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Essays on the Economics of Search Frictions

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Essays on the Economics of Search Frictions

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Doctor of Philosophy
in
Economics

by

Travis Alexander Cyronek

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June 2020

The Dissertation of Travis Alexander Cyronek is approved.

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Essays on the Economics of Search Frictions

To my late uncle Todd and my parents, Daniel and Deborah.

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Abstract

Essays on the Economics of Search Frictions

by

Travis Alexander Cyronek

Search theory has proven useful for describing and modeling many different Economic interactions. More broadly, the frictions it can account for are key to understanding many of the outcomes in observational data. This dissertation explores how such frictions affect the choices of economic agents, and what this implies for measurement and aggregate behavior. In doing so I am interested in the essential connection between theory and empirics: models help the researcher think about the interpretation of data, and data offers a ruler with which to assess the performance of models.

The first chapter explores how worker perceptions about job finding affect where unemployed searchers choose to apply for jobs and how this impacts the behavior of key labor market variables. Motivated by the observed prevalence of optimistic bias in searcher expectations about job finding, I develop a model of directed search where workers are uncertain about the matching technology, but can learn about it with experience searching for employment. I find that misperceptions dampen the volatility of labor market variables. For example, the standard deviation of the unemployment rate decreases by 10% when accounting for this uncertainty, while its correlation with labor productivity decreases by 12%. I show that optimistically biased job finding expectations increase wages by 0.3%, but also increase the average unemployment spell length by 1.5 weeks and the unemployment rate by 0.6pp.

In the second chapter, joint with Christine Braun and Peter Rupert, we study how the presence of on-the-job leisure, that is, non-work at work, drives a wedge between

measured hours of work and actual hours of work. If actual hours of work are lower than measured hours, productivity and wages are actually higher than those calculated by the Bureau of Labor Statistics, for example. Technological innovations, while making an hours of work more valuable, may also make it easier to engage in on-the-job leisure. We document the extent of on-the-job leisure and embed it into a model of technological change with imperfect monitoring to examine its effect on productivity and wages. Using the American Time Use Survey we show that for those workers who engage in OJL spend about 50 minutes per day doing so. We use the model to create a time series of actual hours of work and calculate actual output per hour.

In the third chapter, joint with Daniel Cullen, we ask, "How does the sharing economy affect traditional lodging markets?" The advent of platforms such as *Airbnb* in 2008 has introduced a new channel of market interaction between those with space and those who seek it. This allows for transactions of lodging services that might otherwise be underutilized. This paper develops a framework to help think about how peer-to-peer transactions interact with traditional rental markets, and what this means for property managers and tenants. Specifically, we examine how the introduction of sharing platforms (e.g. *Airbnb*) affect the listing decisions of vacant property managers and the lodging choices of dwelling seekers. The model features landlords who choose where to list vacant properties and renters who search for lodging. Renters can be either short or long-term, referencing how long they wish to occupy the property. Sharing platforms give landlords the option of accessing these short-term renters who would otherwise occupy hotels, affecting traditional, long-term renters. We find that *Airbnb*s decrease hotel prices by about $24 while they increase average rents by $39 per month.

Contents

Chapter 1

Job Finding (mis)Perceptions and Where Searchers Look for Work

1.1 Introduction

Accounting for the experiences of job seekers when looking for work is important for understanding the problems faced, and choices made, by labor market participants. The present paper studies how these experiences can influence workers' assessments about job finding, how this affects where they direct their search, and what this means for individual and aggregate labor market outcomes. Motivated by recent work on the ubiquity of bias in worker perceptions about the probability with which they find jobs, this research also aims to better understand how conventional analyses of the labor market–those which assume workers know precisely how unfilled vacancies and job seekers come together in a frictional labor market–change when uncertainty over this process is accommodated. This is accomplished by developing a model of directed search where workers have beliefs over the matching technology that are updated with experience finding (or not finding) jobs.

This paper makes several contributions, the first of which is to advance theory to handle rich heterogeneity in job finding beliefs in a quantitatively feasible manner. Second, in its departure from settings of full information, the model's equilibrium can endogenously sustain fully rational, on-average optimism (or pessimism) using limited labor market histories and learning frictions. Critical to this result is the disconnection of subjective job finding assessments by workers and realized vacancy filling assessments by firms. Though workers may be incorrect in these judgments, firms still demand labor and are thus willing, in some capacity, to post vacancies for it, meaning that biased perceptions are not unraveled by firm decisions. Third, the model produces novel insights about how misperceptions in job finding affect the labor market. Using the calibrated model I find that optimistic beliefs increase the mean, decrease the standard deviation, and decrease the counter-cyclicality[1] of the unemployment rate. Regarding the results on volatility, this is, to the best of my knowledge, the first formal assessment of the dynamic implications of biased beliefs about job finding.

A general theme in the above findings is the distinction of *composition* and *individual* effects. That is, how job finding misperceptions affect the types of workers searching throughout a business cycle versus how they directly affect their choices. In standard Diamond-Mortensen-Pissarides (DMP) settings with random search, the composition effect is the only channel that operates by affecting the vacancy posting decisions of firms. For workers, directed search allows another margin with which to adjust in order to limit the costs of unemployment. These two effects are found to move in opposite directions, necessitating use of the calibrated model to resolve which one has quantitative bite. I ultimately find that composition effects prevail. To give some numbers, I find that misperceptions attenuate the standard deviation of the unemployment rate by 10% and its counter-cyclicality by 12%. Using the model as a laboratory to study what the

[1] "Cyclicality" is measured as the absolute value of a variable's correlation with labor productivity.

economy would look like if everyone's beliefs were correct, I find that wages would be 0.3% lower, but that the average unemployment spell would be 1.5 weeks shorter and the unemployment rate would fall by 0.6pp.

In 1.2 I situate the current work among the broader literature. Most related is recent work by [1] and [2] which have found a prevalence of optimistic bias in the elicited beliefs of job seekers' assessments of their job finding probabilities. I then further motivate this topic in 1.3 by documenting the importance and extent of biased beliefs for workers. Using the Current Population Survey (CPS) I find that roughly 8% of individuals designated as "marginally attached" cite beliefs about job finding as the primary reason for having not recently looked for work. This suggests that workers' perceptions are an important element of their attachment to the labor market.[2] Further, I show that the marginally attached population citing job finding beliefs varies at the business cycle frequency, and thus may have important cyclical implications. To get a precise understanding of what these abstract "beliefs" are, I utilize the Survey of Consumer Expectations (SCE) to characterize them in the context of job finding probabilities. I find that, on average, workers elicit beliefs about the job finding probability twice as high as what is realized.

I formulate a model in 1.4, calibrate it to US data in 1.5, and then use it to understand how beliefs drive labor market behavior in 1.6. It features a frictional labor market with directed search by workers who differ in their beliefs about the job finding probability and unemployment history. Beliefs reflect uncertainty over the matching technology and are updated through experience searching in the labor market. In particular, agents are uncertain about a parameter of the matching function, and this uncertainty affects which sub-markets they search in. Optimistic workers, those who believe the job finding

[2] Important to note is that while the *extensive* distinction of active vs. inactive is an interesting one–and natural to think about in the context of beliefs that deteriorate as unemployment spells lengthen–the current research instead focuses on the *intensive* margin. In other words, I abstract away from the participation decision. Though this is done *not* without loss of generality, it makes the findings more comparable to the existing literature and hopes to serve as a step toward further study of this margin.

probability is higher than it actually is, are "picky," searching in relatively high-value and slack sub-markets. Pessimistic workers, those who believe the probability is low, "settle," searching in low-value and tight sub-markets. Belief heterogeneity and idiosyncratic labor market histories generate wage dispersion in workers who are equally productive. Those who do not find jobs quickly revise their beliefs downward, redirect their search search to tighter sub-markets, and have lower reemployment wages than their counterparts who exit unemployment fast.

With directed search, vacancy-posting firms are able to back out the worker's type, meaning that the expected value of finding a worker in a given sub-market does not depend on the endogenous distribution of workers across employment states. The induced self-selection from directed search coupled with free entry yields meeting probabilities that also do not depend on this distribution. This property carries through for workers' value and policy functions, including the joint value of a match, greatly simplifying the computation of these objects since one does not have to keep track of a highly-dimensional distribution–or its evolution–arising from rich heterogeneity in beliefs. In other words, the environment admits a unique Block Recursive Equilibrium (BRE) and can thus be solved outside of the steady state, facilitating study of the dynamic implications of job finding misperceptions.

Shocks to the production function affect the vacancy posting behavior of firms and is the channel through which aggregate fluctuations affect labor market variables. When aggregate productivity is high, firms post more vacancies in a given sub-market and the unemployment rate decreases. Job finding beliefs interact with this mechanism in interesting ways. The calibrated model finds that uncertainty in the job finding technology dampens the dynamic behavior of the labor market variables. This result is driven by two primary forces, one of which relates to the composition of workers. Since the degree of optimism is pro-cyclical, and because optimism reduces the tightness of the sub-market job seekers search in, there is downward pressure on the standard deviation and pro-cyclicality of the job finding probability and thus downward pressure on the variance and counter-cyclicality of the unemployment rate. The other force is idiosyncratic and works in the opposite direction. Optimism makes the perceived cost of unemployment low, making workers more inclined to "wait it out" for positive aggregate shocks. On one hand, optimistic workers will respond relatively more to positive shocks by searching in tighter sub-markets. On the other, they will also search in relatively slacker sub-markets in response to negative shocks as the assessed cost of doing so is small. Overall, the model finds that the first effect dominates.

The above exercises are carried out by calibrating two models (with and without job finding misperceptions) to fit key moments in the data. This is to ensure the dynamic comparisons of each mechanism are done about otherwise similar economies. For example, both economies are calibrated to have the same average job finding probability, and so have virtually identical unemployment rates. I thus ask, what are the costs of biased job finding perceptions for the US economy? To answer this question, I simulate the full model and then "turn off" job finding uncertainty by correcting all agents' beliefs. Workers begin to search for lower wage jobs which firms are more inclined to post vacancies for. Increased posting raises job finding probabilities, increasing unemployment hazard and lowering the unemployment rate.

Finally, I discuss the broader implications of this research and conclude in 1.7.

1.2 Related Literature

The current paper is most closely related to work documenting the ubiquity of bias in job seeker expectations about their job finding probabilities. [1], using data from from a survey conducted by [3], finds that searchers expect to find a job within 6.8 weeks, but actually find jobs in about 23 weeks. In the paper's focus on unemployment benefit policy, the author advises that increasing benefits may be optimal as workers do not adequately save for (or manage their savings during) unemployment. [2] explores the implication of optimistic beliefs on long-term unemployment using data from the SCE and the Survey of Unemployed Workers in New Jersey. Finding qualitatively similar, on-average optimism of the searching pool, they determine that 15% of the high incidence of long-term unemployment is explained by slow unemployment hazard induced by these beliefs. Also using SCE data, I find evidence that workers, on average, believe that the job finding probability is roughly twice as high as what is realized at the monthly frequency. Whereas the other works focus on the provision of unemployment benefits and the disentangling of the sources of long-term unemployment, the present paper considers the aggregate and dynamic implications of these perceptions.

Theory on the idea that beliefs affect worker application strategies dates back at least to [4]. Systematic, or sequential, search expanded on the earliest treatments of random search and has been shown to have power in describing actual worker search strategies. Early work by [5] and more recent studies by [6] and [7] have shown that workers direct their search to "better," high wage jobs first.[3] In the context of subjective beliefs about jobs, the current paper naturally relates as searchers seek out high-value jobs early in an unemployment spell, and low-value jobs later on as their beliefs are updated and agents learn about the job finding technology. It should be noted that this paper is not the first to embed learning in a directed search framework. In [8] agents learn about their idiosyncratic productivity. Here, however, workers are homogenously productive and learn about the matching technology that is common to all searchers. In this effort, I see the model below as a generalization of other models which assume workers and firms know precisely the structure of search frictions in the labor market.

[3] Though, wages themselves do not need to be explicitly stated or posted.

More technically relevant is work by [9], [10], [11] on the concept of Block Recursive Equilibria (BRE). In dynamic settings with a great degree of idiosyncratic heterogeneity, some of which is unobservable to firms, solving models numerically can quickly become infeasible as agents must keep track of a high-dimensional and endogenous distribution of searching worker types (a "curse of dimensionality"). This equilibrium concept is such that the agents' value and policy functions depend on the aggregate state only through realizations of the aggregate shock (and not on the "cursed" distribution of workers across employment states). The cited work is influential in establishing the theory of BRE for a wide range of applications, most notably for environments with search on-the-job. Essential for the present work is that these equilibria can be solved outside of the steady-state, supporting examination of the model's dynamic behavior. Novel to the environment presented below is that, though there is no search on-the-job, subjective beliefs about the matching function introduce a potential violation of the block recursive structure. Under reasonable conditions, however, these "technically" unobserved beliefs can be backed out so that firms do not need to track the distribution of priors across searching workers.

This work relates more generally to two broad literatures on *optimal unemployment insurance* and *unemployment duration / dependence* to the extent that worker beliefs may affect the incentives of job seekers and thus feed into their unemployment tenure. Of concern is the provision of benefits to individuals in order to provide insurance against the costs of unemployment while maintaining their incentives to look for work. Increasing benefits induce workers to search for better jobs, leading to longer spells of unemployment. An ongoing debate asks whether these benefits should increase, decrease, or be flat over the course of an unemployment spell ([12], [13], [14], [15], [16], [17], [18], [19], [20]). Though questions of optimal policy are not directly addressed below, the advancements made hope to better equip these analyses.

