort is a reasonable proxy for the rest of the population and the NLSY sample captures this cohort well.

A.1.3 Job Quality Alternate Regressions and Robustness Checks

This section details some of the alternative regressions and robustness checks for my job quality results in Section 1.4. I start with Table A2, which shows regressions from Equation 1.1 for the following outcomes: log real hourly wages, hours worked, part-time status, and access to any benefits. In the main specifications, I found outsourced jobs had insignificantly lower weekly wages; these results suggests hourly wages are insignificantly higher. The reason these have different signs is that outsourced workers work about half an hour less each week, although this is also insignificant. Outsourced workers are equally likely to work part-time. Just as outsourced workers are less likely to have access to health insurance or retirement benefits, they are significantly less likely to have access to any benefits at all.

In Table 1.6 from the main body of the paper, I compared job quality outcomes for workers with and without a bachelor's degree. In Table A3, I divide education even further: less than high school diploma, high school diploma, associate's degree, bachelor's degree, and postgraduate degree. The main specification showed that workers without a bachelor's degree had lower weekly wages, access to benefits, and total compensation. The more detailed specification shows that most of these loses are felt by workers with high school diplomas and associate's degrees. Their jobs are worse by each measure, and their total compensation are significantly lower by 8.3 and 14.7 log points, respectively. These jobs are also mostly worse for workers with less than a high school diploma, but their total compensation is not significantly lower.

For workers with a bachelor's degree, the main specification shows significantly less access to benefits but insignificantly higher weekly wages and total compensation. The more detailed specification shows that these aggregates hide very different outcomes for workers with just a bachelor's degree versus a postgraduate degree. Workers with only a bachelor's are paid insignificantly more, have significantly less access to benefits, and earn total compensation 2.6 log points lower. Workers with a postgraduate have significantly higher wages, insignificantly fewer benefits, and earn total compensation 25.0 log points higher. Overall, these results suggest that outsourced jobs are significantly worse for workers with high school diplomas and associate's's degrees, potentially worse for workers with less than high school diplomas and bachelor's degrees, and significantly better for workers with postgraduate degrees.

In Figure 1.2 from the main text, I follow the spirit of Card et al. (2013) and plot residual access to health insurance by previous and current outsourcing status. Here, I repeat similar exercises for health insurance levels and for total compensation 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. Workers currently outsourced have higher total compensation and access to health insurance in their previous jobs than currently traditional workers. Because of this selection, controlling for worker fixed effects is important. The residual plots and level plots for health insurance access paint the same picture: workers transitioning from outsourced to traditional jobs gain access to heath insurance and workers transitioning from traditional to outsourced jobs lose access to health insurance. For raw total compensation, there is a clear loss when transitioning from traditional to outsourced jobs but only small gains moving from outsourced to traditional. The residual plot shows that this is due to observables,

Table A2: Quality of Outsourced Jobs: Alternative Measures

	Log Real Hourly Wages	Hours Worked Per Week	Part-Time	Any Benefits[a]
Outsourced	0.010	−0.669	0.003	−0.120**
	(0.026)	(1.287)	(0.032)	(0.036)
R^2	0.80	0.63	0.60	0.64
Observations	9,411	10,273	10,581	10,583

Note: Regressions of worker outsourcing status on job outcomes. Data comes from 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, and marital status. All observations are at the person-job level,, where jobs observed more than once use average or modal characteristics. All regressions are weighted at the person level and all standard errors are clustered by demographic sample. Stars represent significance at the .10 level *, .05 level **, and .01 level ***.
[a] Benefits measure if worker reports access to benefit through employer.

Table A3: Quality of Outsourced Jobs by Education

	Log Real Weekly Wages	Health Insurance[a]	Retirement Plan[a]	Log Real Total Compensation[b]
Less High School ×	−0.052	−0.033	0.127	−0.075
Outsourced	(0.088)	(0.088)	(0.102)	(0.102)
High School ×	−0.057	−0.056**	−0.070***	−0.083**
Outsourced	(0.036)	(0.023)	(0.015)	(0.038)
Associate's Degree ×	−0.135	−0.161***	−0.194***	−0.147*
Outsourced	(0.090)	(0.051)	(0.061)	(0.072)
Bachelor's Degree ×	0.032	−0.097***	−0.099**	−0.026
Outsourced	(0.135)	(0.033)	(0.046)	(0.141)
Postgraduate Degree ×	0.285**	−0.080	−0.063	0.250***
Outsourced	(0.100)	(0.123)	(0.141)	(0.080)
R^2	0.77	0.65	0.65	0.77
Observations	18,901	21,278	21,100	18,638

Note: Regressions of worker outsourcing status by education level on job outcomes. Data comes from the NLSY. Regressions control for education dummies multiplied by job type (default is traditional). Regressions also include worker and occupation fixed effects, a quartic in age and job tenure, and year started and ended job, union status, dummies for region, whether in an MSA or central city, and marital status. All observations are at the person-job level, where jobs observed more than once use average or modal characteristics. All regressions are weighted at the person level, and all standard errors are clustered by demographic sample. Stars represent significance at the .10 level (*), .05 level (**), and .01 level (***).
[a] Benefits measure if worker reports access to benefit through employer.
[b] Total compensation is imputed using log real weekly wages and access to health insurance and retirement plans. The value of these benefits is calculated using data from the NCS. See Appendix A.2.3 for more details.

controlling for them shows these transitions have similar effects in the opposite direction. Both the level and residual plots confirm that outsourced jobs are lower quality on average.[2]

[2]Similar plots confirm results for other measures of job quality and for the impact of outsourcing by bachelor's degree attainment (details available upon request).

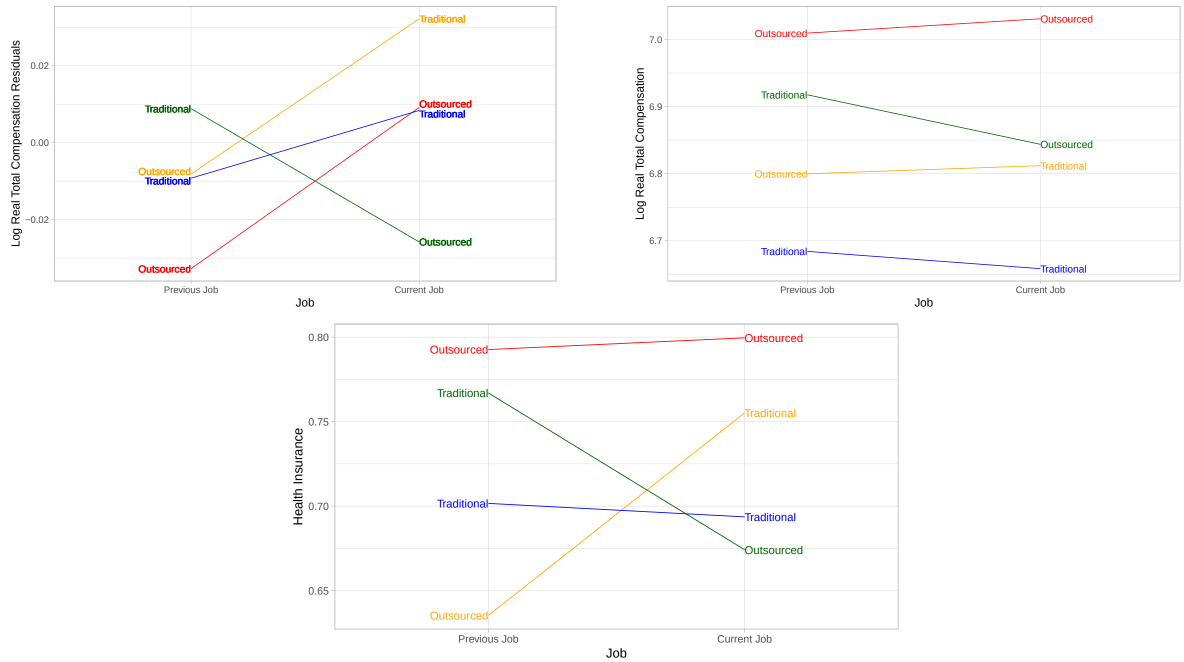

Figure A2: Job quality at previous and current job by current and previous job type. Top left shows log real total compensation. Top right shows log real total compensation residuals. Residuals come from a regression similar to the one described in Table 1.5 but without the variable $outsourced$, which indicated if a job was outsourced (see Footnote 16). Bottom figure shows access to health insurance.

A.1.4 Other Job Types

This section shows the characteristics of jobs other than contracted-out (my measure of outsourcing) and traditional. These are independent contractors, temp workers, self-employed, and on-call jobs. Table A4 shows summary statistics. Compared to contracted-out and traditional jobs, these jobs tend to pay similar to lower hourly wages and lower weekly wages. This is partially because they are worked fewer hours each week and are more likely to be part-time. The self-employed have tenures similar to traditional workers, independent contractors and on-call workers have similar tenure to outsourced workers, and temp worker's have the shortest tenure. These jobs are about 30–60 pp less likely to have access to any benefits, including health insurance or retirement plans. As a result, all of these jobs have imputed total compensations more than half a log point lower. On the other hand, there may be some compensating differentials not captured in wages and benefits. The NLSY asks workers to rate their job satisfaction, with 1 as the highest satisfaction and 4 as the lowest. Despite worse observable outcomes, self-employed and independent contractors are more satisfied with their jobs than outsourced or traditional workers, and on-call workers are more satisfied than outsourced workers. Temp workers rate their jobs significantly worse.

Table A4: Job Summary Statistics

Variable	Outsourced	Traditional	Self-Emp.	Ind. Contractor	On-Call	Temp
Log Real	2.98	2.91***	2.81***	2.91*	2.51***	2.42***
Hourly Wage	(0.04)	(0.01)	(0.03)	(0.05)	(0.03)	(0.03)
Log Real	6.60	6.48***	5.98***	5.91***	5.52***	5.96***
Weekly Wage	(0.05)	(0.01)	(0.04)	(0.06)	(0.06)	(0.04)
Hours Worked	40.48	39.01***	33.46***	29.57***	27.79***	37.04***
Weekly	(0.59)	(0.16)	(0.58)	(1.01)	(0.92)	(0.50)
Part Time	0.18	0.22**	0.48***	0.53***	0.60***	0.23**
	(0.02)	(0.00)	(0.01)	(0.02)	(0.02)	(0.02)
Tenure	115.21	273.54***	296.01***	111.39	111.42	49.68***
(Weeks)	(5.88)	(3.54)	(7.85)	(5.97)	(6.64)	(2.83)
Union	0.10	0.05***	0.01***	0.07*	0.04***	0.05***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Any Benefits[a]	0.72	0.79***	0.09***	0.32***	0.33***	0.31***
	(0.02)	(0.00)	(0.01)	(0.02)	(0.02)	(0.02)
Health	0.64	0.68**	0.05***	0.15***	0.23***	0.30***
Insurance[a]	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)
Retirement	0.51	0.58***	0.03***	0.10***	0.20***	0.12***
Plan[a]	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
Subsidized	0.05	0.07*	0.00***	0.02***	0.03**	0.01***
Childcare[a]	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Dental	0.56	0.60**	0.03***	0.11***	0.19***	0.19***
Insurance[a]	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)
Flex	0.37	0.45***	0.07***	0.25***	0.20***	0.15***
Schedule[a]	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)
Life	0.54	0.58**	0.04***	0.10***	0.17***	0.14***
Insurance[a]	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)
Maternity	0.46	0.57***	0.02***	0.10***	0.17***	0.08***
Leave[a]	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Profit	0.16	0.20***	0.03***	0.06***	0.06***	0.02***
Sharing[a]	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Training[a]	0.29	0.41***	0.03***	0.10***	0.14***	0.07***
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Log Real	6.74	6.63***	5.99***	5.94***	5.57***	6.01***
Total Compensation[b]	(0.05)	(0.01)	(0.04)	(0.06)	(0.06)	(0.04)
Job Satisfaction	1.89	1.82**	1.48***	1.74***	1.79**	2.00***
(Lower Better)	(0.04)	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)
Observations	741	19,967	2,668	927	906	975

Note: Summary statistics of jobs in the NLSY for each 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] Benefits measure if worker reports access to benefit through employer.

[b] Total compensation is imputed using log real weekly wages and access to health insurance and retirement plans. The value of these benefits is calculated using data from the NCS. See Appendix A.2.3 for more details.

My main regressions (see Table 1.5) showed that outsourced jobs are significantly worse than traditional jobs on average. Lower quality is mostly due to lower access to health insurance and retirement benefits.