Integral to the above discussion is the duration of unemployment. From a social policy perspective, long tenures of unemployment can be very detrimental to workers, and something governments may want to ameliorate. Of note specifically is the distinction of “true” duration dependence from heterogeneity in job finding probabilities (sometimes called “population-level” duration dependence) ([21], [22], [23], [24], [25], [26]). “True” duration dependence refers to the notion that the probability of finding a job is directly affected by the length of the unemployment spell, the prime example being skill decay. Measuring this in the presence of innate job finding heterogeneity is difficult, but important for the purposes of constructing optimal and incentive-conforming policy. The treatment of worker beliefs below encompasses a notion of true dependence in that they affect where workers search (and thus their unemployment hazard).

Last, this paper relates to a literature on the *participation* margin ([27], [28], [29], [30], [31], [32], [33]). While much research, including this one, makes a two-state abstraction of labor market statuses (employment and unemployment), there is a growing interest in taking more seriously the implications of the inactive, or out of the labor force, state. [34] advise that not accounting for this third state may be fine in some cases, but a “serious omission” in others, for example when trying to understand cross-county labor market patterns. Dynamically, [35] find that a third of the cyclical behavior in the unemployment rate is driven by this extensive labor supply margin. Naturally, the concept of worker misperceptions about job finding is closely related to this topic. Indeed the marginally attached designation by the BLS noted earlier is excluded in the often-cited U3 measure of unemployment. Again, though the inclusion of a discrete participation decision is not made here, I view the implementation of these beliefs as an initial step toward tackling the issues and implications of inactivity.

1.3 Empirical Regularities

In this section I detail various considerations of a worker's labor market attachment. Thinking of attachment as a vector of worker characteristics, I identify an important aspect that varies at the business cycle frequency using the CPS: beliefs about finding a job. Suggesting that these perceptions are an important facet of workers' labor market decisions, I then turn to express these beliefs in terms of subjective job finding probabilities using the SCE. The discrepancies between these probabilities and realized outcomes will be how beliefs are introduced into the model.

1.3.1 The Components of Labor Market Attachment

Typical definitions of labor market attachment, for instance those used by state governments when assessing the provision of unemployment benefits, are categorical: one either *is* or *is not* considered to be making reasonable efforts to find gainful employment. Because these efforts are often unobserved by economists, the term sometimes describes those demographic groups most likely to participate in the labor market and is more synonymous with "desire" or "ability" to work. The Bureau of Labor Statistics (BLS) identifies a similar, yet distinct, group in those who are *marginally attached* to the labor force. These individuals would work, were it available, but were not counted as unemployed for one of several reasons. In addition to having looked for work at least once in the previous 12 months, an individual is considered marginally attached if they gave any of the reasons presented in 1.1 for not looking for work in the previous 4 weeks. The distinction of *discouraged* workers is sometimes used, and references recent negative experiences of individuals looking for work. Overall, an average of 8% of marginally attached workers (1.4 million) cite beliefs about job search as the reason why they have stopped looking for work each month. The remaining respondents largely cite skill considerations, discrimination, family, health, and transportation issues as the reason for not searching.

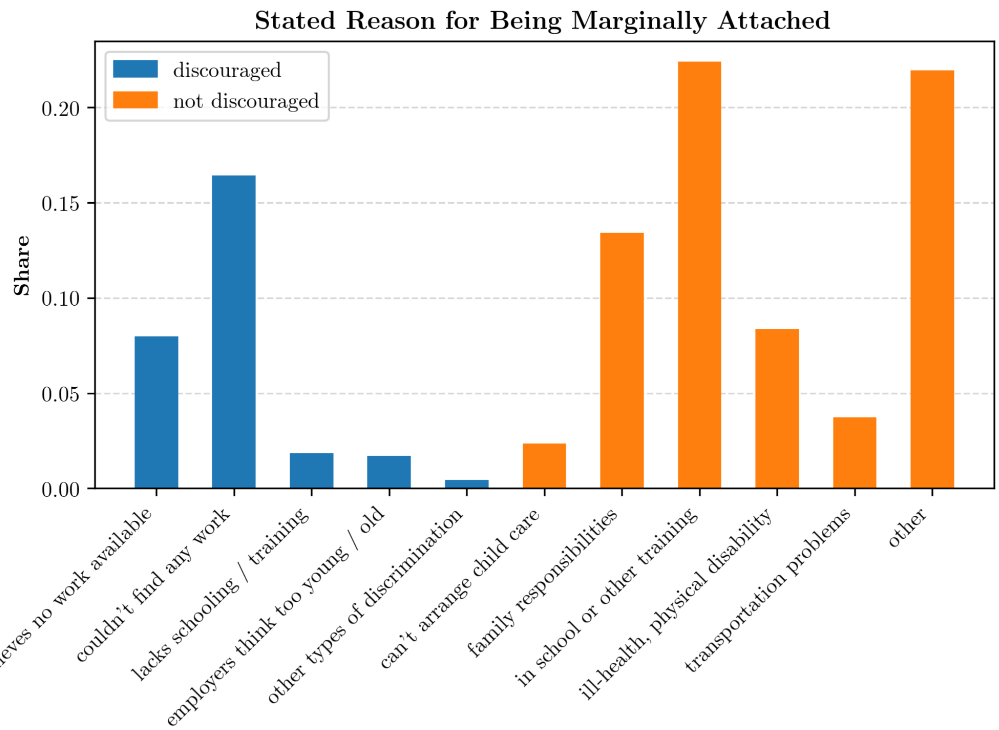


Figure 1.1: The above displays the share of the marginally attached population by the reason given for not searching for work. The BLS classifies an individual as marginally attached if the respondent cites any of the above reasons for not searching for work in the previous 4 weeks *and* has looked for work at least once in the previous 12 months. These shares are monthly averages calculated using the CPS basic monthly files from January 1994 through December 2018.

I restrict the focus of this paper to beliefs about job finding, in part, because they comprise a reasonably large proportion of the motives given for the BLS classification of marginally attached. Further, these motives vary at the business cycle frequency and so plausibly play an interesting role in the cyclical behavior of labor market variables. I plot the cyclical behavior of the marginally attached population for belief-related reasons in 1.2, where I calculate the total number of marginally attached persons using the CPS basic monthly files and the CPS sample weights. The cyclical component is then measured using series of quarterly averages as log deviation from a Hodrick-Prescott filtered trend with smoothing parameter 1,600. Some summary statistics are presented in 1.1.

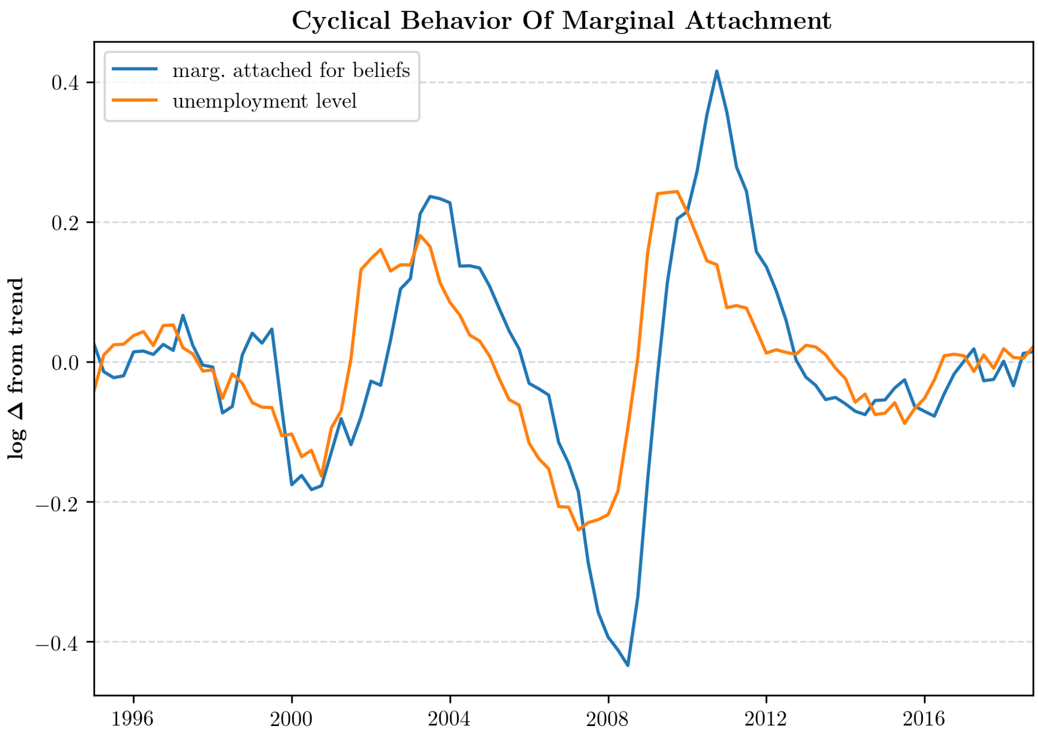


Figure 1.2: The above plots the cyclical component of the marginally attached population for belief-related reasons with the number of unemployed workers using the CPS basic monthly files from January 1994 through December 2018. The above are calculated using series of quarterly averages as log deviations from a Hodrick-Prescott filtered trend with smoothing parameter equal to 1,600. CPS sample weights are used.

We can see that beliefs about finding jobs is an important determinant for an individual's attachment to the labor market and that this measure is time varying at the business cycle frequency (correlation of 0.74 with the unemployed population). Adding in those who stated that they simply could not find any work increases the share to 24% of the marginally attached (4.5 million individuals monthly) and is similarly time varying. To the extent that other aspects of this BLS measure are also important determinants of a worker's attachment, they are found to be relatively acyclic or the mechanisms underlying them are beyond the scope of the structural modeling presented here (e.g. family responsibilities or "other" reasons).

Summary Statistics

	# of Persons	Share	corr(·, U)	p-value
Total Marginally Attached	17,298,601	1.00	0.72	0.00
believes no work available	1,424,255	0.08	0.74	0.00
couldn't find any work	2,907,445	0.16	0.73	0.00
lacks schooling / training	305,513	0.02	0.02	0.81
employers think too young / old	287,239	0.02	0.26	0.01
other types of discrimination	67,763	0.00	-0.07	0.50
can't arrange child care	395,920	0.02	-0.06	0.58
family responsibilities	2,306,409	0.13	0.27	0.01
in school or other training	3,833,386	0.22	0.27	0.01
ill-health, physical disability	1,417,637	0.08	-0.17	0.09
transportation problems	627,731	0.04	-0.18	0.08
other	3,725,331	0.22	-0.13	0.20

Table 1.1: This table gives some summary statistics about the marginally attached population from the CPS. Reported are monthly averages. Correlations with the unemployment level are given with the p-value for a two-sided test of non-correlation. These correlations are calculated using quarterly averaged series as log deviations from a Hodrick-Prescott filtered trend with smoothing parameter equal to 1,600. CPS sample weights are used.

1.3.2 Bias in Job-Finding Beliefs

Having shown that beliefs about one's labor market prospects are an important component of an individual's attachment, I next turn to more concretely characterize these perceptions in terms of job finding probabilities. To do so I make use of the SCE, a monthly survey with a representative sample of household heads in the US. Run by the Federal Reserve Bank of New York, the survey started in December 2012 and elicits the perceptions of unemployed workers' job finding prospects. Its rotating panel structure allows for ex-ante beliefs to be linked to actual, realized outcomes. Specifically, the survey asks unemployed individuals the following.

> *And looking at the more immediate future, what do you think is the percent chance that within the coming 3 months, you will find a job that you will*

accept, considering the pay and type of work?

To get an understanding about the bias of job seekers, I follow a procedure similar to that in [2]. Because the question is asked about the coming 3 months, the sample is restricted to those observations which are followed with at least 3 consecutive responses (that is, at least 4 consecutive months responding to the survey). This is to verify whether or not these respondents did ultimately find jobs. Next, because the panel is somewhat limited in how long individuals are tracked (we do not consistently observe multiple unemployment spells for each respondent), I calculate the realized rate for respondents in period t as the fraction of unemployed individuals in that period who found jobs in $t+1$, $t+2$, or $t+3$. That is, though nothing concrete can be said about individual bias, this exercise allows the examination of the average bias in expected job finding probabilities.

Bias in Job-Finding Beliefs

Horizon	Believed Prob.	Realized Prob.	Difference	Ratio	Observations
3-month	0.47832	0.3680	0.1141	1.4958	871
	(0.0137)	(0.0010)	(0.0142)	(0.0529)	
1-month	0.2696	0.1459	0.1261	2.1373	871
	(0.0127)	(0.0005)	(0.0125)	(0.0978)	

Table 1.2: The above gives the means of the believed probabilities and realized probabilities of finding a job in the SCE for both the 3-month horizon and 1-month (imputed) horizon. The sample is restricted to respondents aged 25-65 and with at least 3 follow-up interviews. standard errors are reported in parentheses. Survey weights are used in all calculations.

Next, because I later calibrate to a monthly frequency, I impute an estimate of a 1-month probability as follows. First, I assume that the arrival of jobs follows a Poisson process and that they are believed to arrive at some continuous rate $\hat{\lambda}$. As in [36], I further assume that an econometrician only observes the fruits of job search at discrete points $t = 1, 2, 3, \ldots,$ where $[t, t+1)$ is "period t." The subjective probability that a job will arrive by t follows an exponential distribution: $\Pr(t; \hat{\lambda}) = 1 - e^{-\hat{\lambda}t}$. Next, for each individual with an elicited 3-month probability, I calculate their implied $\hat{\lambda}$:

$$\hat{\lambda} = -\frac{1}{3}\ln\big(1 - \Pr(3)\big). \tag{1.1}$$

Then, I use this to evaluate $\Pr(1; \hat{\lambda})$. The same procedure is used in order to back-out the realized one-month probability. Last, I condition on workers aged 25-65. The results of this exercize are displayed in 1.2. On average, workers believe the monthly job finding probability is about 12.6 percentage points higher than what is realized. This translates to a belief that the job finding probability is 2.14 times higher than what is observed in the sample. To give an idea about the distribution of beliefs, I plot the histogram of elicited beliefs relative to the average realized probability of finding a job in 1.3. Further, I include a line indicating the "correct" value; that is, the value that would arise if everyone's beliefs were in-line with realizations. All means and differences are statistically distinguishible from 0 and both ratios are both statistically distinquishible from 1. This is to suggest that there is a significant degree of misperception in job-seeker expectations about finding jobs, the implications of which are studied below.

I also carry out the above procedure conditioning on several demographic characteristics of the respondent: age, education, household income, and gender. The results are displayed in Appendix A.1. Here, realized probabilities are recalculated as the fraction of all unemployed respondents *within* the demographic group that find jobs within the next three months. Interestingly, women appear to be slightly more optimistic than men, on average, but there does not appear to be any pattern by educational attainment or household income. The largest difference in bias centers on a respondents age. At the quarterly frequency, individuals aged 25-45 believe the job finding probability is roughly

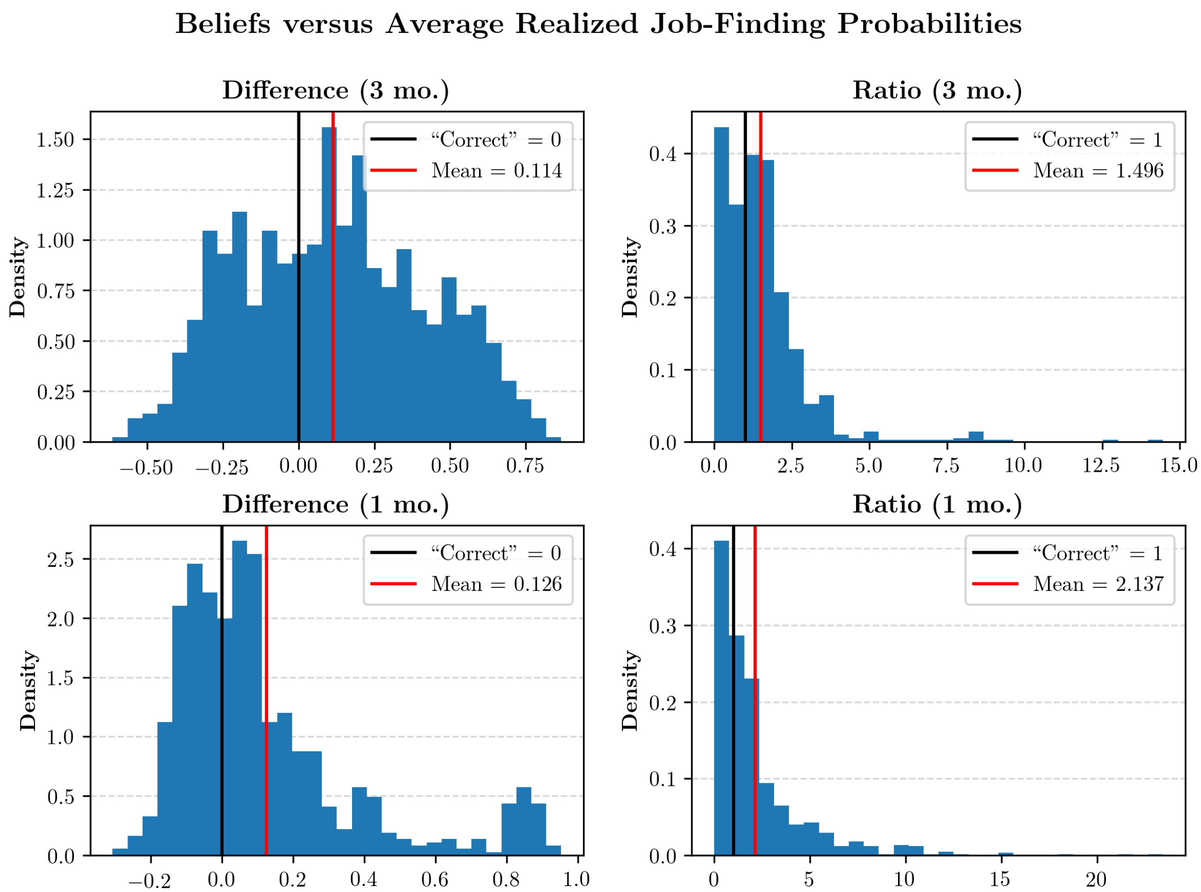


Figure 1.3: The above displays different measures of bias in job finding expectations in the SCE sample. Both for the 3-month horizon and 1-month (imputed) horizon and both as a difference and a ratio, the distribution of elicited beliefs about the probability of finding a job is plotted relative to the average realized probability of finding a job for the month the respondent was surveyed. The implied "correct" value is plotted in black. That is, the value of the measure if everyone's beliefs exactly equaled the realized probabilities.

1.9 times higher than is ultimately realized, while those 46-65 are only 1.3 times optimistic. I interpret this as reflecting the idea that the old generally have more experience and knowledge of the labor market, and therefore have more realistic expectations about their unemployment hazard.

Finally, I test the predictability of an individual's job finding beliefs. It may be the case that, when asked about the likelihood of finding a job, respondents have difficulty in assessing probabilities and that their responses are uninformative. To test the predictability of these beliefs, I regress an indicator of job finding in the next 3 months on their current beliefs, $\hat{f}$ and a vector of demographic characteristics, X_{it}, including up to a quadratic in age, dummies for race, gender, education, and household income indicators.

$$FindJob_{it} = \beta_0 + \beta_1 \hat{f}_{it} + \beta_2' X_{it} + \varepsilon_{it} \tag{1.2}$$

The results of this exercise are given in 1.3 and show that the elicited beliefs are predictive of actual job finding. A 1 percentage point increase in the believed job finding probability is associated with a 0.47 percentage point increase in the probability the respondent finds a job. By varying the controls included in the specification I find that beliefs explain *more* of the variation in job finding than do the demographic characteristics, presumably because these beliefs include private information about one's self that is unobservable to the econometrician yet important for finding gainful employment. In sum, these subjective beliefs are informative about job finding, however they are systematically biased upward on average.

Predictability of Job-Finding Beliefs

	(1)	(2)	(3)
constant	0.1135	0.4570	0.2131
	(0.025)	(0.281)	(0.269)
$\hat{f}$	0.5282		0.4707
	(0.048)		(0.051)
X_{it}		✓	✓
$\overline{R}^2$	0.108	0.068	0.146
N	871	871	871

Table 1.3: The above table reports results for a regression of job finding (in the next 3 months) on an individual's beliefs about job finding and a vector of characteristics.

1.4 A Model with Job Finding Misperceptions

In this section I formulate a model that I later use to understand how misperceptions about finding a job affect the labor market. Key to its construction is the ability to handle rich heterogeneity in a quantitatively feasible manner. Further, towards the goal of assessing dynamics, the model's solution should preferably avoid steady state assumptions.

1.4.1 Environment

A unit measure of workers and positive measure of firms populate the economy in discrete time, discounting the future with a factor $\widetilde{\beta} \in (0, 1)$. Workers live indefinitely, retiring with replacement each period with probability $\delta \in (0, 1)$. They can be either employed and producing (E) or unemployed and directing their search for work (U). Workers are homogeneously productive, normalized to 1, but differ in their beliefs about job finding. These beliefs are private and reflect uncertainty about the technology that matches unemployed workers with vacant firms, and can be learned about through experience searching in the labor market.

The output of an employed worker is given by $A \in \mathbb{R}_+$, which is common to all worker-firm pairs and time varying. At the beginning of any period, the aggregate state of the economy is denoted $\psi \in \Psi = (A, u)$, where u is a function that maps worker types into the measure that is searching for work. Unemployed workers receive utility $b \in \mathbb{R}_+$ and direct their search to sub-markets indexed by x and worker observables. $x \in \mathbb{R}_+$ denotes a firm's promised present expected value of employment to workers and is delivered with some wage schedule w and a separation probability $s \in [\underline{s}, 1)$, where $\underline{s}$ designates the exogenous probability that a match is dissolved.

In the spirit of [11], contracts between workers and firms are assumed to be bilaterally efficient: they maximize the joint surplus of a match. Briefly, [9] show under fairly general assumptions that profit maximizing contracts are bilaterally efficient if the contract space is complete–an assumption I, in turn, make. It should be noted that the exact wage setting mechanism is unnecessary to specify at this point as all that matters when workers are deciding where to search is the continuation value x. Next, the endogenous portion of the separation contingency ensures that matches which become undesirable are terminated and, therefore, in keeping with bilateral efficiency. For example, this could be due to a decline in aggregate productivity which make high-wage employment relationships unprofitable for firms (fires), or an increase in aggregate productivity which makes searching for higher-wage jobs valuable for workers (quits).

Sub-markets are formed by a market maker who posts x and the required, observable worker characteristics for each sub-market[4]. These markets are such that any match within them must pay x in expectation to workers with the specified characteristics. For now workers are observationally identical, but this is modified below. In order to find workers, firms must post vacancies in sub-markets at a cost $\kappa \in \mathbb{R}_+$ per period. The

[4] As noted in [37], the assumption of a market maker is isomorphic to assuming firms (or even workers) post values x and then search is directed to these postings.

key informational asymmetry in the model is that workers do *not* observe the vacancy posting decisions of firms, but firms observe the search behavior of workers. I assume that workers submit applications to sub-markets using their beliefs about job finding to infer the measures of vacancies that firms will post. Firms then observe these applications and post vacancies to potentially locate a worker. These workers never observe how many actual vacancies were posted in these sub-markets–they only observe the outcome of their job search. This keeps workers from being able to "undo" the firm's problem and eliminate the uncertainty over matching, and enables there to be a disconnect between objective and subjective meeting probabilities.

Hiring within a sub-market takes place according to a CRS matching function which takes the measures of unemployed workers and vacanct firms as inputs. Letting j denote a sub-market's index, $m_j = \mu v_j^{\eta} u_j^{1-\eta}$. v_j is the measure of vacant job postings, and $\mu \in \mathbb{R}_+$, $\eta \in \mathbb{R}_+$ are structural and do not vary by sub-market. The probability of finding a job for a worker is given by $f_j = m_j/u_j = \mu\theta_j^{\eta}$, where $\theta_j = v_j/u_j$ is the "tightness" of a particular sub-market. From a firm's perspective, the vacancy filling probability is given by $q_j = m_j/v_j = f_j/\theta_j$. What is important for worker decisions, however, is what she believes her job finding prospects are. A worker is assumed to have a prior mean belief over the scale parameter of the matching function, $\hat{\mu}$, that induces her to search in a sub-market she believes to have tightness $\hat{\theta}_j$, producing a subjective job finding probability $\hat{f}_j = \hat{\mu}\hat{\theta}_j^{\eta}$. Beliefs about the job finding probability, f_j, are then updated according to Bayes' rule after observing the outcome of job search.

To keep the model tractable, I assume that the priors follow a conjugate structure so that the belief and learning mechanism can be characterized by a finite-dimensioned object. This is formalized in *Lemma 1.*

Lemma 1. Let $y \equiv \mathbb{1}(\text{find job})$ denote the indicator function for whether a searcher finds a job. If the worker has a prior mean belief $\hat{\mu}$ which induces search in a sub-market with tightness $\hat{\theta}$ to produce subjective job-finding probability $\hat{f}$, then

(i) there exists a beta distribution with (hyper-) parameters α and γ that can express the prior belief of the job finding probability such that the prior mean is $\hat{f}$,

(ii) the associated posterior is beta distributed with parameters $\alpha_y = \alpha + y$ and $\gamma_y = \gamma + 1 - y$, and

(iii) the posterior mean of μ is

$$\hat{\mu}_y = \left(\frac{\alpha + y}{\alpha + \gamma + 1}\right) \hat{\theta}^{-\eta}.$$

Proof: See Appendix A.2. ■

The structure laid out in the above result admits a belief and learning mechanism for searching workers that can be characterized by a finite number of state variables. This structure, however, is perhaps simultaneously *too* flexible and *too* restrictive. Regarding flexibility, given some $\hat{\mu}$ that induces a choice to search in a sub-market with tightness $\hat{\theta}$, there is an infinitely large set of pairs (α, γ) that can achieve the prior mean $\hat{f}$. That is, there is an issue of initializing α and γ for an individual worker. Regarding restrictiveness, I note that α and γ can roughly be interpreted as the number of "successes" and "failures" of job search, respectively. In an environment where workers are (re-) directing their search over time, it is unrealistic that the series of chosen sub-markets over time have exactly a subjective job finding probability of $\alpha/(\alpha + \gamma)$, incremented appropriately.

To address both of these issues, I make the following simplification: workers only keep track of their belief $\hat{\mu}$ and the total number of periods they've searched in the labor market. Letting $e = \alpha + \gamma$, the process works as follows. $\hat{\mu} = \mu_0$ and $e = e_0$ at the start of life. These induce search in a sub-market with tightness (believed to be) $\hat{\theta}$, yielding a subjective job finding probability $\hat{f}$. Both α and γ can then be uniquely backed-out to be consistent with $\hat{f}$ and used, in turn, to evaluate how $\hat{\mu}$ is to be updated depending on the result of job search, $\hat{\mu}_y$. For a worker, $e - e_0$ is her job search experience and affects the *speed* with which $\hat{\mu}$ is updated.[5] Further, interpreting e in this way, I assume that it is observable by employers and makes up an individual's "résumé."