What happens when we expand the comparison to all jobs? To find out, I run regression (1.1) for access to health insurance in three batches. Results are in Table A5. The first regression compares contracted-out jobs to all other job types (rather than only traditional jobs). This regression implies that contracted-out workers are slightly more likely to have access to health insurance. The second regression adds independent contractors and the self-employed. Outsourced jobs are significantly worse than the remaining job types, but the effect is less than half of the main specification. The final batch is the full regression with all job types reported. While contracted-out workers face significant health insurance penalties, their negative effects are dwarfed by other non-traditional jobs. These jobs are 25–65 pp less likely to come with access to health insurance. Similar results arise for other quality measures. Contracted-out jobs are worse than traditional jobs but much better than other job types, at least when comparing wages and benefits. The results in this section justifies focus on contracted-out jobs, because they are the most comparable to traditional jobs.

Table A5: Quality of Outsourced Jobs, Comparison Robustness: Health Insurance

	Outsourced	Self-Employed	Full
Outsourced	0.015	-0.039^{**}	-0.074^{***}
	(0.018)	(0.017)	(0.021)
Self-Employed	–	-0.653^{***}	-0.660^{***}
		(0.033)	(0.033)
Independent Contractor	–	-0.381^{***}	-0.409^{***}
		(0.022)	(0.020)
On-Call	–	–	-0.285^{***}
			(0.046)
Temp Worker	–	–	-0.328^{***}
			(0.032)
R^2	0.59	0.64	0.65
Observations	21,371	21,369	21,366

Note: Regressions of job type on access to health insurance. Data comes from 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, and marital status. All observations are at the person-job level, where jobs observed more than once use average or modal characteristics. All regressions are weighted at the person level, and all standard errors are clustered by demographic sample. Stars represent significance at the .10 level (*), .05 level (**), and .01 level (***).

A.1.5 Comparing to Dube and Kaplan (2010)

This section compares my measure of outsourcing using self-reported outsourcing status to other measures of outsourcing using occupation and industry, most notably Dube and Kaplan (2010) (DK). Like my paper, they study outsourcing in the US and their main identification strategy is selection on observables and worker fixed effects. The main differences are which workers are studied and method of identifying outsourced workers. Their data comes from the CPS Outgoing Rotation Groups (ORG) and March Supplement for the years 1983 to 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 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 how similar they are, 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 A6 and Table A7. I compare outsourcing in my data set using their measure (rows 3 and 4) to their

Table A6: Summary Statistic Comparison to Dube and Kaplan (2010) for Janitors

	Self-Reported (This Paper)		Industry-Occupation (Dube and Kaplan)	
Variable	Outsourced	Not Outsourced	Outsourced	Not Outsourced
Log Real	2.22	2.49***	2.42	2.50
Hourly Wage	(0.06)	(0.03)	(0.07)	(0.03)
Log Real	5.41	5.77***	5.50	5.86***
Weekly Wage	(0.12)	(0.05)	(0.10)	(0.06)
Hours Worked	27.46	31.64*	26.56	33.62***
per Week	(2.83)	(0.85)	(1.46)	(0.94)
Part Time	0.64	0.43**	0.65	0.34***
	(0.10)	(0.03)	(0.04)	(0.03)
Any Benefits	0.35	0.53**	0.26	0.64***
	(0.09)	(0.03)	(0.04)	(0.03)
Health Insurance	0.29	0.41	0.15	0.52***
	(0.09)	(0.03)	(0.03)	(0.03)
Union	0.02	0.06	0.04	0.06*
	(0.02)	(0.01)	(0.01)	(0.01)
Job Satisfaction	1.81	1.85	1.97	1.79**
(Lower Better)	(0.15)	(0.04)	(0.07)	(0.05)
No HS Diploma	0.15	0.20	0.19	0.21
	(0.07)	(0.03)	(0.04)	(0.03)
HS Diploma	0.85	0.65**	0.72	0.63*
	(0.07)	(0.03)	(0.04)	(0.04)
AA Degree	0.00	0.07	0.03	0.09**
	(0.00)	(0.02)	(0.02)	(0.02)
BA Degree	0.00	0.04	0.05	0.03
	(0.00)	(0.01)	(0.02)	(0.01)
Postgraduate	0.00	0.00	0.00	0.00
Degree	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.37	0.38	0.56	0.29***
	(0.10)	(0.03)	(0.05)	(0.03)
Black	0.63	0.28***	0.33	0.28
	(0.12)	(0.02)	(0.04)	(0.03)
Hispanic	0.04	0.06	0.03	0.07
	(0.03)	(0.01)	(0.01)	(0.01)
Age	48.78	47.87	47.40	48.13*
	(0.78)	(0.26)	(0.39)	(0.31)
Observations	30	537	173	394

Note: Summary statistics for janitors (occupation 4220) who are outsourced vs not outsourced. In the left two columns, outsourced is self-reported by the worker as in the rest of this paper. In the right two, outsourced the worker is assumed outsourced if their industry is 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 significance difference from outsourced of same determination method at the .10 level (*), .05 level (**), and .01 level (***).

Table 1 (pg 291) and Table 2 (pg 292). Due to the nature of my data set, I have a much smaller sample size 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 to 2000. Using their measure, I find

Table A7: Summary Statistic Comparison to Dube and Kaplan (2010) for Security Guards

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	2.39	2.58***	2.41	2.69***
Hourly Wage	(0.06)	(0.04)	(0.03)	(0.07)
Log Real	5.81	5.99*	5.85	6.07**
Weekly Wage	(0.12)	(0.08)	(0.08)	(0.12)
Hours Worked	34.13	34.22	35.10	33.19
per Week	(2.48)	(1.39)	(1.51)	(1.94)
Part Time	0.30	0.31	0.26	0.37**
	(0.09)	(0.05)	(0.05)	(0.06)
Any Benefits	0.50	0.65**	0.59	0.65
	(0.09)	(0.04)	(0.05)	(0.06)
Health Insurance	0.40	0.54*	0.47	0.56*
	(0.08)	(0.05)	(0.05)	(0.06)
Union	0.07	0.07	0.07	0.07
	(0.04)	(0.02)	(0.02)	(0.02)
Job Satisfaction	2.14	1.77***	1.96	1.72***
(Lower Better)	(0.10)	(0.07)	(0.09)	(0.07)
No HS Diploma	0.13	0.06*	0.11	0.03***
	(0.07)	(0.02)	(0.04)	(0.01)
HS Diploma	0.65	0.68	0.67	0.67
	(0.09)	(0.05)	(0.06)	(0.06)
AA Degree	0.13	0.14	0.09	0.18**
	(0.06)	(0.04)	(0.04)	(0.05)
BA Degree	0.04	0.07	0.03	0.10**
	(0.04)	(0.02)	(0.02)	(0.03)
Postgraduate	0.00	0.01	0.02	0.00
Degree	(0.00)	(0.01)	(0.01)	(0.00)
Female	0.32	0.22	0.30	0.17***
	(0.09)	(0.03)	(0.05)	(0.04)
Black	0.25	0.38*	0.40	0.31*
	(0.07)	(0.05)	(0.06)	(0.05)
Hispanic	0.07	0.10	0.10	0.08
	(0.03)	(0.02)	(0.02)	(0.02)
Age	49.66	47.49***	47.57	48.32
	(0.99)	(0.55)	(0.62)	(0.63)
Observations	54	243	163	134

Note: Summary statistics for security guards (occupation 3920) who are outsourced vs not outsourced. In the left two columns, outsourced is self-reported by the worker as in the rest of this paper. In the right two, outsourced the worker is assumed outsourced if their industry is 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 significance difference from outsourced of same determination method at the .10 level (*), .05 level (**), and .01 level (***).

31% and 55% over my entire sample, which is slightly higher but consistent with the story that outsourcing is growing in these occupations. My janitors make about $11 per hour (in 2016 dollars) outsourced and $12 per hour otherwise, while security guards make about $11 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 are close.[3] I also find similar percentages of workers receiving health insurance (their data) or with access to health insurance (my data) 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. Finally, my janitor sample has fewer women while my security guard sample has more. We both find women are more likely to be outsourced in janitor roles, but I find they are more likely to be outsourced as security guards too. Overall my sample is roughly in line with theirs, especially given the differences in underlying populations and years studied.

When I compare their measure of outsourcing to my measure, the most obvious difference is the number of outsourced workers. Only 5% and 18% of janitors and security guards are outsourced by my measure. Despite these differences, most of the differences in summary statistics are qualitatively similar, especially for measures of job quality. What is causing such a wide discrepancy in measured outsourcing? To find out, I break down jobs by self-reported job type (my measure) and occupation-industry matching (DK's measure) for both janitors and security guards in Table A8 and Table 1.8 (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 outsourcing, contracted-out workers, are not always considered outsourced by their measure. About 25% of contracted-out janitors and 20% 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 are not part of my measure of outsourcing.[4] 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. Industry-Occupation measures classify 24% of traditional janitors and 45% of traditional security guards as outsourced.[5] These workers are 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 data from the CPS's Contingent Worker Supplement (CWS). I use data from all six rounds. 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 A9 and Table A10. For the CWS, the occupation-industry measure misses 30% of contracted-out janitors and 8% of security guards and falsely reports 16% of traditional janitors and 36% of security guards as outsourced. Overall, the industry-occupation method aligns better in the CWS sample, but there are still considerable disagreements. It seems that self-reported outsourcing status and self-reported industry and occupation are fundamentally different measures of outsourcing.

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

[4] In the data, the industry-occupation classification classifies many temp workers as outsourced. DK hoped these workers would be excluded from their measure.

[5] 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, 134 (31%) and 66 (33%) of jobs were pre-assigned traditional. Of the these pre-assigned traditional jobs, 25 (19%) and 35 (53%) were outsourced according to industry-occupation measures, which make up 6% and 17% 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.

Table A8: Job Type Classification Comparison to Dube and Kaplan 2010 for Janitors

	Industry-Occupation (Dube and Kaplan)		
Self-Reported	Outsourced	Not Outsourced	Total
Contracted-Out (This Paper)	19	11	30
Independent Contractor	5	8	13
Temp Worker	10	17	27
On-Call Worker	6	21	27
Self-Employed	30	10	40
Traditional Employee	103	327	430
Total	173	394	567

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

Table A9: Job Type Classification Comparison to Dube and Kaplan 2010 for Janitors: CWS

	Industry-Occupation (Dube and Kaplan)		
Self-Reported	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

Note: 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. Rows show the worker's self-reported job type.

The industries that DK study are professional business service (PBS) industries, which specialize in providing intermediate services to other firms. Papers such as (Berlingieri, 2013) and (Bloom et al., 2018) define a worker as outsourced if the are in PBS. To shed light on how this measure of outsourcing differs from mine, Table A11 breaks down job types for both PBS and non-PBS industries in the NLSY.[6] I find PBS jobs are over-represented in non-traditional job types, especially contracted-out, independent contractor, and temp work. These jobs are associated with outsourcing. Despite this, a majority of PBS workers self-report as traditional and about 70% of contracted-out jobs are not in PBS industries. The fact that PBS workers report traditional jobs is partially due to how I define outsourcing. If, for example, an accountant performs audits for many different clients, then they would be providing an intermediate good (and could plausibly be classified as outsourced) but working directly for their firm. For this reason,

[6] I find similar results when studying PBS versus non-PBS jobs in the CWS (details available upon request).

Table A10: Job Type Classification Comparison to Dube and Kaplan 2010 for Security Guards: CWS

	Industry-Occupation (Dube and Kaplan)		
Self-Reported	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

Note: 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. Rows show the worker's self-reported job type.

Table A11: Job Types of Personal Business Service Workers

Self-Reported	PBS	Not PBS	Total
Outsourced (Contracted-Out)	219	470	689
Independent Contractor	137	664	801
Temp Worker	452	381	833
On-Call Worker	72	704	776
Self-Employed	552	2069	2621
Traditional Employee	1651	16974	18625
Total	3083	21262	26184

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

they would not be considered outsourced by my definition. The results for security guards and janitors, whose outsourcing status is less ambiguous, suggest that these are not the only differences.