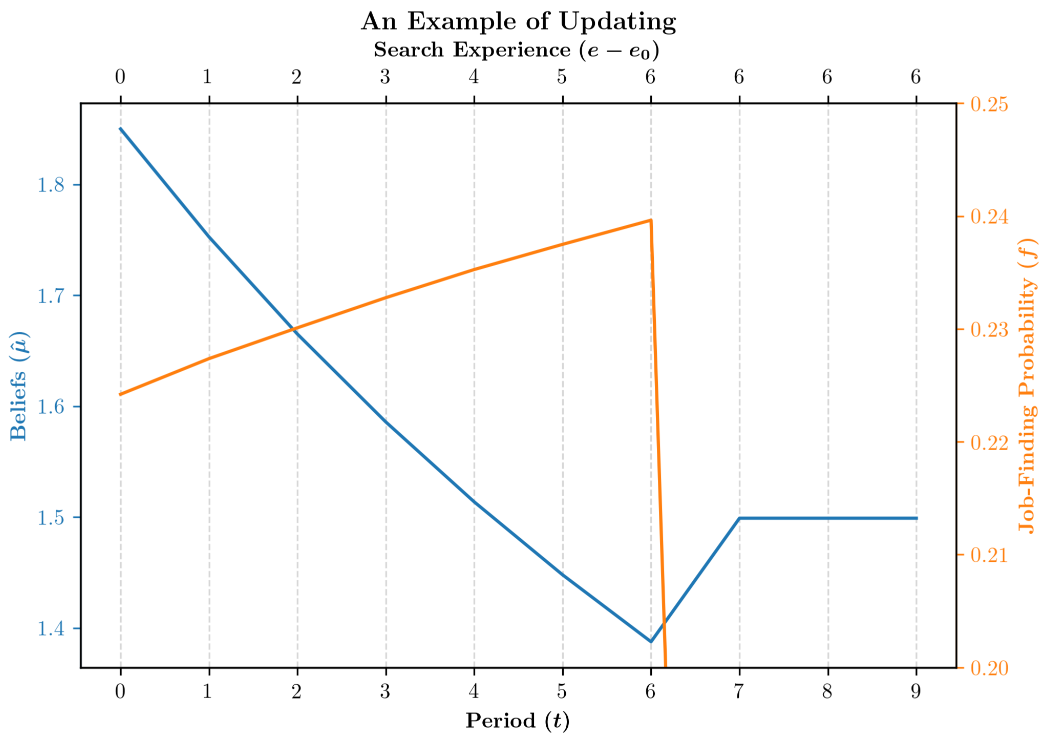


Figure 1.4: The above graphically shows how updating works in the model. This particular individual is tracked starting in period $t = 0$ with beliefs $\hat{\mu} = 1.85$ and labor market experience $e = 0$. This individual is optimistic, choosing to search in a slack sub-market, and so has a low probability of finding a job. As unemployment tenure extends, search experience accumulates, and her beliefs are adjusted downward. As this happens, she searches in tighter sub-markets, increasing her job finding probability. In period $t = 6$ the worker finds a job; her beliefs are revised upward as a result and her job finding probability drops thereafter to 0 (there is no on-the-job search).

To visualize how updating works in practice, I plot an example in 1.4 with the key state and choice variables for a worker as she looks for a job. Further, to highlight

[5] If large, updates are small. If small, updates are large.

only the updating mechanism, the example assumes that the aggregate state is constant throughout. The particular individual is tracked for 10 periods, starting in period $t = 0$. She starts out unemployed with 0 periods of search experience and initially believes that the scale parameter of the matching function is relatively high at 1.85. Since she believes job finding is easy, she chooses to search in relatively slack sub-markets, and thus has a relatively low probability of actually finding a job. As she searches and fails to find a job, her beliefs deteriorate, and she responds by searching in tighter sub-markets, raising the likelihood of finding a job. At $t = 6$ a job is found; beliefs are adjusted upward slightly, and the probability she finds a job thereafter drops to 0 as there is no on-the-job search. Note also that her search experience stops incrementing at the time she finds a job.

Each period is characterized by five stages. In the first stage, learning takes place: beliefs $\hat{\mu}$ are updated based on the results of the previous period's search experiences y and e is appropriately incremented. In the second stage the aggregate state ψ is established with a draw for A. Additionally, separations and death (with replacement) occur. Those who lose their job at this stage cannot find a job until the following period. Production and consumption occur in the third stage. Unemployed workers receive b in utility while employed workers produce A and are paid according to their employment contract. Vacancy posting and search happens in the fourth. Finally, in the fifth stage, matching occurs.

1.4.2 Value Functions

Let the market tightness function for the sub-market promising x to individuals with experience e with aggregate state ψ be written as $\theta_{x,e,\psi} = \theta(x, e, \psi)$. Future values of ψ are written with a "prime." At the start of the production and consumption stage, an unemployed worker receives b in the current period and chooses which sub-market to search in given $\hat{\mu}$ and e. Should they find a job, which is believed to occur with probability $\hat{f}$, they earn x in expected lifetime utility, otherwise they remain unemployed next period with updated beliefs $\hat{\mu}_y$ and experience $e+1$.

$$\mathcal{V}_U(\hat{\mu}, e, \psi) = b + \beta \mathbb{E}_{\psi'|\psi} \max_x \Big\{ \underbrace{\hat{\mu}\hat{\theta}^{\eta}_{x,e,\psi}}_{\hat{f}_{x,e,\psi}} x + \big(1 - \hat{f}_{x,e,\psi}\big) \mathcal{V}_U(\hat{\mu}_0, e+1, \psi') \Big\}, \tag{1.3}$$

where $\beta = \widetilde{\beta}(1-\delta)$ is the effective discount factor. The joint surplus of a job includes the sum of the worker's continuation utility and the firm's continuation profit.

$$\mathcal{V}_E(\hat{\mu}, e, \psi) = A + \beta \mathbb{E}_{\psi'|\psi} \max_s \Big\{ s\mathcal{V}_U(\hat{\mu}, e, \psi') + (1-s)\mathcal{V}_E(\hat{\mu}, e, \psi') \Big\} \tag{1.4}$$

1.4.3 Equilibrium

Due to free entry, any sub-market with a positive measure of searchers will have a market tightness function that satisfies

$$\kappa \geq q_{x,e,\psi} \Big[\mathbb{E}_{\psi'|\psi} \mathcal{V}_E(\hat{\mu}_1, e+1, \psi') - x \Big] \tag{1.5}$$

and $\theta_{x,e,\psi} \geq 0$ with complementary slackness. Workers are assumed *not* to observe the vacancy posting decisions of firms. Instead, they have beliefs of this behavior given by substituting $\hat{q}_{x,e,\psi} = \hat{\mu}\hat{\theta}^{\eta-1}_{x,e,\psi}$ into the above for $q_{x,e,\psi}$:

$$\kappa \geq \hat{q}_{x,e,\psi} \Big[\mathbb{E}_{\psi'|\psi} \mathcal{V}_E(\hat{\mu}_1, e+1, \psi') - x \Big] \qquad \text{and} \qquad \hat{\theta}_{x,e,\psi} \geq 0 \quad \text{w/ c.s.} \tag{1.6}$$

I now turn to characterize where a searcher looks for jobs. Consider an unemployed worker with experience e and aggregate state ψ as given. Write the *subjective* sub-market tightness function of concern for this worker as $\hat{\theta}_x = \hat{\theta}(x|e, \psi)$. The value of a job that a worker searches for can be written as a function of $\hat{\theta}_x$ by rearranging the subjective free entry condition:

$$x = \mathbb{E}_{\psi'|\psi} \mathcal{V}_E(\hat{\mu}_1, e+1, \psi') - \frac{\kappa \hat{\theta}_x^{1-\eta}}{\hat{\mu}}. \tag{1.7}$$

The above expression makes clear the trade-off faced by searchers: higher value jobs come at the cost of a low probability to locate them. It may also be used to rewrite the search problem of an unemployed worker in terms of a choice of market tightness by substituting 1.7 into 1.3. The solution to that problem is

$$\hat{\theta}_x = \left\{ \frac{\eta \hat{\mu}}{\kappa} \mathbb{E}_{\psi'|\psi} \Big[\mathcal{V}_E(\hat{\mu}_1, e+1, \psi') - \mathcal{V}_U(\hat{\mu}_0, e+1, \psi') \Big] \right\}^{\frac{1}{1-\eta}}. \tag{1.8}$$

We can see that the worker's choice of tightness is increasing in the matching elasticity, increasing in the beliefs about the matching scale, decreasing in the cost to post a vacancy, and increasing in the surplus generated from a match. Finally, substituting 1.8 into 1.7 yields an expression for the searching worker's policy.

$$x(\hat{\mu}, e, \psi) = \mathbb{E}_{\psi'|\psi} \Big[(1-\eta) \mathcal{V}_E(\hat{\mu}_1, e+1, \psi') + \eta \mathcal{V}_U(\hat{\mu}_0, e+1, \psi') \Big] \tag{1.9}$$

Rearranging the expression inside the brackets, one can show that workers choose to search in sub-markets promising their outside value, $\mathcal{V}_U$, plus a share $1-\eta$ of the surplus of the match, $\mathcal{V}_E - \mathcal{V}_U$.

It is important to stress that workers are *not* indifferent between all possible sub-markets available to them. It is easy to verify that the RHS of 1.9 is strictly increasing in $\hat{\mu}$: workers who are more optimistic search in sub-markets promising more in expected lifetime utility. To put it differently, workers with different $\hat{\mu}$ (but the same e) choose to search for different jobs. This is important because firms observing the e of a sub-market can uniquely back-out the $\hat{\mu}$ of searchers and thus construct w and s to deliver x and maintain complete contracts. This result is re-stated below.

Lemma 2. Firms do not need to track the distribution of prior mean beliefs about μ among searching agents when evaluating their decision to post a vacancy in a sub-market.

Intuitively, because workers self sort across different sub-markets, firms can use the one-to-one relationship between $\hat{\mu}$ and x given e and ψ to know exactly what type of worker it will encounter when choosing to post in the (x, e, ψ) sub-market. Though workers have misperceptions about the probability that they will meet firms (and the probability that firms will meet workers), firms are still willing to post vacancies because workers are productive. Optimistic workers expect values greater than they would otherwise, but fewer firms can support these demands leading to lower job finding probabilities. In the other direction, pessimistic workers search for values less than they would otherwise, inducing more firms to post vacancies, and leading to higher job finding probabilities.

The distinction between *objective* and *subjective* probabilities should also be noted. Though this distinction is less important for understanding the tradeoff between payouts and meeting probabilities, it is important for outcomes. The subjective (i.e. worker) probabilities can be summarized by 1.8. One may find the objective probabilities by plugging 1.9 into 1.7 and solving for θ:

$$\theta_x = \left\{ \frac{\eta\mu}{\kappa} \mathbb{E}_{\psi'|\psi} \Big[\mathcal{V}_E(\hat{\mu}_1, e+1, \psi') - \mathcal{V}_U(\hat{\mu}_0, e+1, \psi') \Big] \right\}^{\frac{1}{1-\eta}}. \tag{1.10}$$

The *only* difference between 1.8 and 1.10 is that $\hat{\mu}$ is replaced with μ. I define the "misperception factor" of a worker as the ratio of the subjective and objective probabilities of finding a job, which is later used to calibrate the model using SCE data.

$$\frac{\hat{f}}{f} = \left(\frac{\hat{\mu}}{\mu}\right)^{\frac{1+\eta}{1-\eta}} \tag{1.11}$$

I plot $\hat{f}/f$ in 1.5 using the calibrated value for η. When the belief of μ is correct, i.e. $\hat{\mu} = \mu$, there is no distortion and $\hat{f}/f = 1$. As one becomes optimistic or pessimistic–moving to the right or left–the subjective probability becomes distorted. Before moving to formally define and establish the equilibrium, a schematic summarizing the model and the key acting agents is presented in 1.6.

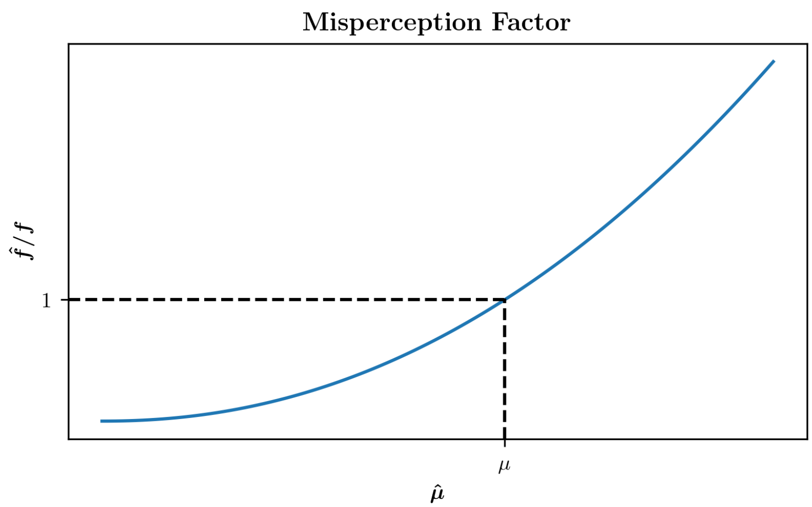


Figure 1.5: The above plots an example of the value of the misperception factor for different beliefs $\hat{\mu}$. This factor is used later to calibrate the model.