A.1.6 Job Transitions Supplement

In this subsection, I supplement my work on job transitions in Section 1.7. First, I report summary statistics of job transitions in Table A12, which compares all outsourced and traditional workers in their previous, current, and subsequent job. The first row measures if previous or subsequent jobs are outsourced. There is clear persistence in outsourcing: 16–22% of previous and subsequent jobs are outsourced for currently outsourced workers while only 2–3% of these jobs are outsourced for currently traditional workers. The next two rows compare occupations and industries. Outsourced workers are slightly more likely to stay in the same occupation and industry when switching jobs. 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.[7]

In the main text, I focus on how long it takes 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 lasting one week). Job-to-job transitions account for a little over 40% of job transitions in the sample. For all three measures, the transition between previous and current job are statistically and economically indistinguishable for outsourced versus traditional jobs. There is some evidence that outsourced workers find their next job faster, but they are no more likely to make a job-to-job transition. In Figure 1.4 from the main text, I plot the distribution of transition times for currently outsourced and traditional workers and show they are nearly identical. In Figure A3, I show non-job-to-job transitions are also similarly distributed.

In Table 1.3 of the main text, I show that while outsourced workers may find their next job slightly faster than traditional workers, they are no quicker to find their current job. This suggests that faster job arrival rate is not a compensating differential for outsourcing jobs. In Table 1.6, I show outsourced job quality is very different for workers with and without a bachelor's degree. Table A13 tests if job finding rates are different by education. There is again evidence that outsourced workers find their next job quicker, especially for workers without a bachelor's degree, but there are no significant effects for time to current job. This is despite the fact that outsourced jobs are significantly worse for workers without a bachelor's degree. I conclude that outsourced jobs are found no faster than traditional jobs.[8]

A.2 Data Cleaning

In this section, I describe the data cleaning process. The data sets used are the National Longitudinal Survey of Youth 1979 (NLSY), IPUMS Current Population Survey (CPS) and Contingent Worker Sup-

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

[8]I run similar regressions breaking down into the more detailed education categories similar to Table A3. The only effect for time to current job that is significant is for associate's degree holders in weeks to current job, and it is only significant at the 10% level. Given that these workers are the most negatively affected by outsourcing, it is unsurprising that if any workers were to require a compensating differential, it would be them. While this gives marginal support for the theory that outsourced jobs are found faster, most of the evidence suggest that they are not.

Table A12: Summary Statistics for Previous, Current, and Next Jobs

	Outsourced Currently			Traditional Currently		
	Previous	Current	Next	Previous	Current	Next
Outsourced	0.16***	1	0.22***	0.02***	0	0.03***
	(0.02)		(0.03)	(0.00)		(0.00)
Same	0.30	–	0.36	0.25	–	0.24
Occupation	(0.03)		(0.03)	(0.01)		(0.01)
Same	0.29	–	0.33	0.27	–	0.27
Industry	(0.03)		(0.03)	(0.01)		(0.01)
Log Real	3.02	3.02	2.94*	2.86***	2.95	2.84***
Hourly Wage	(0.04)	(0.04)	(0.05)	(0.01)	(0.01)	(0.01)
Log Real	6.70	6.72	6.61**	6.47***	6.60	6.43***
Weekly Earnings	(0.05)	(0.05)	(0.06)	(0.02)	(0.01)	(0.02)
Hours Worked	42.12	42.14	41.14	40.15***	40.71	39.66***
Weekly	(0.61)	(0.55)	(0.63)	(0.21)	(0.15)	(0.21)
Part-Time	0.14	0.12	0.14	0.20***	0.17	0.22***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)
Union	0.06***	0.10	0.10	0.04***	0.05	0.05
	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
Health	0.68	0.69	0.66	0.63***	0.73	0.60***
Insurance[a]	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
Retirement	0.54	0.56	0.52	0.51***	0.63	0.50***
Plan[a]	(0.03)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
Any Benefits[a]	0.76	0.77	0.73	0.72***	0.84	0.72***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)
Log Real	6.85	6.87	6.76*	6.61***	6.76	6.57***
Total Compensation[b]	(0.05)	(0.05)	(0.06)	(0.02)	(0.01)	(0.02)
Weeks To	27.83	–	21.62	29.37	–	31.92
Find Job	(2.97)		(2.09)	(0.78)		(0.82)
Weeks To	47.86	–	35.69	48.94	–	51.96
Find Job (> 1 week)	(4.73)		(3.20)	(1.20)		(1.23)
Job-to-Job	0.43	–	0.41	0.41	–	0.39
Transition	(0.03)		(0.03)	(0.01)		(0.01)
Observations		616			16,392	

Note: 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 significance difference from current job (except for outsourced which represents significance difference from 0) at the .10 level (*), .05 level (**), and .01 level (***).
[a] Benefits measure if worker reports access to benefit through employer.
[b] Log real total compensation imputed using year, occupation, log real weekly wage, access to health insurance and retirement benefits.

plement (CWS), the Employer Costs for Employee Compensation (ECEC), and the Employee Benefits Survey (EBS).[9] In Subsection A.2.1, I describe how I combine various surveys within the NLSY. In Sub-

[9]To weight NLSY observations, I use 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 to 2016.

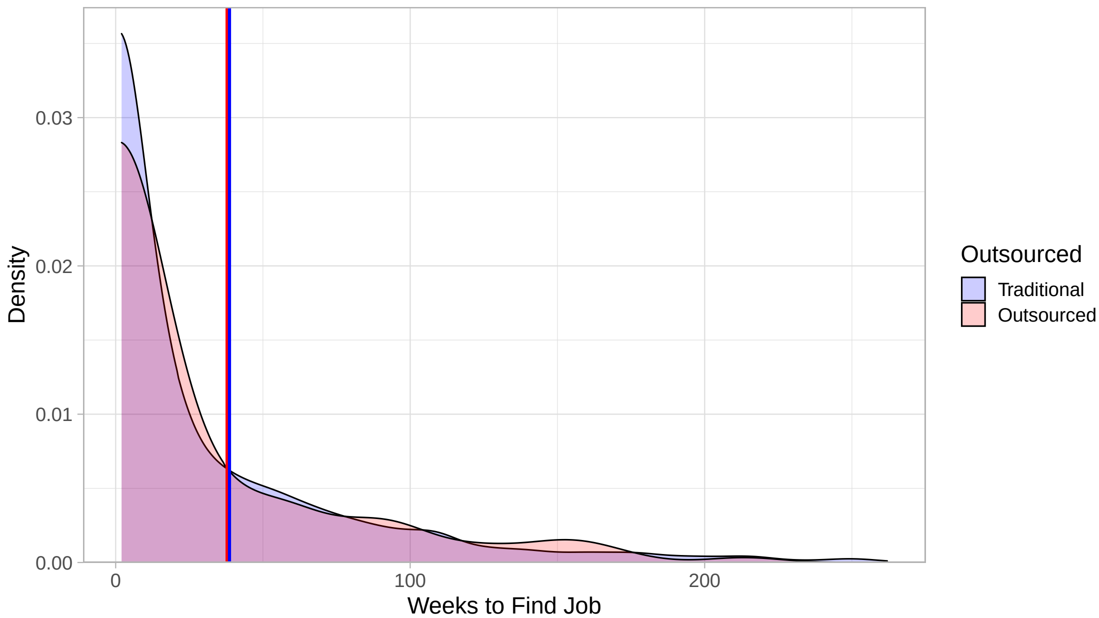

Figure A3: Weeks between previous job and current job excluding one week transitions for currently outsourced and currently traditional workers. Vertical lines are average weeks for outsourced and traditional. Figure excludes the longest 5% of transitions

Table A13: Weeks to Find Current Job by Bachelor's Degree Attainment

Variables	Weeks to Job	Weeks to Job (> 1)	Job-Job Transition
No Bachelor's ×	−1.335	0.052	0.028
Outsourced Current	(4.455)	(9.370)	(0.026)
Bachelor's ×	0.404	−12.684	−0.122
Outsourced Current	(5.404)	(9.737)	(0.082)
No Bachelor's ×	−11.451**	−15.710	0.054
Outsourced Previous	(4.822)	(13.408)	(0.053)
Bachelor's ×	−7.318	−10.961	0.007
Outsourced Previous	(9.338)	(15.414)	(0.080)
R^2	0.74	0.83	0.60
Observations	10,746	6,435	10,265

Note: Regressions of outsourced at current and previous job interacted with bachelor's degree attainment on weeks to find current job (both overall and conditional on the transition 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) interacted with bachelor's attainment and fixed effects for occupation. Regressions contain a dummy for year current job began, and the following demographic variables: a quartic in age, dummies for region, whether in an MSA or central city, and marital status. 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 significance at the .10 level (*), .05 level (**), and .01 level (***).

section A.2.2, I clarify how I clean the data and define variables. In Subsection A.2.3, I detail how I impute total compensation using ECEC and EBS data. In Subsection A.2.4, I list all of the variables used from each data set.

A.2.1 Matching On Jobs to the Employer Supplement

For the NLSY, I use survey responses for all respondents from 2002 to 2016, where respondents are surveyed every 2 years.[10] My analysis focuses on 3 questionnaires within the sample: On Jobs (sometimes On Jobs New or On Employers), Employer Supplement, and Employer History Roster.[11] 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.

When answering the survey, 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 (PDLI), and new jobs not reported previously (NEWEMP).[12,13] The main part of this questionnaire asks if the respondent is still working at this job and, if not, when he stopped working. Starting in 2002, respondents are also asked if their job is non-traditional: contracted-out, self-employed, an independent contractor, a temp worker, or an on-call worker.[14] If respondents start this loop (Q6-8E_1A for DLI), they are asked a series of questions about their job type.[15] I use this measure to find job type; if workers 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 he is contracted-out at this job.

Respondents then fill out the questionnaire for the Employer Supplement. The order jobs are listed in 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.[16] In the Employer Supplement, respondents are asked a rich subset of questions about the first 5 listed jobs, including: wages, hours

[10] 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`.

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

[12] Jobs held prior to the last interview include jobs respondents reported working in last interview but which they were not working at the time of last interview.

[13] Interview years 2014 and 2016 do not have a PDLI or NEWEMP section, all jobs are lumped together in DLI.

[14] 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 PDLI) record if these jobs were skipped (about 90% of jobs), which I assume are traditional.

[15] Typically, if respondents 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 zeros. 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.

[16] For more on how the Employer Supplement roster is created, 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`.

Table B1: Matching Steps

Subset	Number
Starting Data Set	69,757
Unmatched with On Jobs	-16
Conflicting Start or Stop Dates	-306
Missing/Conflicting Job Types	-1,439
Matched Data Set	67,996

Note: 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.

worked, occupation, industry, weeks of tenure, and access to various benefits. Through employer UID and Employer History Roster, these statistics can be connected throughout a respondent's career.

Prior to 2021, there was no official link between the On Jobs survey and the Employer Supplement, despite the fact that the list of jobs in the latter is derived from the former. Fortunately, the NLS has released new variables that match jobs in the On Jobs section to their entries in the Employer Supplement. I use question DLILINK (for DLI) to match the two surveys. I allow for Employer Supplement jobs to be matched multiple times across interviews. 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.[17] I also drop any conflicting start or end months between the data sets. Table B1 shows the number of observations added/subtracted at each step of the matching process from the Employer Supplement/Employer History Roster Side. Most jobs are matched with an On Jobs entry. Table B2 shows the match quality from the On Jobs side. While there are more missing matches on the On Jobs side compared to the Employer Supplement side, a majority of unmatched jobs have no job type information anyway. When comparing jobs with usable information, the number of unmatched jobs is similar. Unfortunately, outsourced jobs are more likely to be unmatched.

A.2.2 Creating Data Sets

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

[17] 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, contracted-out, temp worker, self employed, and on-call workers.

Table B2: On Jobs Match Quality

Subset	Unmatched	Total	Percent Missing
On Jobs	3,249	71,153	4.57
On Jobs with Information	1,426	30,696	4.65
On Jobs Outsourced	77	826	9.32

Note: The match quality from the On Jobs section in 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 jobs with information about job type in On Jobs.

I first cover variables from On Jobs, which are listed in Table B3 and Table B4. 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 B5.[18] From these variables, I can find start and stop week of job spells, weeks of job tenure, hours worked at job per week, industry and occupation using 2000 census codes, if job is part of union, and hourly wage. I use FRED's measure of CPI, CPIAUCSL, to make wages real in 2016 dollars.[19] I multiply hourly wage by weekly hours worked to obtain weekly wages. I drop wages of people making less than $3.00 (Federal minimum wage in 2002 was $5.15, which is equivalent to about $6.60 in 2016) or more than $500 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 to 2024 which correspond to January 2001 to October 2016. Weekly data starts to become scarce after October 2016 as respondents complete the 2016 round of the survey, so I do not use weeks after this month. Each week, I measure if a worker is employed, unemployed, or not working. I use weeks started and stopped working each job to match to the job worked each week.[20] With this timeline, I can see what percent of workers are outsourced in the average week, my main measure of overall outsourcing. I measure average weekly outsourcing for each occupation, and define an occupation as high-outsourcing if more than twice the average number of workers are outsourced each week (over 3.48%). I define ever high-outsourcing workers (the target of my calibration) as those who ever work in such an occupation.