Definition 1. A Block Recursive Equilibrium (BRE) consists of market tightness functions θ and $\hat{\theta}$, value functions $\mathcal{V}_U$ and $\mathcal{V}_E$, and policy functions x and s such that the following hold:

(i) θ, $\hat{\theta}$, $\mathcal{V}_U$, $\mathcal{V}_E$, x, and s depend on ψ only through A;

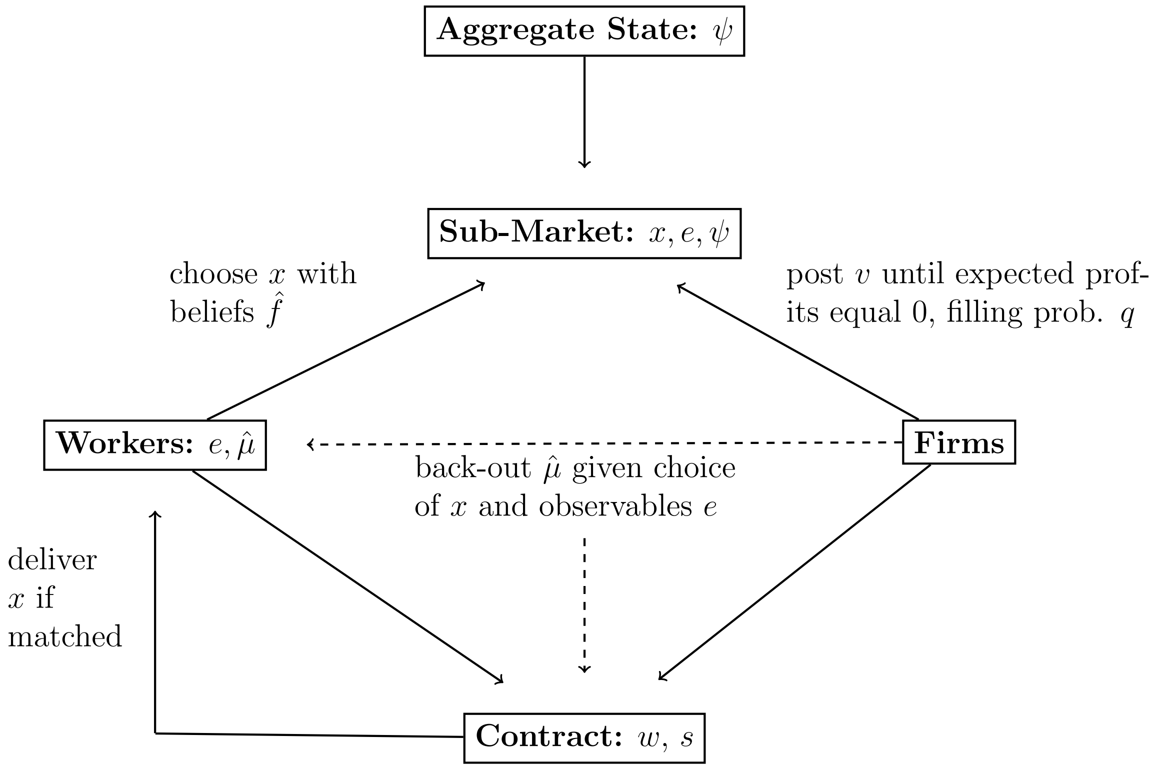


Figure 1.6: Schematic summary of the model. Displayed are the various agents, their choices, and how contracts are constructed.

(ii) θ and $\hat{\theta}$ satisfy 1.5 and 1.6, respectively;

(iii) $\mathcal{V}_U$, and x satisfy 1.3;

(iv) $\mathcal{V}_E$ and s satisfy 1.4.

Theorem 1. The unique recursive equilibrium is a BRE.

Proof: See Appendix A.3. ■

Important to the above result is that the market tightness, value, and policy functions depend on the aggregate state only through realizations of the aggregate shock, and not on the endogenous distribution of workers across employment states. Intuitively, directed search leads workers to self-sort across sub-markets. When firms post vacancies to these sub-markets, they therefore know exactly what type of worker they might match with. In other words, the expected value of a filled job does not depend on the whole distribution of unemployed workers. Coupled with free entry, the meeting probability also does not depend on this distribution. This property carries through to the value and policy functions.

Novel to this environment is that the subjective probability of finding a job and the objective probability of filling a vacancy do *not* need to agree. Sub-markets promise values x, but do not guarantee probabilities f. As noted earlier, even though observationally similar workers search for different x, firms are willing to post vacancies for those with high $\hat{\mu}$ (because they are still productive) and low $\hat{\mu}$ (because their labor is sold at a discount). The tradeoff is that fewer firms can support vacancies for high $\hat{\mu}$, and more firms can support vacancies for low $\hat{\mu}$. In equilibrium, pessimists will tend to leave unemployment quickly, while optimists will stay unemployed longer. Interesting to note is that, in this model, "lucky" optimists can find jobs paying *more* than if their beliefs were correct, leading to a possibility of being "blissfully" misperceived. "Unlucky" workers, those who take a while to find jobs, may receive wages *lower* than if their beliefs were correct.

Finally, it is implicitly assumed that firms do not reveal the true μ to workers. I argue that this assumption is not strong for the following reasons. First, suppose firms could reveal μ to workers when posting vacancies. They would do so if there exists potential profits to be made. Because of free entry, any possible gain in profits would be wiped out by additional firm entry making the expected profits of the vacancy 0. Second, suppose that firms, after meeting a worker, were to reveal μ. Again, there would be no incentive to do so because, given that search occured in a sub-market with promised payment x, the expected cost to firms at the start of the employment contract is still x.

1.5 Calibrating to the US Economy

In this section I calibrate the parameters of the model presented above using data on worker transitions and job finding beliefs. I organize these parameters into four groups: those related to preferences, search and matching, aggregate productivity, and a workers' beliefs. Since multiple nested models are considered and compared, I carry out the calibration exercise twice: with and without beliefs. Below I detail the procedure used when calibrating the full (with beliefs) model. To start, a period is chosen to be 1 month. In order to make data and model generated series comparable I measure them as log deviations from a Hodrick-Prescott filtered trend using smoothing parameter set to 1,600 for series of quarterly averages where appropriate.

Preferences are described by a discount factor $\widetilde{\beta}$, an exogenous death probability δ, and unemployment utility b. $\widetilde{\beta}$ is set to 0.9957 implying a 5% annual discount rate. δ is set to 0.0021 so that the average worker is in the labor market for 40 years (i.e. from 25 to 65). I interpret b as the value of leisure and calibrate it such that its ratio with the average labor productivity is 0.71 as in [38].

Search and matching frictions are described by a matching function scale parameter μ, a curvature parameter η, an exogenous separation probability $\underline{s}$, and a per-period vacancy posting cost κ. μ is normalized to 1.0. η is set so that the elasticity of the job finding probability with respect to the sub-market tightness in the model is the same as in the data. The model's aggregate unemployment and vacancy measures are given by $\int u$ and $\int \theta u$, respectively. The equivalent series in the data are taken to be the civilian noninstitutionalized unemployment level from the CPS and total unfilled job vacancies ("job openings") from the BLS's Job Openings and Labor Turnover Survey (JOLTS) for the period from December 2000 to December 2018.

For the job finding probability I calculate and use the "UE" transition probability directly from the CPS basic monthly files by matching individuals in consecutive months as in [36].[6] Since there is no on-the-job search (that is, all search comes from unemployment), η can be set directly and is estimated using a log-linear specification with linear and quadratic trends. The exogenous separation probability and vacancy posting cost, $\underline{s}$ and κ, are calibrated to target the mean "EU" and "UE" transition probabilities observed in the data (again, measured as in [36]). The model equivalents are $\int s$ and $\int f(\theta)$.

Aggregate productivity is assumed to follow an AR(1).

$$A' = (1-\rho)\overline{A} + \rho A + \varepsilon \tag{1.12}$$

$\overline{A}$ is normalized to 1.0 and $\varepsilon \sim N(0, \sigma)$. σ and ρ are chosen such that the model's implied standard deviation and autocorrelation of aggregate labor productivity is the same as in the data. Model labor productivity is given by $\int \frac{Azh}{1-u}$. In the data I use the BLS's estimate of the real output per hour in the nonfarm business sector.

Beliefs are characterized by an initial auxillary parameter e_0 and μ_0. The initial, prior mean belief of $\hat{\mu}$ is assumed to be drawn point-mass at μ_0 and, with e_0, is calibrated such that the average belief-to-realized job finding probability ratio, the "misperception factor", and dispersion in beliefs match the SCE sample described earlier. In other words, μ_0 and e_0 are calibrated to match the mean and standard deviation of $\hat{f}/f$ in the searching pool.

In total, there are 12 parameters. 5 are set before the main calibration ($\widetilde{\beta}$, δ, μ, η, $\overline{A}$) and 7 are jointly determined with 8 targeted moments (b, $\underline{s}$, κ, σ, ρ, μ_0, e_0). Full results of the calibration are displayed in 1.4. Calibrated outcomes for the both models

[6]Note also that because I abstract away from a participation margin, I "correct" all transition probabilities accordingly. That is, so the probabilities appropriately sum to unity.

are reported in 1.5.

First, note that across model specifications the sensitivity of the vacancy posting cost, κ. Since workers are calibrated to be optimistic on-average and because the economies are targeted to have identical "UE" flow probabilities, the implied value of κ is much lower than it would otherwise be. Next, note that the calibrated value for e_0 is relatively high, implying relatively small successive updates from search experience. This slow learning is consistent with findings by [2] that suggest workers do not update their beliefs about the job finding probability as search tenure increases. Here, it is important to note that while the agents are updating, they are *not* updating directly about the job finding probability, but rather the scale parameter of the matching function. This coupled with directed search means that, as they learn about μ, agents redirect their search to sub-markets with larger θ, generating relatively constant (and under certain parameterizations, possibly increasing) subjective probabilities of finding a job.

1.6 The Effects of Job Finding Misperceptions

In this section, I use the model presented above to study how misperceptions about job finding affect the labor market. Due to the nature of the model, analytic exercises are limited. Thus, I use the calibrated model to isolate the effects of these channels on aggregate variables, and how aggregate shocks to productivity interact with them. This is accomplished in three steps.

In the first step, I study how biased beliefs affect the levels (means) of key model variables. This is done as follows. The economy's steady state is simulated at the mean of aggregate productivity, $\overline{A}$, where the distribution of workers across idiosyncratic states is given by the ergodic distribution associated with this level of productivity. Next, I separately double μ_0 and e_0 and compare the new steady state values. Foreshadowing

Calibration Results

Parameter	Value	Description	Target
Preferences			
$\widetilde{\beta}$	0.9957	discount factor	5% annual discount rate
δ	0.0021	death prob.	average working life of 40 years
b	0.710	unemployment utility	leisure-to-labor prod. ($\star$)
Search & Matching			
μ	1.0	matching function, scale	normalization
η	0.36	matching function, curvature	estimated
$\underline{s}$	0.0141	exogenous separation prob.	mean EU prob. ($\star$)
κ	4.505	vacancy posting cost	mean UE prob. ($\star$)
Aggregate Productivity			
$\overline{A}$	1.0	mean aggregate prod.	normalization
ρ	0.965	autocorr. of aggregate prod.	autocorr. of US labor prod. ($\star$)
σ	0.0063	st. dev. of aggregate prod.	st. dev. of US labor prod. ($\star$)
Beliefs			
μ_0	2.154	initial belief	mean bias ($\star$)
e_0	47.752	initial update speed	st. dev. of beliefs ($\star$)

Moment	Data	Model
value of leisure to average labor productivity ratio	0.7100	0.7100
average job separation probability	0.0141	0.0141
average job finding probability	0.2608	0.2608
autocorrelation of aggregate labor productivity	0.7244	0.7235
standard deviation of aggregate labor productivity	0.0100	0.0100
average “misperception factor”	2.1373	2.1373
standard deviation of job finding bias	0.3011	0.3011

Table 1.4: Results of the calibration. The top panel displays the parameters and the bottom reports the moments targeted in the joint exercise. Jointly calibrated parameters are “starred” in the top panel.

Model Comparison

Parameter	Description	No Beliefs	Beliefs
b	unemployment utility	0.710	0.710
$\underline{s}$	exogenous separation prob.	0.014	0.014
κ	vacancy posting cost	5.525	4.50
ρ	autocorr. of aggregate prod.	0.965	0.965
σ	st. dev. of aggregate prod.	0.006	0.006
μ_0	initial belief	1	2.15
e_0	initial update speed	∞	47.75

Table 1.5: Calibration results comparing the two models. Only jointly calibrated parameters are shown.

interest in the dynamic implications, I also simulate the steady state when $\overline{A}$ is increased by 1%. This is done to generate relationships between aggregate productivity and other model variables (interpreted as elasticities), which will be important for understanding the model with aggregate shocks.

Second, I study how the dynamics of labor market variables are affected by misperceptions. I start the two economies–with and without beliefs–in the steady state and then "turn on" aggregate shocks. I then use these simulations to compare standard deviations, correlations, and serial correlations. Noting that this exercise is carried out with separate calibrations targeting, for example, the average UE flow probability, I carry out a third, counterfactual exercise. I ask, "What effect do biased job seeker beliefs have on the economy?" I answer this by taking the model and "correct" everyone's beliefs. That is, I set $\mu_0 = 1$ and $e_0 \to \infty$ for all agents.

1.6.1 Comparative Statics

The results of the first exercise are displayed in 1.6 and are reported as percentage changes from the benchmark steady state values. I report average values of the unemployment rate, vacancy rate, job finding probability, labor productivity, wages, beliefs of

μ (both separated by the employed and unemployed population), and search experience $e - e_0$. In the construction and calibration of the model, a wage setting mechanism was unnecessary to specify. Indeed, many different wage schedules can achieve an expected value of x. For example, wages could increase with employment tenure, decrease with tenure, have a hump shape, etc. For simplicity, I assume that wages are constant over the course of an employment spell. For details, see Appendix A.4.