[18]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`.

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

[20]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.

I next cover variables in the Employer Supplement, which are listed in Table B6. These are job variables 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 variable proxies for total job satisfaction summarized by wages, earnings, other compensation, and working conditions. I also look at dummies for whether a job provides access to various benefits: health, life, or dental insurance; maternity leave; retirement benefits; flexible hours; profit sharing; training or education; and company provided child care. I then combine these together to record if respondent had access to any benefits.[21]

I finally cover variables from the rest of the NLSY, which are listed in Table B7. These are mostly demographic variables. I record sample ID, which is the demographic portion (based on sex, race, family income, and military) 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.[22] Each year, I take marital status and record if single, married, or other (divorced/widowed/separated).

Every interview, the NLSY asks highest degree received, but often skips responses if the 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 had a high school education or less, as this bracket is not given as an option. I divide the sample into education bins: less than high school, high school diploma, associates degree, bachelors degree (of arts or science), postgraduate degree, and other. Because education does not change often, I take the modal education level over the sample and assign the worker this education level for the entire sample. When dividing workers into those with and without a bachelor's degree, I drop all workers with the other category of education, as they are ambiguous.

Once I clean all of the data, I go thorough the matching process described in Subsection A.2.1 above to create a person-job-year data set. To create the job-year data set, I use average and modal job characteristics over each interview.[23] I then use job start and end weeks to match the job-year data set to the timeline data set. To create the 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.[24] I then link current jobs to the previous and next job. Finally, I group the timeline data by occupation and month to create the aggregate occupation data set.

I use IPUMS CPS data in two different ways. The first is to use the main survey to compare to the NLSY 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 the timeline are in Table B8, and for the CWS are in Table B9. For the timeline, I use the monthly survey from January 2001 to October 2016, looking

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

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

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

[24] Because workers can be employed at multiple jobs simultaneously, overlapping jobs can look like job transitions even when no transition has occurred. Keeping only jobs with the same ranked start and end date drops these occurrences. If a new job is reported to start before the current job ends, I list the time between jobs as the minimum 1 week.

only at ages 18–65. I match NLSY definitions for each variable such as race/ethnicity and education. For the timeline data sets, the CPS uses 2010 occupation codes while the NLSY uses 2000 codes, so I use a crosswalk to match occupations.[25] To match the NLSY data, I make weekly wages real in 2016 dollars, dropping observations earning less that $50 per week. I also drop wage observations that are flagged for imputation. I use this timeline to create two data sets. The first divides jobs into high-outsourcing occupations. I use it to compare the wage distribution of these occupations and examines how different these workers are from the general population. 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 all employed workers in all rounds of the supplement: 1995, 1997, 1999, 2001, 2005, and 2017. I divide workers by self-reported 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).

A.2.3 Imputing Total Compensation

The main analysis finds outsourced jobs tend to have statistically lower benefits but usually not statistically lower wages. To get a better measure of the overall value of jobs, I calculate total compensation by combining log real weekly wages with access to health insurance and retirement benefits, the two most valuable benefits that employers typically offer employees. Because the NLSY does not have good measures of the value of these benefits, I impute them using the BLS's Employer Costs for Employee Compensation (ECEC) and Employee Benefits Survey (EBS). These data sets, derived from the National Compensation Survey (NCS), respectively attempt to measure employers' total cost of compensating workers and the total number of workers who have access to or receive employer benefits.[26] The imputation will follow 3 steps. First, I find the overall value of health insurance and retirement benefits as a percent of the value of wages in the ECEC. Second, I divide the overall value of these benefits by the share of workers with access to these benefits from the EBS. Third, I use a worker's access to benefits and the imputed value of these benefits to create a multiplier that converts weekly wages into weekly total compensation.

The ECEC measures the total cost employers pay to compensate employees for an hour of work. Compensation includes wages as well as benefits. I focus on the biggest components of total compensation: wages and salary, health insurance, and retirement benefits. These costs are aggregated for all workers, including the fixed costs of finding a health insurance provider, the expected future contributions for a defined benefit retirement plan, and workers who receive neither benefit. I use quarterly ECEC data from 2004 to 2016 and take yearly averages. The ECEC has five categories of worker occupations: management,

[25]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."

[26]For more information on the ECEC, see `https://www.bls.gov/ncs/data.htm`. For more information on the EBS, see `https://www.bls.gov/ncs/ebs/#data`.

professional and related; service; sales and office; natural resources, construction, and maintenance; and production, transportation, and material moving. For each of these occupations (and for workers overall), I find the percent of compensation that comes from each of these components. I then divide the percent of compensation from health insurance and retirement benefits by the percent of compensation from wages and salary. This gives me the overall ratio of health insurance and retirement plan benefits to wages.

The ECEC is designed to estimate the average cost of compensating workers. Benefit costs include zeros for workers who do not have access to these benefits.[27] The NLSY provides information on whether workers have access to health insurance or retirement benefits, so I do not want to include these zeros. To remove the zeros from my measure, I use EBS data on worker access to health insurance and retirement benefits for each occupation category.[28] I then divide my compensation ratios by the share of workers with access to benefits to find the ratio of health insurance and retirement plan benefits to wages for those with access to each benefit.

I use this ratio to impute the weekly total compensation of workers in the NLSY. I start with log weekly earnings, which helps account for both wage rate and hours worked each week. I then match workers to an ECEC/EBS category by year and occupation.[29,30] For each worker in occupation k in year t, I calculate the following multiplier

$$1 + Health_t \times \text{Health Benefit}_{k,t} + Retirement_t \times \text{Retirement Benefit}_{k,t}.$$

The 1 represents log real weekly wages, which is always part of total compensation. The variables *Health* and *Retirement* represent whether the worker reported access to that benefit in the NLSY. The variables Health Benefit and Retirement Benefit represent the imputed value of access to these benefits (as a share of wages) from the ECEC/EBS. The log of this value is added to log real weekly wages to impute log real weekly total compensation.

[27] For example, if health insurance costs $1 per hour of work and half of all workers receive health insurance, then the ECEC reports that health insurance makes up $0.50 of total worker compensation.

[28] I retrieve most access data from the EBS website in the excel file *employee-benefits-in-the-united-states-dataset.xlsx*, which contains quarterly data from 2010 to 2016. I also use hand extracted data for the years 2008 and 2009 from the following sources: `https://www.bls.gov/ncs/ebs/benefits/2008/ownership/civilian/table05a.htm`, `https://www.bls.gov/ncs/ebs/benefits/2008/ownership/civilian/table02a.htm`, `https://www.bls.gov/ncs/ebs/benefits/2009/ownership/civilian/table05a.htm`, and `https://www.bls.gov/ncs/ebs/benefits/2009/ownership/civilian/table02a.htm`.

[29] My NLSY data runs from 2001 to 2016 but my benefit measures only goes back to 2008. For years prior to 2008, I use values from 2008. My measure starts in 2008 because the EBS only reports benefit access for all civilian workers starting this year. From 2003 to 2007, they only reported access to benefits for workers in private sector jobs and these jobs were not broken up into the same occupational categories I use in later years. For comparison, in 2008, the share of civilian workers with access to retirement and health insurance benefits were 66% and 74% respectively. In the private sector, these figures were 61% and 71%, which are slightly smaller but comparable. From 2004 to 2008, the share of private sector workers with access to these benefits grew 3% each. Meanwhile, these benefit's share of overall compensation relative to wages for all civilian workers grew 9% and 10%, respectively. Because of this, my measure of total compensation likely overstates the value of benefits for years before 2008.

[30] If a worker's occupation is unknown, I use the measure for workers overall.

A.2.4 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 to 2016. I also used FRED's CPIAUCSL from 2001 to 2016 `https://fred.stlouisfed.org/series/CPIAUCSL#0` and 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 to 2016.

Table B3: Variables from the On Jobs section of the NLSY.

Variable	Description	Years
Q6-15	Date began job (PDLI)	2002
PDLI-15	Date began job (PDLI)	2004–2012
Q6-27A	Date began job (NEWEMP)	2002–2012
Q6-9	Last stopped working job (DLI)	All
Q6-17	Last stopped working job (PDLI)	2002–2012
Q6-27K	Last stopped working job (NEWEMP)	2002–2012
Q6-8F	Job preassigned traditional (DLI)	2002–2010
Q6-16F	Job preassigned traditional (PDLI)	2002–2012
Q6-8H_A1	Self-employed (DLI)	All
Q6-16H_A1	Self-employed (PDLI)	2002–2012
Q6-27E_A1	Self-employed (NEWEMP)	2002–2012
Q6-8H_A2	Independent contractor (DLI)	All
Q6-16H_A2	Independent contractor (PDLI)	2002–2012
Q6-27E_A2	Independent contractor (NEWEMP)	2002–2012
Q6-8H_A3	Temp worker (DLI)	All
Q6-16H_A3	Temp worker (PDLI)	2002–2012
Q6-27E_A3	Temp worker (NEWEMP)	2002–2012
Q6-8H_A4A (B)	On-call worker (DLI)	All
Q6-16H_A4A (B)	On-call worker (PDLI)	2002–2012
Q6-27E_A4A (B)	On-call worker (NEWEMP)	2002–2012
Q6-8H_A5A (B)	Contracted (DLI)	All
Q6-16H_A5A (B)	Contracted (PDLI)	2002–2012
Q6-27E_A5A (B)	Contracted (NEWEMP)	2002–2012

Table B4: Variables from the errata for the On Jobs section of the NLSY.

Variable	Description	Years
Q6-15	Date began job (PDLI)	2002
Q6-9	Last stopped working job (DLI)	2002
Q6-17	Last stopped working job (PDLI)	2002
NEWEMP_STARTDATE	Date began job (NEWEMP) (Eqiv Q6-27A)	2012
NEWEMP_CURFLAG	Currently working job (NEWEMP) (Eqiv Q6-27I)	2012

Table B5: Variables 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 to 2024 correspond to months January 2001 to October 2016.

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 B6: Variables from the Employer Supplement of the NLSY.

Variable	Description	Years
JOB_UID_EMPROSTER	Employer UID	All
QES-84D	Access to any benefits	2002–2004
QES-84E	Access to health insurance	2002–2004
QES-84F	Access to life insurance	2002–2004
QES-84G	Access to dental insurance	2002–2004
QES-84H	Access to maternity leave	2002–2004
QES-84I	Access to retirement benefits	2002–2004
QES-84J	Access to flexible hours	2002–2004
QES-84K	Access to profit sharing	2002–2004
QES-84L	Access to training or education	2002–2004
QES-84M	Access to company provided childcare	2002–2004
QES-84E (.Job)∼(Benefit)	All above benefits grouped	2006–2016
QES-89	Job Satisfaction	All
DLILINK	Link to On Jobs (DLI)	2002–2012
PDLILINK	Link to On Jobs (PDLI)	2002–2012
NEWLINK	Link to On Jobs (NEWEMP)	2002–2012
EMPLINK	Link to On Jobs (DLI)	2014–2016

Table B7: Variables taken from other parts of the NLSY.

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

Table B8: Variables from IPUMS:CPS. I use the monthly survey from January 2001 to October 2016, restricting the sample to ages 18–65.

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
OCC2010	Occupation, 2010 Basis
WKSTAT	Full/Part-Time
EDUC	Education
EARNWT	Earnings Weight
UNION	Union Status
EARNWEEK	Weekly Earnings
QEARNWEE	Weekly Earnings Imputation Flag

Table B9: Variables from IPUMS:CPS related to the Contingent Worker Supplement (CWS) for years 1995, 1997, 1999, 2001, 2005, and 2017, restricting the sample to the employed.

Variable	Description
YEAR	Survey Year
MONTH	Survey Month
CPSIDP	Person ID
AGE	Age
SEX	Sex
RACE	Race
MARST	Marital Status
HISPAN	Hispanic
EMPSTAT	Employment Status
OCC1990	Occupation, 1990 Basis
IND1990	Industry, 1990 Basis
CLASSWKR	Measure Self-Employed
WKSTAT	Full/Part-Time
EDUC	Education
EARNWT	Earnings Weight
HOURWAGE	Hourly Wage
UNION	Union Status
EARNWEEK	Weekly Earnings
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 B10: Variables from the Employer Costs for Employee Compensation. Each variable is measured for all civilians and records data as percent of total compensation; these are dropped from the description for clarity. I use quarterly data from 2004 to 2016.