In the benchmark model's steady state, the unemployment rate is 5.6%, the measure of vacancies is 0.0014, producing an average job finding probability of 26.08% (a calibrated target). Labor productivity is equal to 1.00, by construction, with an average wage of 0.9918. The average belief in μ that produces a subjective job finding probability 2.1373 (calibrated) times as high as the actual job finding probability is around 1.6. Notice that average belief in the employed pool is *lower* than in the unemployed pool. This is because a higher $\hat{\mu}$ makes workers more picky and therefore they tend select into unemployment, producing a higher degree of optimism in the unemployed pool. The average worker in the economy has been unemployed and searching for work for for 20.38 months (or roughly 82 weeks).

First, consider the increased initial optimism exercise (where μ_0 is doubled). Here, workers start out relatively more optimistic, leading to an increase in the equilibrium mean level of $\hat{\mu}$. Note that because the mean $\hat{\mu}$ is endogenous, the doubling of μ_0 does not double the mean. This increased optimism leads workers to search in slack sub-markets with higher wages. Firms are less inclined to post vacancies in high wage sub-markets, so v and the average job finding probability decreases. The lower unemployment hazard thus increases the mean unemployment rate and raises the average level of search experience as workers select into long(er) term unemployment.

Next, consider the exercise when e_0 is doubled. Recall that $e - e_0$ is a worker's search experience, where e controls the speed of updating. When e_0 is increased, successive updates are smaller and workers take longer to revise their beliefs to the true value of μ. This translates to an increased mean level of $\hat{\mu}$ in both employed and unemployed populations. As with the first static exercise, this induces unemployed workers to search for higher wage jobs which firms are less inclined to post vacancies for, decreasing the job finding probability and increasing unemployment.

The last row presents the results when aggregate productivity is increased by 1%; that is, these numbers can be interpreted directly as elasticities. Moreover, since the source of volatility in the model comes from shocks to A, these relationships will be key in understanding some future results pertaining to the dynamics of labor market variables. When A is increased workers are more productive (i.e. labor productivity increases) so more vacancies are posted. This leads to an increase in the job finding probability, a decrease in the unemployment rate, and an increase in wages. Because jobs are being found more frequently, there is also an increase in the average $\hat{\mu}$ and decrease in the average e.

Comparative Statics

	u	v	f	lp	w	$\hat{\mu}_E$	$\hat{\mu}_U$	$e - e_0$
Benchmark	0.0585	0.0014	0.2608	1.0000	0.9918	1.6037	1.6134	20.38
$\uparrow \mu_0$	+24.74%	-35.33%	-21.06%	0.00%	+0.26%	+86.03%	+87.33%	+10.28%
$\uparrow e_0$	+6.67%	-11.87%	-6.64%	0.00%	+0.08%	+11.88%	+11.35%	+72.84%
$\uparrow \overline{A}$	-1.00%	+2.00%	+1.08%	+1.00%	+0.99%	+0.30%	+0.28%	-0.40%

Table 1.6: The above table displays the comparative static results, relative to the benchmark model, for the means of key model variables of the three comparative static exercises described above.

1.6.2 Dynamics

The results of the dynamics exercise are reported in 1.7. Briefly, we can see that when uncertainty over job finding is introduced, dynamic measures of key labor market variables are dampened. To understand why, it will be useful to think about two effects: *composition* and *individual* effects. That is, how do beliefs affect the composition of workers in the unemployed pool versus how they affect an individual's choices? I guide consideration of these two effects using the equilibrium sub-market tightness function because it contains information on the decisions of both searching workers and hiring firms. It will be beneficial to contextualize how aggregate shocks affect what the average worker looks like and where she searches for employment. Since the source of dynamic fluctuations in the model comes from shocks to aggregate productivity, this is done by inspecting how the equilibrium sub-market tightness function responds to changes in A and how this is affected by beliefs. In other words, it is sufficient to study how the total derivative of θ with respect to changes in A depends on worker beliefs about μ.

Dynamics

Variable	u	v	f	lp	u	v	f	lp
	Without				With			
Std(·)/Std(lp)	2.05	6.47	2.68	1.00	1.85	5.95	2.45	1.00
Autocorr(·)	0.48	0.19	0.34	0.72	0.45	0.13	0.27	0.72
Corr(·, *Variable*):								
u	1.00	-0.34	-0.58	-0.34	1.00	-0.33	-0.56	-0.30
v		1.00	0.96	0.40		1.00	0.97	0.35
f			1.00	0.44			1.00	0.40
lp				1.00				1.00

Table 1.7: The above table displays the dynamic results for the two models of interest, with and without worker beliefs about μ. Reported are quarterly averages of monthly series. All variables are reported as log differences from a Hodrick-Prescott filtered trend with smoothing parameter 1,600. Standard deviations are reported relative to labor productivity, which is normalized to 1 by construction.

To begin, θ is a function of the promised payment x, experience e, and aggregate state ψ. We can use properties of the model's equilibrium to rewrite this function as follows. Because the equilibrium is block recursive, ψ can be reduced to A as it does not depend on the endogenous distribution of workers across employment states. Next, given the results in *Lemma 2*, we can replace x with $\hat{\mu}$ as firms can back out $\hat{\mu}$ from the choice of x given e. Finally, we can write the equilibrium market tightness function as $\theta(\hat{\mu}, e, A)$. Its total derivative is given by

$$d\log(\theta) = \frac{\partial \log(\theta)}{\partial \hat{\mu}} d\hat{\mu} + \frac{\partial \log(\theta)}{\partial e} de + \frac{\partial \log(\theta)}{\partial A} dA, \tag{1.13}$$

where logs are taken so that interpretations can be made in percentage terms. By dividing through by dA we can get an expression for the semi-elasticity of θ with respect to changes in A.

$$\frac{d\log(\theta)}{dA} = \frac{\partial \log(\theta)}{\partial \hat{\mu}} \frac{d\hat{\mu}}{dA} + \frac{\partial \log(\theta)}{\partial e} \frac{de}{dA} + \frac{\partial \log(\theta)}{\partial A}. \tag{1.14}$$

The above expression makes clear that $d\log(\theta)/dA$ depends critically on three things: a direct effect from A, a belief effect through $\hat{\mu}$, and a learning effect through e. Moreover, before returning to interpret the results of the exercises, it will also be useful to note that the equilibrium sub-market tightness function (and the derivative of its log) is itself a function of $\hat{\mu}$, e, and A. This is to say that the direct effect on θ from changes in A may also be affected by job finding misperceptions. Thus, I later plot how the semi-elasticity of the sub-market tightness function (with respect to changes in A) is affected by $\hat{\mu}$ and e.

Focusing on the $\hat{\mu}$ term in 1.14, the calibrated model finds that $\partial \log(\theta)/\partial\hat{\mu}$ is negative and, recalling the earlier steady-state exercise, $d\hat{\mu}/dA$ is positive. The opposite signs indicate that uncertainty over the job finding technology has an attenuating compositional effect on (log) changes in θ as A changes. To put it more intuitively, beliefs are procyclical: they more optimistic in expansions and more pessimistic in recessions. Because optimistic workers are "picky" and search in slack, high-valued sub-markets, the average sub-market searched in is thus relatively tighter in recessions and slacker in expansions. This means that the cyclical fluctuations in θ, and therefore the job finding probability and the unemployment rate, decrease.

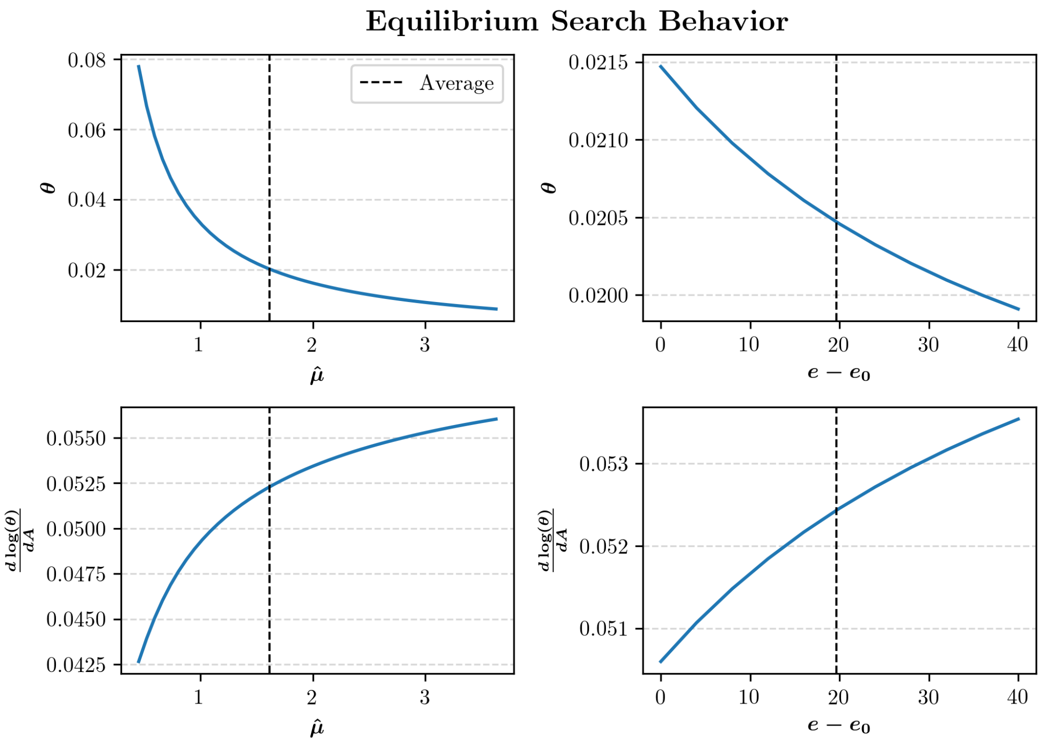


Figure 1.7: The top panels plot the equilibrium sub-market tightness function across the supports of $\hat{\mu}$ and e, evaluated at the mean values of other variables for a searching worker in the economy. The bottom panel displays the semi-elasticity of the sub-market tightness function for changes in A across these domains.

What about at the individual level? I plot key features of an average individual's search behavior in 1.7. In the top panel I plot the equilibrium sub-market tightness function for an average unemployed worker along the support of $\hat{\mu}$. Immediately we can see the downward slope of θ along $\hat{\mu}$, that is a higher mean belief of $\hat{\mu}$ leads to workers choosing to search in high-valued and slack sub-markets. In the bottom panel, I show how a worker's search response to aggregate shocks is affected by $\hat{\mu}$. As $\hat{\mu}$ increases, the percentage change in θ from an infinitesimal change in A gets larger. Optimism makes the perceived cost of unemployment low, which compels workers to respond more to aggregate conditions, and less to idiosyncratic ones. To phrase this in terms paralleling the concept of a reservation wage, workers are more inclined to "wait it out" for better economic conditions the more optimistic they are. On the one hand, optimistic workers will respond relatively more to positive shocks by searching in tighter sub-markets. On the other, they will also search in relatively slacker sub-markets in response to negative shocks as the assessed cost of doing so is small. That is, there is upward pressure on measures of volatility and cyclicality as the degree of optimism is increased.

Overall, these two effects have opposite implications for the dynamic measures of labor market variables, and that the composition effect dominates.

Now consider the search experience term in 1.14. In 1.7 we can see that θ is downward sloping in e. Search experience is a measure of how much information has been collected by an individual and affects the value of learning. Experience is valuable, which can be seen in 1.8: otherwise similar searchers are better off–that is, they have a higher expected utility–the more experience they have. Recalling that workers search for jobs that pay their outside option *plus* a fraction of the match surplus, the value of the job she searches for increases in e. This reduces the willingness of firms to post vacancies for her work, and so θ declines. Next, referring back to the comparative static exercise, $de/dA < 0$ as high aggregate productivity leads to increased hiring and therefore a decrease in unemployment tenures. Because both of these terms are negative, there is upward compositional pressure on labor market dynamics. High productivity decreases the average level of search experience in the economy, and those with low search experience search in relatively lower value, easy-to-find jobs. Thus, aggregate job finding increases *even more* when A is high. The opposite holds for when A is low.

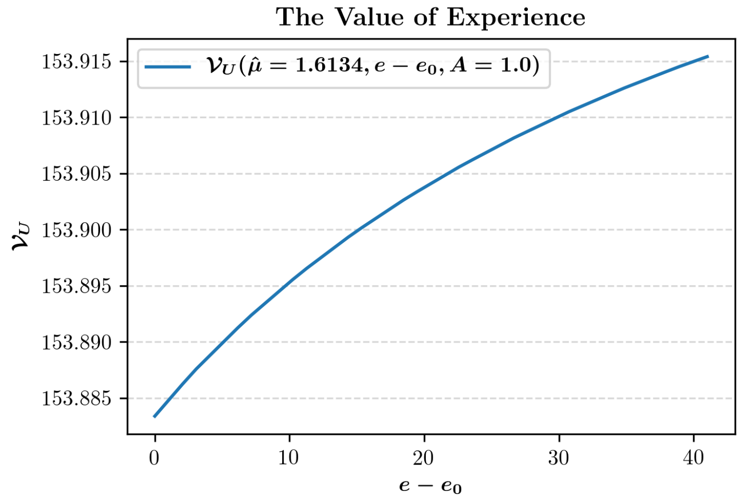


Figure 1.8: Plotted above is the value of unemployment for the average, steady-state searcher for different amount of search experience.

Also in 1.7 we can see that the semi-elasticity of the market tightness function to aggregate shocks is increasing in experience. In other words, the direct effect of A increases in e. While experience is valuable to searchers, the value of *learning* is decreasing in it. This can be seen by the concavity in 1.8. To put this differently, the addition in expected utility from one more period of experience gets smaller and smaller. This is intuitive as a high e reduces the amount that $\hat{\mu}$ is updated, therefore limiting the value in information that can be gained by searching. Since this learning value decreases, workers weight aggregate considerations more than idiosyncratic ones, therefore raising $\partial \log(\theta)/\partial A$ as e increases. Altogether, both compositional and individual effects have upward pressure on measures of dynamics. However, this being said, it should be noted that both of these effects are found to be quantitatively small. This can be seen by noting the scale of the vertical axes in the plots cited above.

1.6.3 Counterfactual Experiment

While the above exercises highlight how misperceptions in job finding interact with other variables and affect model performance, this experiment sheds light onto what effects these misperceptions have on aggregate quantities. Specifically, it answers the question, "What would the economy look like if everyone's beliefs about job finding were correct?" I report the results of this experiment in 1.8.

Counterfactual Experiment

	u	v	f	lp	w	$\hat{\mu}$	$e - e_0$
			Benchmark				
Mean	0.059	0.0014	0.261	1.000	0.992	1.604	20.380
Std(·)/Std(lp)	1.85	5.95	2.45	1.000			
			Correct Beliefs				
Mean	0.053	0.0017	0.287	1.000	0.989	1.000	17.488
Std(·)/Std(lp)	1.97	5.76	2.41	1.000			

Table 1.8: Results of the counterfactual experiments. Variables are reported as quarterly averages of monthly series. Standard deviations are calculated as log deviations from a Hodrick-Prescott filtered trend with smoothing parameter 1,600.

When beliefs are corrected the on-average optimism of the searching pool is eliminated. Less picky agents search in tighter sub-markets where firms are more inclined to post vacancies for their work. This has upward pressure on vacancies and job finding probabilities, and downward pressure on the unemployment rate. In particular, I find that corrected misperceptions would lead to a decrease in the unemployment rate by 0.6pp. Further, the 2.6pp increase in the job finding probability means workers, on-average, spend less time unemployed and searching. This increase in unemployment hazard reduces the average amount of time spent unemployed by roughly 3-months (or 12 weeks). Also interesting to note is that though there is an increase in employment, the correction of beliefs is not necessarily benefial to all workers. Though jobs are found more quickly, they are for a lower wage. Thus, "lucky" workers who ended up finding jobs relatively quickly when optimistic are made worse off. Further, there is an increase in labor market volatility. In addition to the reasons discussed above about how misperceptions affect the dynamic behavior of labor market variables, the added level change in, for example, u leads to a mechanical decline in standard deviations as relative fluctuations are less dampened by an overall higher level of unemployment.

1.7 Conclusion

This paper studies how worker job finding perceptions affect where unemployed workers choose to search and what impacts this has on the behavior of aggregate labor market variables. I begin by documenting how beliefs are an important aspect of a worker's attachment to the labor market, and that they are time varying at the business cycle frequency. Next, I characterize these beliefs in terms of job finding probabilities with the SCE. In particular, I find that workers believe that the monthly job finding probability is twice as high as the realized probability, on-average, which is consistent with findings by [1] and [2] on the ubiquity of bias in job seeker perceptions about job finding. To assess the implications of these misperceptions, I develop a model of directed search with uncertainty over the matching technology and learning frictions, allowing for a disconnect between workers' *subjective* and *objective* job finding probabilities.

The model is able to sustain biased job seeker beliefs in equilibrium. Though agents are assumed to update after experience searching in the labor market, search and learning frictions keep them from perfectly learning about the uncertainty. The model is also consistent with other findings that the subjective job finding probability is flat (or sometimes increasing) with unemployment tenure ([2]). I interpret this *not* as agents failing to update, but that updates are slow and that search re-direction leads workers to apply to lower-valued jobs in tighter sub-market. This idea is born out with other evidence on systematic, or sequential, job search where workers typically apply to favorable, higher paying jobs early in an unemployment spell, and relatively worse ones later ([6]).

After calibrating I find that job finding misperceptions dampen the volatility of labor market variables. Key to these results is the distinction of composition and individual effects. That is, how these beliefs affect the type of workers searching versus how they affect an individual's choices. Whereas the composition effect suggests that this uncertainty attenuates volatilities, the individual effects governing where individuals search for work is found to work in the opposite direction. This contrasts with models of random search, for example the standard DMP setup, where workers cannot adjust to directly affect their job finding probability. There, all effects from beliefs would occur as a result of changing the bargaining position of workers or the vacancy posting behavior of firms. In any regard, the composition effect is found to dominate quantitatively, reducing the volatility of the unemployment rate by about 10%.[7] Finally, using the model as a laboratory to carry out a counterfactual experiment, I find that on-average optimistic beliefs inflate the equilibrium unemployment rate 0.6pp and increase the average number of weeks spent in an unemployment spell by 1.5 weeks.

What is not clear is whether workers are better off when their beliefs are corrected. Less time is spent unemployed and there are fewer agents searching for work, but wages are lower and unemployment volatility is higher. Further, higher wages when beliefs are optimistic are experienced by a large proportion of the labor force, while the decreased unemployment hazard is incurred by a relatively small proportion.

Overall, the findings of the model suggest an important role for biased job seeker perceptions for the behavior of labor markets. More broadly they motivate the importance of understanding how the experiences of job seekers when looking for work affect labor

[7]That is, one can view these findings as a conservative estimate for the effects on dynamics.

market decisions. Next, while the present paper abstracts away from the participation margin, the notion of labor market attachment studied above is naturally related to the decision of workers to look for work at all. Moreover, job finding beliefs in the presence of on-the-job search may also help to contextualize other observations in data, such as the patterns of job-to-job transitions. Such channels are ostensibly important, and left for future research.

Chapter 2

On-the-Job Leisure

with Christine Braun and Peter Rupert

2.1 Introduction

The presence of on-the-job leisure (OJL), that is, non-work at work, drives a wedge between measured hours of work and actual hours of work. OJL here is not time off at work, such as scheduled lunch or breaks, but time spent not working outside of official time off. If actual hours of work are lower than measured hours, productivity and wages are actually higher than those calculated by the Bureau of Labor Statistics, for example. We document the extent of on-the-job leisure and embed it into a model of technological change with imperfect monitoring to examine its effect on productivity and wages. Using the American Time Use Survey we show that for those workers who engage in OJL spend about 50 minutes per day doing so.

Technological innovations, while making an hour's of work more valuable, may also make it easier to engage in OJL. Apps, such as Snapchat and Facebook provide random opportunities during the workday to communicate with family and friends. Amazon allows shopping to be done quickly at any time. The fact that these opportunities arrive randomly during the day makes it less advantageous to take leisure through a shorter workday. OJL, then, is an optimal arrangement between the firm and worker to split the returns from better technologies. The amount of OJL is determined via Nash bargaining over wages and OJL.

This paper makes several contributions. First, empirically, we explore the importance of OJL coming from random opportunities to respond to non-work emails, social media, shopping, etc., that we label *distractions*. Second, we construct a model of OJL and use the model to construct a longer time series than that in the ATUS beginning in 2003. The longer time series is then used to see how the mismeasurement of hours might be affecting the measurement of such things as productivity and wages.

We find evidence that new innovations increase OJL on the extensive margin as more people engage in it. However, we also find that new innovations do not increase the intensive margin of OJL for those already engaging in it. At the aggregate level, we find that on-the-job leisure is pro-cyclical. We also explore how how wages and unemployment rates affect engagement in OJL. We find evidence that higher wages and higher unemployment rates act as a deterrent to engaging in on-the-job leisure; but, workers will undertake *more* OJL should they already choose to do so.

2.2 Related Literature

The present paper, since it focuses on the correct measurement of hours of work, relates closely to a literature on quantifying the labor input. This "quality hour adjustment" literature has roots at least as early as [39]. Its main focus stems from the idea that workers' hours are not directly comparable, especially when trying to back out estimates of productivity. For example, in the presence of skill-biased technical change, hours supplied by segments of the workforce that do not procure benefits of the technological innovations may dilute productivity measurements. A feature of the corrections implied by this line of work suggest that quality adjusted series, in relation to standard hours, are less cyclical and (depending on the nature of the corrections) display different secular trends [40, 41, 42]. These adjustments, however, do not directly account for agency on the part of employees to not work when at work.

Recent work by [43] has indicated that time spent in non-work is significant (about 7% of the workday). They also find that on-the-job leisure is pro-cyclical, providing support for the efficiency wage hypothesis of labor markets. More specifically, the pro-cyclicality of shirking (or "loafing" as it's distinguished in their paper) suggests wages form such that they are above the market clearing level, and that this induces relatively higher productivity and efficiency by workers when unemployment is high because the costs associated with job separation are more costly. In the classic model of [44], this mechanism is driven by a principal-agent problem wherein imperfect monitoring opens up the possibility of shirking. More broadly, [45]'s synthesis of the efficiency wage literature highlights four main channels through which they may arise: to avoid shirking, worker turnover, to combat adverse adverse selection, or because of social convention. In these different models, the efficiency wage mechanism functions in part because of contracting limitations. With shirking, firms cannot easily contract directly on effort. In the labor turnover models, costly training suggests an opportunity of charging new hires a fee to begin employment. The adverse selection flavor of this class of models, for example [46], casts the contracting struggle as one of uncertainty about the productivity of the employee. Last, social conventions, oftentimes outside of the scope of a formal modeling environment, can inhibit the nature of the employee-employer relationship.

The present paper extends the preliminary work of [43], focusing primarily on constructing an aggregate U.S. time series for on-the-job leisure. Combining both intensive (how much time is spent) and extensive (the decision to spend any time) margin results, we also find that (on net) on-the-job leisure is pro-cyclical. This is qualitatively consistent with the efficiency wage hypothesis, where wages form above market clearing levels so as to induce workers to not shirk. Unlike the standard implementation of the theory, we document and utilize the importance of real wages, the unemployment rate, and a measure of "distractions" on the decision to engage in non-work at work.

This paper also contributes to understanding some documented changes in postwar U.S. data by, for example, [47]. Most notably, they find that labor productivity, like many other aggregate series, is much less pro-cyclical than it once was. In the context of mis-measuring the number of hours actually worked by employees, the present paper finds that productive advancements can be partially absorbed by on-the-job leisure motives, which can be reflected in both reported labor productivity and wages. Due to the procyclicality of leisure, labor productivity (and real compensation) may have correlations with aggregate output that are attenuated. Further, by distinguishing between reported (observed) and actual (observed less leisure time) hours, we find that these series appear to be less volatile than they actually are because of the presence of an alternative margin of adjustment by workers and firms, namely the ability to adjust hours worked without much affecting the total number of hours spent at work.

This paper, in its focus on the effects of productivity estimates, is also related to a series of other works about measurement and accounting. One literature, in its assessment of the post-2004 productivity slowdown, examines whether or not the United States is experiencing stagnating productivity growth, or if the gains of technological progress are in someway unobserved or unaccounted for ([48, 49, 50, 51]). [52] find little evidence that the productivity slowdown is arising from growing mis-measurement of the gains from IT advances. [53] takes a different approach and argues that *intangible* capital, which is invested into at rates similar to that of tangible capital, is ignored in standard measures of GDP. As a result, estimated TFPs may understate and fail to reflect the true aggregate measure of productivity. While these papers focus on the capital side of the production function, the present paper complements these findings and may suggest interesting extensions to determine how, and by how much, these forces interact.

One last literature to note of, and perhaps most closely related to the end-goal of the present work, looks closely at the growth accounting of productivity series in the U.S. economy ([54, 55, 56]). Of particular importance to the alternative series that are proposed are corrections for fluctuations in factor utilization. Heterogeneity across the business cycle in the composition or efficacy of labor and capital can have meaningful effects on measured productivity, and so appropriately controlling for these changes is key. Our findings suggest that on-the-job leisure is an additional ingredient in getting the correct inputs for backing out productivity estimates.

2.3 Data and Empirics

The main source of data comes from the 2003-2016 releases of the ATUS, which (on top of a host of individual characteristics) contain information on what (and where) Americans spend their time. Conducted by the US Census Bureau and sponsored by the BLS, the ATUS contains a random sample of individuals who, within the last 2 to 5 months, have completed their final CPS interview. Typically conducted over the phone, a respondent is asked to recount what activities they engaged in, when and where these activities took place, and whether or not the activity was primary or secondary (for activities that are performed simultaneously). All of the activities in the diary day are then coded into one of over 400 categories. Because the present paper is concerned about leisure at work, we follow a sample selection protocol identical to that of [43]. To start, we keep only those observations which were recorded as having been performed at the workplace. Next, since this paper fundamentally concerns the implications of worker agency (at some cost to a principal), all workers that report being self-employed are dropped. Last, we keep only those respondents who report their usual weekly hours. This both allows us to control for differences in the chosen amount of time spent in non-work arising from differences in a more stable measure of how much time is spent at work (since weekly hours fluctuate less than daily hours) and also to disentangle differences in this decision that may arise because of circumstances of a particular diary day.

Using this sample, the main variables of interest are constructed as follows. *Total time at work* is straightforwardly defined as the sum of the time spent in all activities at the workplace. The *total amount of non-work* is calculated as all of the time spent in activities that are not classified as work. Specifically, time spent working is coded as categories 50101-50299 in the ATUS activity lexicon. This includes time spent working (typically the bulk of the time), but also time spent eating, socializing, relaxing, cleaning, etc. as part of the job. That is, time spent in mandatory breaks, for example, is classified as work. The measure for the *proportion of time at work spent in non-work* (total non-work over total time at work), thus, does not pick up differences in workers' contractual arrangements to perform duties not explicitly related to their main job. This is a desirable feature insofar as this measure captures all time that firms are not directly aware of being spent in non-work, which is of primary concern for the present research in its assessment of observed productivity. Less desirable, though, is that workers are presumably disinclined from disclosing information about time spent not doing work at work. This ubiquitous facet of survey-based data, however, will serve to understate the true effects of interest.