Variable	Description
CMU1020000000000P	Wages and salaries (W + S) for all occupations
CMU1020000100000P	W + S for management, professional, and related occupations
CMU1020000300000P	W + S for service occupations
CMU1020000200000P	W + S for sales and office occupations
CMU1020000400000P	W + S for natural resources, construction, and maintenance occupations
CMU1020000500000P	W + S for production, transportation, and material moving occupations
CMU1150000000000P	Health for all occupations
CMU1150000100000P	Health for management, professional, and related occupations
CMU1150000300000P	Health for service occupations
CMU1150000200000P	Health for sales and office occupations
CMU1150000400000P	Health for natural resources, construction, and maintenance occupations
CMU1150000500000P	Health for production, transportation, and material moving occupations
CMU1180000000000P	Retirement and savings (R + S) for all occupations
CMU1180000100000P	R + S for management, professional, and related occupations
CMU1180000300000P	R + S for service occupations
CMU1180000200000P	R + S for sales and office occupations
CMU1180000400000P	R + S for natural resources, construction, and maintenance occupations
CMU1180000500000P	R + S for production, transportation, and material moving occupations

Appendix B

Appendices for Chapter 2

B.1 Proofs

B.1.1 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. Firms only need to compare marginal benefits. Using the free entry and envelope conditions of the firm from (2.5), (2.6), (2.8), and (2.9), we compare the benefit of hiring to the benefit of outsourcing

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

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 per period profits from hiring. The right hand side is the benefit of outsourcing, which is the present value of the per period profits from outsourcing. Both sides are increasing in productivity y, but using bargained wages in (2.19), 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 production equation (2.22), 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 $\tilde{c} > 0$. Define $y_{high} = \frac{p-(1-\eta)(b+\Gamma)}{\eta}$, where $w(y_{high}) = p$. Because $q(\theta) \leq 1$ the RHS is (weakly) greater. Because the LHS is greater for some y_{low}, the RHS is (weakly) greater for some $y_{high} > y_{low}$, and both monotonically increase in y with the RHS increasing faster, 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. $\square$

B.1.2 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. The planner only needs to compare marginal benefits. Using the net production of hiring and outsourcing firms in (2.31) and (2.32), 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 $y_{low} = b - \Gamma^P$. From Assumption 2, $q(\theta^P) < 1$, so it is clearly positive for some y and strictly increasing in y. 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. □

B.2 Decentralizing Planner's Solution w/Transfers

In this section, 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 or subsidize vacancy creation by firms and outsourcers and use lump sum taxes from/transfers to all workers to balance the budget. Let $\tau(y)$ be the per vacancy transfer to firms (or tax if negative) and $\tilde{\tau}$ be the transfer to outsourcers. In Proposition 4 below, I show these tools are sufficient to decentralize the planner's solution.

Proposition 4. *The planner can decentralize her solution through the following tax and transfer schedule*

- *Per vacancy transfers for firms following*

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

- *Per vacancy transfers for outsourcers following $\tilde{\tau} = \eta\tilde{c} - T$.*

- *Lump sum transfers to/from workers to balance the government budget.*

Where T depends on total entry of hiring firms and outsourcers

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

Proof. 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 (2.34)–(2.36) to planner's spread in (2.37)–(2.39) 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

$$\tau(y) - \tau(z) = \eta\big(c[v^P(y); y] - c[v^P(z); z]\big) \qquad \forall\, z \leq y \leq \hat{y}^P \tag{B1}$$
$$\tau(y) - \tau(z) = 0 \qquad \forall\, \hat{y}^P \leq z \leq y \tag{B2}$$
$$(1-\eta)q(\theta)\tau(y) - \tau(z) + \tilde{\tau} = -\eta\big(c[v^P(z); z] - \tilde{c}\big) \qquad \forall\, z \leq \hat{y}^P \leq y. \tag{B3}$$

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 (2.40) and (2.41) to planner's entry in (2.42) and (2.43) to show total entry must be

$$\begin{aligned}
&\int_{\underline{y}}^{\hat{y}^P} (x-b)v^P(x)dx + \int_{\hat{y}^P}^{\bar{y}} (x-b)\hat{v}^P(x)dx = \\
&\quad \frac{r+\delta+\eta\theta^P q(\theta^P)[1-\pi^P+\pi^P q(\theta^P)]}{(1-\eta)q(\theta^P)} \int_{\underline{y}}^{\hat{y}^P} v^P(x)\big(c[v^P(x);x] - \tau(x)\big)dx \\
&\quad + (r+\delta)\int_{\hat{y}^P}^{\bar{y}} \hat{v}^P(x)\big(c[\hat{v}^P(x);x] - \tau(x)\big)dx + \frac{r+\delta+\eta\theta^P[1-\pi^P+\pi^P q(\theta^P)]}{1-\eta}\tilde{v}^P(\tilde{c}-\tilde{\tau}).
\end{aligned} \tag{B4}$$

It is easy to show the proposed transfer schedule satisfies the spread and entry requirements. □

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 zero taxes. Hiring firms and outsourcers are compensated for the benefits 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 and lose less to bargaining, so they receive smaller transfers. All vacancies exert the same externality, so this tax is the same for all firms. As a result, low-productivity firms pay higher taxes. For clarity, I now focus on the case when Hosios rule holds, worker bargaining power equals match elasticity $\eta = \alpha$. In this case, the externality tax $T = \alpha[(1-\pi^P)\int_{\underline{y}}^{\hat{y}^P} c[v^P(x);x]dF^P(x) + \pi^P\tilde{c}]$ is the match elasticity times the average marginal benefit of a labor market vacancy. Firms and outsourcers compensate each other depending on which has a higher average marginal benefit, and taxes on workers will be zero. 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.

B.3 Calibrated Model

In this section, I build upon the baseline model from Section 2.2 to create the model I calibrate to the data. The model adds a few key features:

1. It allows for 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 for the calibrated model. Most of the notation is covered in the main text, so I will only note where it differs.

B.3.1 Model Overview

Previously, all firms and outsourcers had the same exogenous firing probability δ. Firms still have this firing probability, but now outsourcers' firing probability is $\tilde{\delta}$. I let outsourcers have different exogenous job loss to better match the shorter tenure and higher rates of quits to unemployment in the data.

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 $\tilde{F}(o) = \int_{\underline{o}}^{o} \frac{\tilde{v}(a)}{\tilde{v}} da$. Outsourcing firms now demand $\hat{n}(y)$ units of 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 fraction $\zeta = \frac{\tilde{n}}{n+\tilde{n}}$ of employed workers are at an outsourcer and fraction $\pi = \frac{\tilde{v}}{v+\tilde{v}}$ of 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 traditional worker at firm y is indifferent between the two jobs. Let $\tilde{R}(o) \equiv R^{-}(o)$ 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 $\tilde{G}(o) = \frac{1}{s}\left\{u + \xi\left[(1-\delta)\int_{\underline{y}}^{\tilde{R}(o)} n(x)dx + (1-\tilde{\delta})\int_{\underline{o}}^{o} \tilde{n}(a)da\right]\right\}$.

B.3.2 Value Functions

I now cover the value functions for the competitive equilibrium. A hiring firm with productivity y and size n has value

$$J(n;y) = n[y - w(y)] + \max_v \{-C(v;y) + \beta J(n_+;y)\} \tag{C1}$$
$$\text{s.t. } n_+ = (1-\delta)[1-\xi\ell(\theta)D(y)]n + q(\theta)G(y)v,$$

an outsourcing firm with productivity y and size n has value

$$\hat{J}(n;y) = n(y-p) + \max_v \left\{-C(v;y) + \beta \hat{J}(n_+;y)\right\} \tag{C2}$$
$$\text{s.t. } n_+ = (1-\delta)n + v,$$

and an outsourcer with productivity o and size n has value

$$O(n;o) = n[op - \tilde{w}(o)] + \max_v \left\{-\tilde{C}(v;o) + \beta O(n_+;o)\right\} \tag{C3}$$
$$\text{s.t. } n_+ = (1-\tilde{\delta})[1-\xi\ell(\theta)\tilde{D}(o)]n + q(\theta)\tilde{G}(o)v.$$

The intuition is similar to before, with two changes. The first is that outsourcer's revenue is the price of outsourcing times her productivity. The second is that 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 (C1)–(C3) 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

$$W(y) = w(y) + \beta\Bigg\{\delta U + (1-\delta)\xi\ell(\theta)\left[(1-\pi)\int_y^{\hat{y}} W(x)dF(x) + \pi\int_{R(y)}^{\bar{o}} \tilde{W}(a)d\tilde{F}(a)\right] + (1-\delta)[1-\xi\ell(\theta)D(y)]W(y)\Bigg\} \tag{C4}$$

$$\tilde{W}(o) = \tilde{w}(o) + \beta\Bigg\{\tilde{\delta} U + (1-\tilde{\delta})\xi\ell(\theta)\left[(1-\pi)\int_{\tilde{R}(o)}^{\hat{y}} W(x)dF(x) + \pi\int_{o}^{\bar{o}} \tilde{W}(a)d\tilde{F}(a)\right] + (1-\tilde{\delta})[1-\xi\ell(\theta)\tilde{D}(o)]\tilde{W}(o)\Bigg\} \tag{C5}$$

$$U = b + \beta\left\{\ell(\theta)\left[(1-\pi)\int_{\underline{y}}^{\hat{y}} W(z)dF(z) + \pi\int_{\underline{o}}^{\bar{o}} \tilde{W}(a)d\tilde{F}(a)\right] + [1-\ell(\theta)]U\right\}. \tag{C6}$$

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.

Using Stole-Zwiebel bargaining, workers and firms/outsourcers Nash bargain over the marginal value of the match, with workers having bargaining power η. Firms/outsourcers bargain after paying vacancy costs, so their marginal outside option is zero, while worker's outside option is unemployment. The bargaining games solve $\eta J_n(n; y) = (1-\eta)[W(y) - U]$ and $\eta O_n(n; o) = (1-\eta)[\tilde{W}(o) - U]$. 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

$$\begin{aligned} \Gamma(y, o) &\equiv \theta \frac{\eta}{1-\eta} \left\{ (1-\pi) \int_y^{\hat{y}} \frac{c[v(x); x]}{G(x)} dF(x) + \pi \int_o^{\bar{o}} \frac{\tilde{c}[\tilde{v}(a); a]}{\tilde{G}(a)} d\tilde{F}(a) \right\} \\ &= \frac{1}{s} \frac{\eta}{1-\eta} \left\{ \int_y^{\hat{y}} \frac{v(x) c[v(x); x]}{G(x)} dx + \int_o^{\bar{o}} \frac{\tilde{v}(a) \tilde{c}[\tilde{v}(a); a]}{\tilde{G}(a)} da \right\}. \end{aligned} \tag{C7}$$

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 $\underline{\Gamma} \equiv \Gamma(\underline{y}, \underline{o})$.

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

$$w(y) = \eta y + (1-\eta) \Big(b + \underline{\Gamma} - (1-\delta) \xi \Gamma[y, R(y)] \Big) \tag{C8}$$

$$\tilde{w}(o) = \eta o p + (1-\eta) \Big(b + \underline{\Gamma} - (1-\tilde{\delta}) \xi \Gamma[\tilde{R}(o), o] \Big). \tag{C9}$$

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

The key to determining how workers find new jobs at firms (outsourcers) is the reservation productivity of the outsourcer (firm) $R(y)$ ($\tilde{R}(o)$) the worker is indifferent to. For a worker to be indifferent between a firm and outsourcer job, they need the values compared to unemployment to be the same $W(y) - U = \tilde{W}[R(y)] - U$. 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

$$\tilde{w}[R(y)] = \frac{X(y; \tilde{\delta}) w(y) + (\tilde{\delta} - \delta) \left\{ \xi \Gamma[y, R(y)] - [1 - \xi \ell(\theta) D(y)](b + \underline{\Gamma}) \right\}}{X(y; \delta)}, \tag{C10}$$

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 comparison 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.

Given these value functions, we can formally define a competitive equilibrium. We can also solve a planner's problem with the additional model features (details available upon request).

B.4 No Bachelor's Degree Calibration Details

Table D1: Calibration parameters for workers without a bachelor's degree who ever work in a high-outsourcing occupation.

Description	Variable	Value
Outside Model		
Interest Rate	r	0.0010
Exogenous Job Loss, Traditional	δ	0.0045
Exogenous Job Loss, Outsourced	$\tilde{\delta}$	0.0050
Match Elasticity	α	0.5
Worker Bargaining Power	η	0.5
Vacancy Cost Curvature	γ	2.0
Minimum Firm Productivity	$\underline{y}$	5.5
Maximum Firm Productivity	$\overline{y}$	11.0
Minimum Outsourcer Productivity	$\underline{o}$	0.6
Maximum Outsourcer Productivity	$\bar{o}$	1.2
Inside Model		
Firm Cost Intercept	c_0	−9.80
Firm Cost Slope	c_1	2.29
Outsourcer Cost Intercept	$\tilde{c}_0$	−11.03
Outsourcer Cost Slope	$\tilde{c}_1$	22.75
Home Production	b	2.67
Match Efficiency	ϕ	0.11
Prob. On-the-Job Search	ξ	0.10

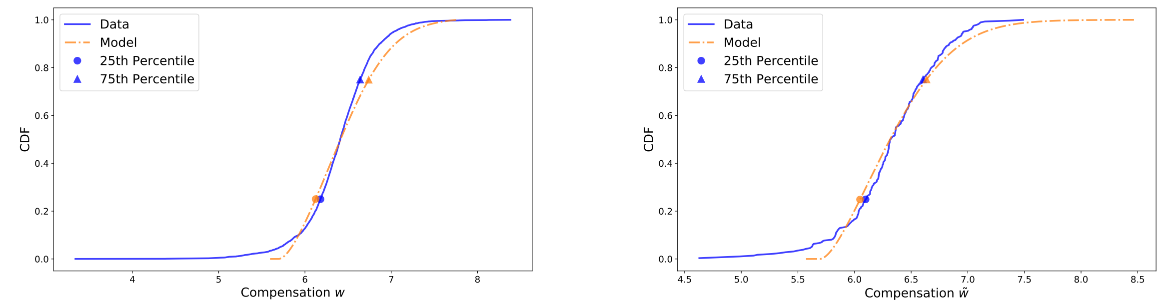

Figure D1: Distribution of log real total compensation residuals versus distribution of wages in calibrated model for workers without a bachelor's degree. Left figure compares traditional jobs in data to model. Right figure compares outsourced jobs in data to model.

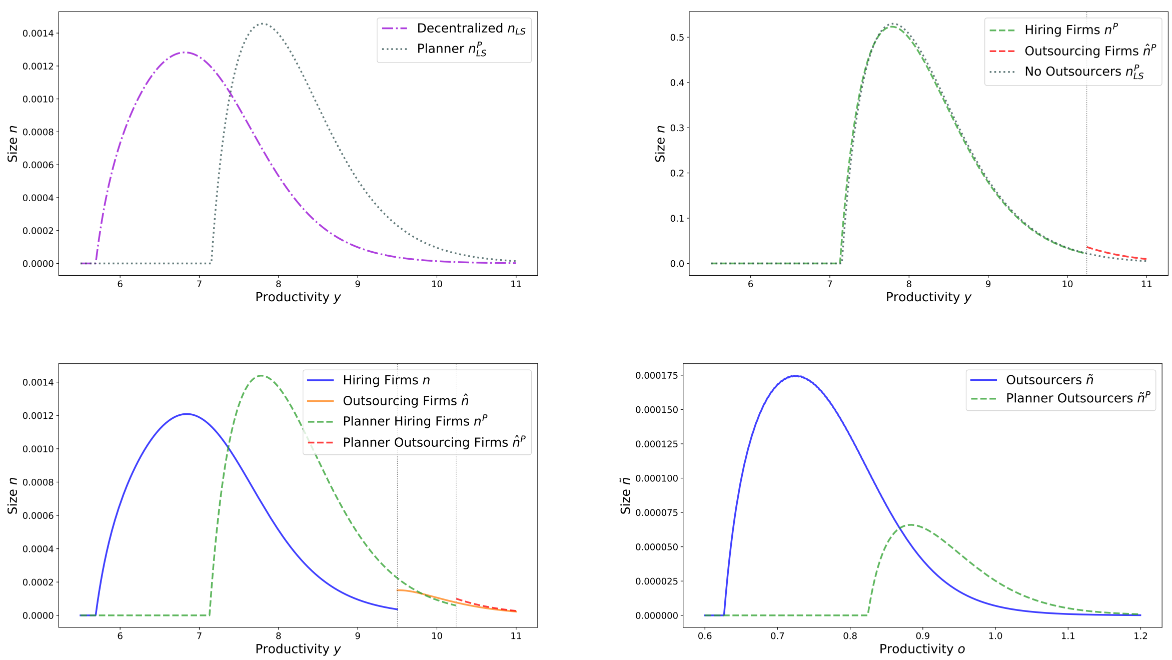

Figure D2: Distributions of firm and outsourcer size in decentralized versus the planner economy. Top left figure shows distributions of firm size in LS model without outsourcing. Top right figure shows the planner's distributions of firm size in an economy with and without outsourcing. Bottom figures show distributions of firm size (left) and outsourcer size (right) in the model with outsourcing. Model parameters come from calibration on workers without a bachelor's degree.

B.5 Bachelor's Degree Calibration Details

Table E2: Calibration parameters for workers with a bachelor's degree who ever work in a high-outsourcing occupation.

Description	Variable	Value
Outside Model		
Interest Rate	r	0.0010
Exogenous Job Loss, Traditional	δ	0.0028
Exogenous Job Loss, Outsourced	$\tilde{\delta}$	0.0027
Match Elasticity	α	0.5
Worker Bargaining Power	η	0.5
Vacancy Cost Curvature	γ	2.0
Minimum Firm Productivity	$\underline{y}$	6.0
Maximum Firm Productivity	$\bar{y}$	11.0
Minimum Outsourcer Productivity	$\underline{o}$	0.6
Maximum Outsourcer Productivity	$\bar{o}$	1.2
Inside Model		
Firm Cost Intercept	c_0	−25.12
Firm Cost Slope	c_1	3.80
Outsourcer Cost Intercept	$\tilde{c}_0$	−22.29
Outsourcer Cost Slope	$\tilde{c}_1$	33.27
Home Production	b	1.20
Match Efficiency	ϕ	0.07
Prob. On-the-Job Search	ξ	0.05

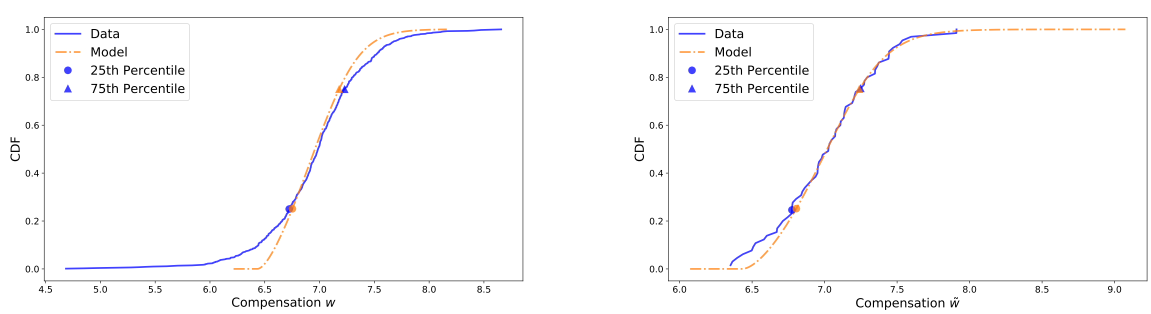

Figure E3: Distribution of log real total compensation residuals versus distribution of wages in calibrated model for workers with a bachelor's degree. Left figure compares traditional jobs in data to model. Right figure compares outsourced jobs in data to model.

Table E3: Calibration results for workers with a bachelor's degree who ever work in a high-outsourcing occupation. All compensation residuals are recentered at mean total compensation for workers with a bachelor's degree.

Moment	Model	Data
Targeted		
25th Percentile Compensation Residual, Traditional	6.75	6.73
75th Percentile Compensation Residual, Traditional	7.18	7.24
25th Percentile Compensation Residual, Outsourced	6.81	6.77
75th Percentile Compensation Residual, Outsourced	7.24	7.21
Weekly EE Rate	0.0016	0.0016
Unemployment Rate	0.030	0.030
Fraction Outsourced	0.062	0.063
Untargeted		
Mean Compensation Residual, Traditional	6.98	6.96
St. Dev. Compensation Residual, Traditional	0.30	0.46
Mean Compensation Residual, Outsourced	7.04	7.01
St. Dev. Compensation Residual, Outsourced	0.31	0.35
Difference in Mean Compensation Residuals	−0.056	−0.053
Fraction Outsourced, Newly Employed	0.054	0.112

Appendix C

Appendices for Chapter 3

C.1 Proof of Proposition 1

Proof. For ease of notation, we suppress all bars representing steady state. First, we take $m' > 0$ as given, so the first order condition from Equation (3.4) for money binds. If Condition (3.7) does not hold then $1 + \gamma_c \geq \alpha(1 + \gamma_m) + (1 - \alpha)\beta$. Rearranging gives

$$\frac{1 + \gamma_c}{\beta} - 1 \geq \alpha \left[\frac{1 + \gamma_m}{\beta} - 1 \right].$$

From the definition of interest rates and binding money first order condition, this implies $i^c \geq \lambda\alpha\big[\alpha\ell(\phi'_\alpha m' + \psi'_\alpha c') + (1 - \alpha)\ell(\phi'_\alpha m')\big]$.

For contradiction, suppose cryptocurrency holdings are positive $c' > 0$ and the first order condition for cryptocurrency binds. This implies $\phi'_\alpha m' + \psi'_\alpha c' > \phi'_\alpha m'$ which means $\ell(\phi'_\alpha m' + \psi'_\alpha c') < \ell(\phi'_\alpha m')$. By the first order condition of cryptocurrency

$$i^c = \lambda\alpha\ell(\phi'_\alpha m' + \psi'_\alpha c') \geq \lambda\alpha\big[\alpha\ell(\phi'_\alpha m' + \psi'_\alpha c') + (1 - \alpha)\ell(\phi'_\alpha m')\big],$$

which would imply $\ell(\omega'_\alpha + \upsilon'_\alpha) \geq \ell(\omega'_\alpha)$, a contradiction. This implies $c' = 0$ if (3.7) does not hold.

Secondly, we take $c' > 0$ as given, so the first order condition of Equation (3.4) for cryptocurrency binds. If Condition (3.8) does not hold then $\frac{\gamma_m - \gamma_c}{\beta} \geq \lambda(1 - \alpha)\frac{\theta}{1-\theta}$. From the definition of interest rates, binding cryptocurrency first order condition, and assumptions about $u(\cdot)$ and $c(\cdot)$, we can show $i^m \geq \lambda\big[\alpha\ell(\phi'_\alpha m' + \psi'_\alpha c') + (1 - \alpha)\frac{\theta}{1-\theta}\big] = \lambda\big[\alpha\ell(\phi'_\alpha m' + \psi'_\alpha c') + (1 - \alpha)\ell(0)\big]$.

For contradiction, suppose money holdings are positive $m' > 0$ and the first order condition for money binds. This implies $\phi'_\alpha m' > 0$ which means $\ell(\phi'_\alpha m') < \ell(0)$. By the first order condition of money

$$i^m = \lambda\big[\alpha\ell(\phi'_\alpha m' + \psi'_\alpha c') + (1 - \alpha)\ell(\phi'_\alpha m')\big] \geq \lambda\big[\alpha\ell(\phi'_\alpha m' + \psi'_\alpha c') + (1 - \alpha)\ell(0)\big],$$

which would imply $\ell(\omega'_\alpha) \geq \ell(0)$, a contradiction. This implies $m' = 0$ if (3.8) does not hold. Thus (3.7) and (3.8) are the sufficient conditions.

If $m' > 0$ and $c' > 0$, then we know first order conditions (3.5) and (3.6) hold with equality. Then

$$\frac{1+\gamma^m}{\beta} - 1 = \alpha\Big[\frac{1+\gamma^c}{\beta} - 1\Big] + (1-\alpha)\lambda\ell(\bar{\phi}'_\alpha m')$$

and (3.7) and (3.8) follow. Thus (3.7) and (3.8) are the necessary conditions. □

C.2 Steady State Comparative Statics

For ease of notation, we suppress all bars representing steady state and denote values from the previous period with a -1 subscript, i.e i_{-1}. Assume $m,\ c > 0$ so that prices are positive and first order conditions bind. Let $\lambda^c = \lambda\alpha$ and $\lambda^m = \lambda(1-\alpha)$ be the unconditional probabilities of meeting with a crypto or money seller. First we find comparative statics for currency growth rate changes. Note that in steady state, $i^j_{-1} = \frac{1+\gamma_j}{\beta} - 1 \ \forall\ j \in \{m,\ c\}$. Our first order conditions from Equation (3.4) are

$$i^m_{-1} = \lambda^c\ell(\phi_\alpha m + \psi_\alpha c) + \lambda^m\ell(\phi_\alpha m), \tag{B1}$$

$$i^c_{-1} = \lambda^c\ell(\phi_\alpha m + \psi_\alpha c). \tag{B2}$$

We start with the money growth rate. Taking partial derivatives of (B1)-(B2) with respect to γ_m

$$\begin{aligned} 1 &= \lambda^c\ell'(\phi_\alpha m + \psi_\alpha c)\frac{\partial[\phi_\alpha m + \psi_\alpha c}{\partial\gamma_m} + \lambda^m\ell'(\phi_\alpha m)\frac{\partial\phi_\alpha m}{\partial\gamma_m}, \\ 0 &= \lambda^c\ell'(\phi_\alpha m + \psi_\alpha c)\frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial\gamma_m}. \end{aligned}$$

Using Cramer's rule, we can rewrite the above equations as

$$\begin{bmatrix} \lambda^c\ell'(\phi_\alpha m + \psi_\alpha c) & \lambda^m\ell'(\phi_\alpha m) \\ \lambda^c\ell'(\phi_\alpha m + \psi_\alpha c) & 0 \end{bmatrix} \begin{bmatrix} \frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial\gamma_m} \\ \frac{\partial\phi_\alpha m}{\partial\gamma_m} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

The determinant of this matrix is $\Delta \equiv -\lambda^c\ell'(\phi_\alpha m + \psi_\alpha c)\lambda^m\ell'(\phi_\alpha m) < 0$. Then $\frac{\partial[\phi_\alpha m+\psi_\alpha c]}{\partial\gamma_m} = \frac{0}{\Delta} = 0$, and $\frac{\partial\phi_\alpha m}{\partial\gamma_m} = -\frac{\lambda^c\ell'(\phi_\alpha m+\psi_\alpha c)}{\Delta} < 0$. Because $q(.)$ is monotonically increasing, this shows $\frac{\partial q^c}{\partial\gamma_m} = 0$ and $\frac{\partial q^m}{\partial\gamma_m} < 0$.

Using the definition of $z(\cdot)$, we find $\phi' = \frac{z[q(\phi_\alpha m)]}{m'}$ and $\psi' = \frac{z[q(\phi_\alpha m+\psi_\alpha c)] - z[q(\phi_\alpha m)]}{c'}$ and using the implicit function theorem we find $q'(w) = \frac{1}{z'[q(w)]}$. From this, we can derive $\frac{\partial\phi'}{\partial\gamma_m} = \frac{z'[q(\phi_\alpha m)]q'(\phi_\alpha m)}{m'}\frac{\partial\phi_\alpha m}{\partial\gamma_m} = \frac{-\lambda^c\ell'(\phi_\alpha m+\psi_\alpha c)}{m'\Delta} < 0$ and $\frac{\partial\psi'}{\partial\gamma_m} = \frac{z'[q(\phi_\alpha m+\psi_\alpha c)]q'(\phi_\alpha m+\psi_\alpha c)}{c'}\frac{\partial[\phi_\alpha m+\psi_\alpha c]}{\partial\gamma_m} - \frac{z'[q(\phi_\alpha m)]q'(\phi_\alpha m)}{c'}\frac{\partial\phi_\alpha m}{\partial\gamma_m} = 0 + \frac{\lambda^c\ell'(\phi_\alpha m+\psi_\alpha c)}{c'\Delta} > 0$.

For total welfare, taking the derivative of (3.9) with respect to γ_m gives

$$\begin{aligned}\frac{\partial \mathcal{W}}{\partial \gamma_m} &= \frac{\lambda_\alpha^c}{\theta}\ell(\phi_\alpha m + \nu_\alpha)\frac{\partial[\phi_\alpha m + \nu_\alpha]}{\partial \gamma_m} + \frac{\lambda_\alpha^m}{\theta}\ell(\phi_\alpha m)\frac{\partial \phi_\alpha m}{\partial \gamma_m} \\ &= \frac{\ell(\phi_\alpha m)}{\theta \ell'(\phi_\alpha m)} \le 0, \qquad \text{(B3)}\end{aligned}$$

with strict inequality if $\gamma_m > \beta - 1$, i.e. money does not satisfy the Friedman rule. Unsurprisingly, people are better off with a low money growth rate.

Now we look at the cryptocurrency growth rate. Taking partial derivatives of (B1)-(B2) with respect to γ_c

$$\begin{aligned}0 &= \lambda^c \ell'(\phi_\alpha m + \psi_\alpha c)\frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial \gamma_c} + \lambda^m \ell'(\phi_\alpha m)\frac{\partial \phi_\alpha m}{\partial \gamma_c}, \\ 1 &= \lambda^c \ell'(\phi_\alpha m + \psi_\alpha c)\frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial \gamma_c}.\end{aligned}$$

Using Cramer's rule, we can rewrite the above equations as

$$\begin{bmatrix} \lambda^c \ell'(\phi_\alpha m + \psi_\alpha c) & \lambda^m \ell'(\phi_\alpha m) \\ \lambda^c \ell'(\phi_\alpha m + \psi_\alpha c) & 0 \end{bmatrix} \begin{bmatrix} \frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial \gamma_c} \\ \frac{\partial \phi_\alpha m}{\partial \gamma_c} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

Notice the determinant Δ is the same as above. Then $\frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial \gamma_c} = -\frac{\lambda^m \ell'(\phi_\alpha m)}{\Delta} < 0$ and $\frac{\partial \phi_\alpha m}{\partial \gamma_c} = \frac{\lambda^c \ell'(\phi_\alpha m + \psi_\alpha c)}{\Delta} > 0$. This shows $\frac{\partial q^c}{\partial \gamma_c} < 0$ and $\frac{\partial q^m}{\partial \gamma_c} > 0$. Using the definition of $z(\cdot)$ and the implicit function theorem as above, we can show $\frac{\partial \phi'}{\partial \gamma_c} = \frac{z'[q(\phi_\alpha m)]q'(\phi_\alpha m)}{m'}\frac{\partial \phi_\alpha m}{\partial \gamma_c} = \frac{\lambda^c \ell'(\phi_\alpha m + \psi_\alpha c)}{m'\Delta} > 0$ and $\frac{\partial \phi'}{\partial \gamma_c} = \frac{z'[q(\phi_\alpha m + \psi_\alpha c)]q'(\phi_\alpha m + \psi_\alpha c)}{c'}\frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial \gamma_c} - \frac{z'[q(\phi_\alpha m)]q'(\phi_\alpha m)}{c'}\frac{\partial \phi_\alpha m}{\partial \gamma_c} = \frac{-\lambda^m \ell'(\phi_\alpha m) - \lambda^c \ell'(\phi_\alpha m + \psi_\alpha c)}{c'\Delta} < 0$.

For total welfare, taking the derivative of (3.9) with respect to γ_c gives

$$\begin{aligned}\frac{\partial \mathcal{W}}{\partial \gamma_c} &= \frac{\lambda_\alpha^c}{\theta}\ell(\phi_\alpha m + \nu_\alpha)\frac{\partial[\phi_\alpha m + \nu_\alpha]}{\partial \gamma_c} + \frac{\lambda_\alpha^m}{\theta}\ell(\phi_\alpha m)\frac{\partial \phi_\alpha m}{\partial \gamma_c} \\ &= \frac{\lambda_\alpha^m \lambda_\alpha^c}{\theta \Delta}[\ell(\phi_\alpha m)\ell'(\phi_\alpha m + \nu_\alpha) - \ell(\phi_\alpha m + \nu_\alpha)\ell'(\phi_\alpha m)] \qquad \text{(B4)} \\ &= \frac{1}{\theta}\left[\frac{\ell(\phi_\alpha m + \nu_\alpha)}{\ell'(\phi_\alpha m + \nu_\alpha)} - \frac{\ell(\phi_\alpha m)}{\ell'(\phi_\alpha m)}\right], \qquad \text{(B5)}\end{aligned}$$

which is positive if and only if $\frac{\ell'(\phi_\alpha m)}{\ell(\phi_\alpha m)} > \frac{\ell'(\phi_\alpha m + \nu_\alpha)}{\ell(\phi_\alpha m + \nu_\alpha)}$. While the sign of this comparison is ambiguous, there is generally a level of wealth for which increasing the cryptocurrency growth rate increases welfare, as shown in Lemma 1 below

Lemma 1. Let $P(w) = \frac{\ell'(w)}{\ell(w)}$. There exists a $\hat{w}$ such that for all $\phi_\alpha m > \hat{w}$, $P'(\phi_\alpha m) < 0$ and $\frac{\partial \mathcal{W}}{\partial \gamma_c} > 0$.

Proof. Note that (throughout suppressing the reliance of u, h, and z on $q(w)$)

$$P'(w) \equiv \frac{\ell(w)\ell''(w) - \ell'(w)^2}{\ell(w)^2}$$

where

$$l'(w) \equiv \theta \frac{u''h' - u'h''}{(z')^3} < 0$$

and

$$l''(w) \equiv \theta \frac{z'(u'''h' - u'h''') - 3z''(u''h' - u'h'')}{(z')^5}$$

which in general has an ambiguous sign. Let $q(w^*) = q^*$. As $w \to w^*$, $\ell(w) \to 0$ by definition, but in general $\ell'(w) \nrightarrow 0$ and $\ell''(w) \nrightarrow 0$ (additionally, neither diverges to infinity or negative infinity). So there exists a $\hat{w}$ such that if $w > \hat{w}$, $P'(w) < 0$, $\frac{\ell'(\phi_\alpha m)}{\ell(\phi_\alpha m)} > \frac{\ell'(\phi_\alpha m + \nu_\alpha)}{\ell(\phi_\alpha m + \nu_\alpha)}$, and $\frac{\partial \mathcal{W}}{\partial \gamma_c} > 0$, which we wanted to show. □

Lemma 1 says that when effective wealth is high enough and cryptocurrency acceptance is low enough, then the losses from buyers holding less effective wealth in crypto meetings is offset by them holding more effective wealth in money meetings and total welfare increases in cryptocurrency growth rate.

Now we find the comparative statics for acceptance rate of cryptocurrency α. Solving (B1)-(B2) for α, we obtain $\alpha = \frac{i^m_{-1} - \lambda\ell(\phi_\alpha m)}{\lambda[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)]}$ and $\alpha = \frac{i^c_{-1}}{\lambda\ell(\phi_\alpha m + \psi_\alpha c)}$. Using Cramer's rule, we can rewrite these as

$$\begin{bmatrix} \frac{-[i^m_{-1} - \lambda\ell(\phi_\alpha m)]\ell'(\phi_\alpha m + \psi_\alpha c)}{\lambda[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)]^2} & \frac{\ell'(\phi_\alpha m)[i^m_{-1} - \lambda\ell(\phi_\alpha m + \psi_\alpha c)]}{\lambda[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)]^2} \\ \frac{-i^c_{-1}\ell'(\phi_\alpha m + \psi_\alpha c)}{\lambda\ell(\phi_\alpha m + \psi_\alpha c)^2} & 0 \end{bmatrix} \begin{bmatrix} \frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial\alpha} \\ \frac{\partial \phi_\alpha m}{\partial \alpha} \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

The determinant of this matrix is $\Delta_\alpha = \frac{i^c_{-1}\ell'(\phi_\alpha m + \psi_\alpha c)\ell'(\phi_\alpha m)[i^m_{-1} - \lambda\ell(\phi_\alpha m + \psi_\alpha c)]}{\lambda^2\ell(\phi_\alpha m + \psi_\alpha c)^2[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)]^2} > 0$. Because $i^m_{-1} - \lambda\ell(\phi_\alpha m + \psi_\alpha c) = \lambda(1-\alpha)[\ell(\phi_\alpha m) - \ell(\phi_\alpha m + \psi_\alpha c)] > 0$ and $i^m_{-1} - \lambda\ell(\phi_\alpha m) = \lambda\alpha[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)] < 0$, we know $\frac{\partial[\phi_\alpha m + \psi_\alpha c]}{\partial\alpha} = \frac{-\ell'(\phi_\alpha m)[i^m_{-1} - \lambda\ell(\phi_\alpha m + \psi_\alpha c)]}{\Delta_\alpha\lambda[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)]^2} > 0$ and $\frac{\partial\phi_\alpha m}{\partial\alpha} = \ell'(\phi_\alpha m + \psi_\alpha c)\frac{i^c_{-1}[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)]^2 - [i^m_{-1} - \lambda\ell(\phi_\alpha m)]\ell(\phi_\alpha m + \psi_\alpha c)^2}{\Delta_\alpha\lambda\ell(\phi_\alpha m + \psi_\alpha c)^2[\ell(\phi_\alpha m + \psi_\alpha c) - \ell(\phi_\alpha m)]^2} < 0$. This shows $\frac{\partial q^c}{\partial\alpha} > 0$ and $\frac{\partial q^m}{\partial\alpha} < 0$. Using the definition of $z(\cdot)$ and the implicit function theorem as above, we can show $\frac{\partial\phi'}{\partial\alpha} < 0$ and $\frac{\partial\psi'}{\partial\alpha} > 0$.

For total welfare, taking the derivative of (3.9) with respect to α gives

$$\begin{aligned} \frac{\partial\mathcal{W}}{\partial\alpha} =& \lambda\left[S(\phi_\alpha m + \nu_\alpha) - S(\phi_\alpha m)\right] + \frac{\lambda^c_\alpha}{\theta}\ell(\phi_\alpha m + \nu_\alpha)\frac{\partial[\phi_\alpha m + \nu_\alpha]}{\partial\alpha} + \frac{\lambda^m_\alpha}{\theta}\ell(\phi_\alpha m)\frac{\partial\phi_\alpha m}{\partial\alpha} \\ =& \lambda\left[S(\phi_\alpha m + \nu_\alpha) - S(\phi_\alpha m)\right] + \frac{1}{\theta\Delta_\alpha[\ell(\phi_\alpha m + \nu_\alpha) - \ell(\phi_\alpha m)]^2} \times \\ & \Bigg\{\ell(\phi_\alpha m)\ell'(\phi_\alpha m + \nu_\alpha)(1-\alpha)\frac{i^c_{-1}[\ell(\phi_\alpha m + \nu_\alpha) - \ell(\phi_\alpha m)]^2 - [i^m_{-1} - \lambda\ell(\phi_\alpha m)]\ell'(\phi_\alpha m + \nu_\alpha)^2}{\ell(\phi_\alpha m + \nu_\alpha)^2} \\ & - \ell(\phi_\alpha m + \nu_\alpha)\ell'(\phi_\alpha m)\alpha[i^m_{-1} - \lambda\ell(\phi_\alpha m + \nu_\alpha)]\Bigg\}, \end{aligned} \tag{B6}$$

the sign of which is generally ambiguous.

C.3 Equilibrium Definition with Hodlers

Definition 3. Let $\boldsymbol{q} = (q^{cs}, q^{ms})$, $\tilde{\boldsymbol{q}} = (\tilde{q}^{cs}, \tilde{q}^{ms})$, $\boldsymbol{m} = (m, c)$, and $\tilde{\boldsymbol{m}} = (\tilde{m}, \tilde{c})$. Given initial prior $\{\hat{\pi}_t\}_{t=1}^{\overline{T}}$ of normal buyers and prior $\tilde{\pi}_{\overline{T}} = 1$ of hodlers, we define a sequential monetary equilibrium as a list of normal buyers' quantities traded
$\left\{\{\boldsymbol{q}_t(\pi_t, \alpha_t)\}_{t \le T},\ \{\boldsymbol{q}_t(\pi_t, \alpha_T)\}_{t=T+1},\ \{\boldsymbol{q}_t(1, \alpha_T)\}_{t>T+1}\right\}_{t=0,\ T=0}^{\infty\quad \overline{T}}$,
hodlers' quantity traded $\left\{\{\tilde{\boldsymbol{q}}_t(0, \alpha_t)\}_{t \le T},\ \{\tilde{\boldsymbol{q}}_t(0, \alpha_T)\}_{t=T+1},\ \{\tilde{\boldsymbol{q}}_t(1, \alpha_T)\}_{t>T+1}\right\}_{t=0,\ T=0}^{\infty\quad \overline{T}}$
normal buyers' real balances $\left\{\{\boldsymbol{m}_t(\pi_t, \alpha_t)\}_{t \le T+1},\ \{\boldsymbol{m}_t(1, \alpha_T)\}_{t>T+1}\right\}_{t=0,\ T=0}^{\infty\quad \overline{T}}$,
and hodlers' real balances $\left\{\{\tilde{\boldsymbol{m}}_t(0, \alpha_t)\}_{t \le T},\ \{\tilde{\boldsymbol{m}}_t(1, \alpha_T)\}_{t>T+1}\right\}_{t=0,\ T=0}^{\infty\quad \overline{T}}$ such that

1. Normal buyers' and hodlers' quantity traded solve the bargaining problem in (3.2);
2. Normal buyers' and hodlers' real balances solve buyers' maximization problem in (3.3);
3. Normal buyers' and hodlers' beliefs update according to Bayes' rule in (3.1);
4. Currency markets clear.

Like with Definition 2, we can prove this equilibrium exits, email authors for details.

C.4 Endogenizing α

We now let sellers choose whether to accept cryptocurrency or not. At the end of each CM, after buyers have chosen currency holdings, the cost of accepting is revealed and sellers can choose to pay a one-time cost to accept cryptocurrency forever. Each seller now has a type $\rho \in [\rho_{min}, \rho_{max}]$ and the one-time cost $\kappa_t(\rho)$ depends on type and period t. We assume that $\kappa_t(\rho)$ is observable by all buyers and sellers and evolves over time according to

$$\kappa_t(\rho) = \begin{cases} \rho g(\kappa_{t-1}) & \text{if } t < T \\ \rho \kappa_{t-1} & \text{if } t \ge T. \end{cases}$$

Where $T \in \{0, 1, ...\overline{T}\}$ is an unknown period and $g(\cdot)$ is a known function such that κ is decreasing over time ($g'(\cdot) < 1$).[1] The measure of sellers accepting cryptocurrency is α.

Sellers discover that costs stopped decreasing in period T when they reach the end of the CM of period $T+1$ and learn κ did not decrease. Agents have a common prior over the steady state date $F(T)$ with pdf $f(t)$. We use π_t to denote agents' beliefs about κ staying constant conditional on κ's history. If $t > T$, agents know that cost has stopped decreasing and $\pi_t = 1$. If $t \le T$, agents know that cost decreased last

[1] We also assume that it is decreasing slowly enough such that sellers do not want to wait for lower prices in the future, even if it would be profitable to accept at current prices.

period but are unsure whether it will decrease this period, so

$$\pi_t \equiv \mathbb{P}(\kappa_{t+1} = \kappa_t \,|\, \kappa_t < \kappa_{t-1}) = \mathbb{P}(t = T \,|\, t \leq T) = \frac{f(t)}{1 - F(t-1)}.$$

Because time is discrete, beliefs are not continuous. Define agents' prior as $F(T) = \{\hat{\pi}_0, \hat{\pi}_1, ..., \hat{\pi}_{\overline{T}}\}$ where $\hat{\pi}_t \equiv \mathbb{P}(t = T)$. Then

$$\pi_t = \begin{cases} \frac{\hat{\pi}_t}{1 - \sum\limits_{\tau < t} \hat{\pi}_\tau} & \text{if } t \leq T \\ 1 & \text{if } t > T. \end{cases} \tag{D1}$$

We assume all agents have the same beliefs.

Intuitively, if more other sellers are accepting cryptocurrency, then the benefit of accepting cryptocurrency increases. As in Lester et al. (2012), this can lead to multiple equilibria with different levels of coordination of acceptance. We focus on equilibria where seller's level of coordination is constant, for example one where sellers always choose the highest level of coordination. Because of this, buyers solve the same problem as the exogenous α case for any given potential paths of α and we can find prices and currency holdings of buyers. As such, our model with exogenous acceptance can have the same outcome as a model with endogenous acceptance.

We now show how different levels of coordination can lead to different acceptance growth paths. Define $R(\rho, \alpha_{t+1}, t)$ as seller type ρ's expected net benefit of accepting cryptocurrency over only accepting money while cost is still decreasing and α_{t+1} other sellers will accept cryptocurrency next DM. Each period, sellers who do not yet accept cryptocurrency will do so if $R(\rho, \alpha_{t+1}, t) - \rho\kappa_t \geq 0$. The benefit of accepting cryptocurrency today is the expected benefit from accepting money and cryptocurrency for the future

$$(1-\theta)\lambda \sum_{\tau=t+1}^{\infty} \beta^{\tau-t} \mathbb{E}\left[S(\phi_{\tau,\alpha_\tau} m_\tau + \psi_{\tau,\alpha_\tau} c_\tau)\right]. \tag{D2}$$

The benefit of not accepting today is tomorrow's benefit of only accepting money plus the ability to choose to accept cryptocurrency tomorrow based on another observation of κ. We assumed κ is not decreasing too quickly, such that sellers cannot gain from waiting to accept even if accepting is profitable today. If κ decreases tomorrow and the seller would still not want to accept cryptocurrency, then they will never want to accept it today. We focus on the in between sellers who would want to accept tomorrow if κ decreases but not if it stops decreasing. Their value of not accepting today is

$$\begin{aligned} (1-\theta)\lambda\beta S(\phi_{t+1,\alpha_{t+1}} m_{t+1}) + (1-\theta)\lambda \sum_{\tau=t+2}^{\infty} \beta^{\tau-t} \mathbb{E}\left[S(\phi_{\tau,\alpha_{t+1}} m_\tau)\right] \\ + (1-\pi_t)\beta\left[R(\rho, \alpha_{t+2}, t+1) - \rho\kappa_{t+1}\right]. \end{aligned} \tag{D3}$$

Taking (D2) minus (D3), the benefit of accepting cryptocurrency today is

$$
\begin{aligned}
R(\rho, \alpha_{t+1}, t) =& (1-\theta)\lambda\beta \left\{ S(\phi_{t+1,\alpha_{t+1}} m_{t+1} + \psi_{t+1,\alpha_{t+1}} c_{t+1}) - S(\phi_{t+1,\alpha_{t+1}} m_{t+1}) \right\} \\
&+ (1-\theta)\lambda \sum_{\tau=t+2}^{\infty} \beta^{\tau-t} \mathbb{E}\left[S(\phi_{\tau,\alpha_\tau} m_\tau + \psi_{\tau,\alpha_\tau} c_\tau) - S(\phi_{\tau,\alpha_{t+1}} m_\tau) \right] \\
&- (1-\pi_t)\beta \left[R(\rho, \alpha_{t+2}, t+1) - \rho\kappa_{t+1} \right]. \qquad \text{(D4)}
\end{aligned}
$$

It is clear that $\frac{\partial[R(\rho,\alpha_{t+1},t)-\rho\kappa_t]}{\partial\rho} < 0$, sellers with lower ρ are more likely to start accepting cryptocurrency. Let $\sim$ denote two terms have the same sign and note the partial with respect to α_{t+1} is

$$
\begin{aligned}
\frac{\partial\left[R(\rho, \alpha_{t+1}, t) - \rho\kappa_t\right]}{\partial\alpha_{t+1}} \sim& S'(\phi_{t+1,\alpha_{t+1}} m_{t+1} + \psi_{t+1,\alpha_{t+1}} c_{t+1}) \frac{\partial[\phi_{t+1,\alpha_{t+1}} m_{t+1} + \psi_{t+1,\alpha_{t+1}} c_{t+1}]}{\alpha_{t+1}} \\
&- S'(\phi_{t+1,\alpha_{t+1}} m_{t+1}) \frac{\partial\phi_{t+1,\alpha_{t+1}} m_{t+1}}{\partial\alpha_{t+1}}. \qquad \text{(D5)}
\end{aligned}
$$

From our comparative statics in Appendix C.2, we argue $S'(\cdot) > 0$, $\frac{\partial[\phi_{t+1,\alpha_{t+1}} m_{t+1} + \psi_{t+1,\alpha_{t+1}} c_{t+1}]}{\alpha_{t+1}} > 0$, and $\frac{\partial\phi_{t+1,\alpha_{t+1}} m_{t+1}}{\partial\alpha_{t+1}} < 0$, so $\frac{\partial[R(\rho,\alpha_{t+1},t)-\rho\kappa]}{\partial\alpha_{t+1}} > 0$. This shows that higher cryptocurrency acceptance makes adopting it more profitable, leading to the potential for multiple equilibria.