We supplement the above ATUS sample with unemployment data from the LAUS. Individuals are matched to their state's unemployment rate in the month in which they were interviewed. Following [43], we also calculate the 3-month average unemployment rate leading up to the interview date in order to help capture longer-term tendencies possibly at play in a worker's assessment of labor market conditions when deciding to engage in non-work. In all cases, use of the contemporary unemployment rate or the 3-month average yield virtually identical results. Real wages for workers are calculated as real weekly earnings,[1] matched from their final CPS interview, over weekly hours using the CPI.

Last, we consider that distractions throughout the day at the workplace are plausibly an important time-varying factor affecting on-the-job leisure. In particular, we hypothesize that changes in innovations may make workers simultaneously more productive with a unit of work but also more likely to get distracted. To test this, we utilize USPTO data on various categorizations of patents in order to proxy for changes in innovations over time. We calculate growth rates of total patents in-force and, inasmuch as we might expect this "distraction motive" to be integrally linked to innovations related to phones or computers, also the growth rates of patents related to communications, computer hardware / software, computer peripherals, and amusement devices.[2] Since the time between the issuance of a patent and the point at which the innovation penetrates markets varies from idea to idea, and something with which we have no prior, we use the growth rates of these patent categories over various time horizons leading up to the interview date. We plot these growth rates for multiple horizons in B.5. To get a general idea of the importance of these categories over time, we also plot the share of total patents for all the mentioned categories in B.6.[3]

Summary statistics are reported in B.1. Means are given unconditionally and conditional on spending any or no time in *on-the-job leisure* (captured by the dummy variable OJL). The average respondent admits to spending 6.7% (34.0 minutes) of their workday

[1] This measure is before tax and includes overtime pay, commissions, and any tips received.

[2] These correspond to NBER categories 21-23 and 62.

[3] It should be noted that at the time of writing, USPTO historical patent data are only available through 2014, and so regression results with patent growths included do not contain observations from the 2015 and 2016 releases of the ATUS.

in leisure. Conditional on reporting any time in leisure at work, this figure increases to 9.9% (or 53.2 minutes) of the workday. Also reported is the significance level of a test of the difference in conditional means. For instance, we can see that those who engage in on-the-job leisure have (on average) lower real wages, spend more time at work, and have about a half of a year more experience.[4] To better understand the choice to engage in non-work at work, we regress many of the above variables on both the proportion of time spent in non-work and whether or not workers engaged in any non-work time. As with the discussions in [57] and [43] about the idiosyncrasies of time use data, we employ a combination of OLS and Probit specifications to tease out the relationships between the observables and on-the-job leisure.

OLS, using the *proportion of non-work at work* as the dependent variable, allows us to disentangle the factors that influence on-the-job leisure along the intensive margin. In addition to the issues surrounding survey-based data mentioned before, due to the presence of both "true" (i.e. censored) zeros and "day-to-day" zeros (i.e. those zeros that are observed because the respondent *does* perform the activity, just not on the day interviewed), the estimates are likely biased downward. As a result, we run OLS both on the whole sample and also conditional on observing a positive amount of non-work at work. In particular, we run

$$\begin{aligned} Prop_{joismy} = \beta_1 UErate_{smy} + \beta_2 ln(Rwage)_{joismy} + \beta_3' PatGrowth(t)_{my} \\ + \alpha' X_{joismy} + \gamma_o + \delta_i + \zeta_s + \eta_m + \varepsilon_{joismy}, \end{aligned} \tag{2.1}$$

where j indexes individuals, o occupation, i industry, s state, m month, and y year. $UErate_{smy}$ is the measure of the unemployment rate mentioned earlier and $ln(Rwage)_{joismy}$ is the log of the real wage. $PatGrowth(t)_{my}$ is a vector of annualized growth rates of

[4]Since job histories are not observed, we use *potential* experience to infer the years of experience: $age - schooling - 6$.

in-force patent categories over the previous t months leading up to the respondent's interview date. We also include occupation, industry, state, and month fixed effects. X_{joismy} contains all other listed variables in B.1, including a female-by-married interaction and quadratic terms in age, experience, usual weekly hours, and total time at work. Concerning the relationships these variables have with non-work along the extensive margin, we run a Probit regression on a dummy variable that indicates a positive level of non-work at work. Per [57], because of the presence of "day-to-day" zeros, a Tobit approach, which may seem sensible, is ill-advised as it assumes that there are only "true" zeros. Indeed, [57] shows that the bias of Tobit estimates increases with the number of zeros (which is a concern with the sample). In particular, we run

$$\begin{aligned} OJL_{joismy} = \Phi\Big(&\widetilde{\beta}_1 UErate_{smy} + \widetilde{\beta}_2 ln(Rwage)_{joismy} + \widetilde{\beta}_3' PatGrowth(t)_{my} \\ &+ \widetilde{\alpha}' X_{joismy} + \widetilde{\gamma}_o + \widetilde{\delta}_i + \widetilde{\zeta}_s + \widetilde{\eta}_m + \widetilde{\varepsilon}_{joismy}\Big). \end{aligned} \tag{2.2}$$

Regression results are presented in B.2. Columns (1), (3), and (5) are the baseline results without controls for changes in innovations. First, consider the OLS results using the whole sample, specification (1). We can see that both coefficients are small, and that the unemployment rate is only marginally significant, but positive. The interpretation of the coefficient is that a 1pp higher (3-mo. average) unemployment rate is associated with 0.0007pp higher proportion of the day spend in non-work. Given a sample average of 41.33 hours of work, this translates to about 1.74 more minutes per week. Recalling the discussion about the issues surrounding survey-based time use data, we can get a better understanding of the relationships of these variables and the intensive margin of on-the-job leisure by conditioning on positive amounts of non-work, which is reported in column (3).

We can see that both the real wage and the unemployment rate are associated with *more* time spent in non-work. To get an idea about magnitudes, a 1% higher (real) wage would be associated with an increase in the proportion of time spent in non-work by .45pp, or roughly 11.2 minutes per week. If we think of this measure of earnings as roughly approximating the incremental gain to consumption and/or savings per unit of time, the above result is consistent with the idea that higher wage rates can lead workers to substitute away from work and towards leisure. To put this in terms of a simple optimization problem, higher wages allow workers the ability to enjoy the same level of consumption with fewer hours of work, where there is added utility from increased leisure at work. Turning to the unemployment rate, an increase in 1pp is associated with a weekly increase in leisure at work of 4.2 minutes. This is consistent with the *labor hoarding hypothesis*. That is, firms find it more profitable to retain certain workers when unemployment is relatively high (and output relatively low), so that they don't have to pay the costs to rehire and retrain new workers later. Further, tying both results above together, those individuals with higher productivity (which should at least be partially born out in the wage) are relatively less dispensable, and so can "afford" to engage in *more* leisure on-the-job than their relatively more dispensable colleagues.

What can be said about the decision to engage in any non-work at all? The baseline Probit results are given in specification (5). Noting briefly the non-linearity of Probit specifications, we report the derivatives from the regression which are interpreted as average marginal effects. We can see that the extensive margin is *negatively* associated with increases in both the wage and unemployment rate. For instance, a 1% increase in the real wage is associated with a 2.35pp lower probability of observing a worker engage in on-the-job leisure. Given a sample average of 53.2 minutes per day spent in non-work by those reporting any positive amount of it, a 5-day work week would be expected to involve a decrease in on-the-job leisure of 6.17 minutes. A 1pp higher unemployment rate similarly decreases this probability by .24pp, yielding an expected weekly decrease of 0.67

minutes per worker, though the coefficient is only marginally significant. In any regard, these results suggest that on-the-job leisure along the extensive margin is consistent with the *efficiency wage hypothesis.* Here, employers pay wages above market clearing levels so as to disincentivize non-productive work. A positive equilibrium unemployment rate helps act as a worker-discipline device, as a worker forgoes lost wages for the duration of any unemployment spell.

At this point it is important to keep in mind that while these numbers may seem small, aggregating over the course of a quarter (13 weeks) and the total working U.S. population (over 150 million full- and part-time workers in 2016) can make the impact of these figures large for aggregate measures of the labor input. Taking both the intensive and extensive margins into account, a quick back-of-the-envelope calculation, simply to fix ideas of these magnitudes at an aggregate scale, would imply that a 1% increase in the real wage is roughly associated with 164 million more hours of on-the-job leisure per quarter, while a 1pp higher unemployment rate would be associated with 115 million more hours per quarter (holding other variables constant).

Still, the preceding results importantly ignore certain longer-term factors that influence the day-to-day decision to engage in this non-work. For example, comparing the daily access to general media (for example through cell phone use and internet access) in 2003 and 2016 is fairly staggering. Ex-ante, it seems plausible that technological advancements, which economists typically model as directly feeding into some notion of the productivity of factor inputs, might also make it easier for workers to engage in on-the-job leisure. Since technological advancements are related to the real wage (thinking of wages as some function of marginal products) and the unemployment rate (insofar as some theoretical notion of "productivity" affects output), not accounting for them potentially biases regression estimates. We add in growth rates of patents to address this concern and report the regression results in columns (2), (4), and (6). It is important to note that these added controls restrict our sample to through 2014 as the patent data are not available for 2015 and 2016. Whilst we run these regressions for various innovation growth horizons, we present the results for $t = 12$ (i.e. the one-year growth rate) in the table.

First, for the OLS regressions, we briefly note that the coefficients on the wage and unemployment rate are roughly the same as before, and that those on the growth rates are statistically indistinguishable from zero. That is, there is no evidence that this distraction motive affects on-the-job leisure along the intensive margin. There are noticeable effects, both statistically and economically, when looking at the extensive margin. The variables are scaled such that the coefficients can be read-off directly as the associated percentage point effect on the probability of observing a worker engage in on-the-job leisure from a 1pp increase in a patent category's growth, holding other category growths fixed. For example, a 1pp increase in total in-force patents, holding the growth rates of the other categories constant, *decreases* the probability of on-the-job leisure by 3.86pp. This translates to approximately 10.3 minutes per week, per worker. Similarly, 1pp higher one-year growth rates of the computer peripheral category, holding other growths constant, *increases* the probability by 0.87pp (2.3 minutes), amusement devices by 1.09pp (2.9 minutes), and computer hard/software by 1.21pp (3.2 minutes). Herein lies a fairly intuitive result. If these types of innovations are growing *faster* than those to innovations generally, there is an associated *increase* in the probability of observing a worker engage in leisure on-the-job. Given the growth rates and shares presented in B.5 and B.6, this evidence is suggestive that this distraction motive has been increasing over time.

Further, adding these controls greatly affects the estimated effect (and how tightly it's estimated) of the unemployment rate along the extensive margin. Without them, it appears as though the coefficient on the unemployment rate is absorbing the positive effects of the distraction motive. This also affects our back-of-the-envelope example earlier: a 1pp higher UE rate reduces the probability of observing a worker engage in non-work by .66pp, or an expected 1.76 minutes per worker per week. Taking into account both margins, a 1pp increase in the unemployment rate is associated with roughly 128 million more hours of on-the-job leisure. Next, we note that the choice to look at just the 12-month growth rate is somewhat arbitrary, though straightforward to interpret. We thus also estimate the model for 1 to 24 month horizons and plot the Probit derivatives, along with their 95% confidence intervals, in B.7.[5]

We can see that all categories have effects that are very small and indistinguishable from zero for very short horizons. Indeed, this is expected as very new innovations have hardly had the time to make their way into consumer products in any meaningful scale. As the horizon is lengthened, however, we see fairly gradual changes to these estimated effects in the order we might expect: the total category declines (recall this is holding the "distraction" categories constant) while all others but the communications category (which is always indistinguishable from zero) increases, peaking in magnitude around 12-16 months. Finally, for very long horizons, the effects (in magnitude) return toward zero. Considering that this "distraction" motive should be driven by *newer* innovations, our results make sense. It should also be noted that, as the horizon is lengthened, the variation of these growth rates over the sample declines, leading to noisier estimates. That is, the estimated effects are "racing against the clock" since, as the horizon increases, the estimates more accurately capture the true effect of this distraction motive even though there is a mechanical decline in the precision of the estimator.

In sum, the above results provide support to the distraction motive hypothesis. That is, technological advancements which would normally be associated with increases in measured productivity could be mitigated by increasing the amount of on-the-job leisure. Interestingly, this motive appears to only affect the extensive margin of leisure while at

[5] All growth rates are annualized so that the coefficients are comparable.

work. Where one might expect advancements of these sorts to increase the *value* of leisure to workers, similar to the findings of [58], the fact that there is no apparent increase in the amount of time an individual spends in non-work is consistent with the idea that these changes are resulting in an increased frequency of distractions pulling *more* people away from productive activities. In other words, should these innovations make leisure more valuable per unit of time, utility maximizing agents would be expected to increase the amount of time spent in non-work activities.

On top of the distraction motive, we have also documented the apparent importance of wages in a worker's leisure decisions at work, and how its net affect seems to be positive with wage increases. Inasmuch as on-the-job leisure and wages are choice variables of optimizing economic agents, there is concern with interpreting the above regression results as causal effects. To the extent that there may still be some confounding unobservables that we cannot control for that influence these variables, we turn to explicitly model, as transparently as possible, mechanisms consistent with the above results. Further, because of concerns with the month-by-month (and year-by-year) sample sizes, we caution the use of directly aggregating the ATUS sub-sample to construct an on-the-job leisure time series for the U.S. By modeling the mechanisms, however, we can not only utilize the relationships discovered above in the regressions, but also construct a longer leisure series for the U.S. by extrapolating with historical patent data (which extends back to 1981).

2.4 Model

The model is in discrete time with a unit measure of workers and an endogenous measure of firms. Agents discount the future at rate r. Workers search for jobs and firms search for workers and match according to a constant returns to scale matching function,

$$m = \mu u^{\psi} v^{1-\psi}, \tag{2.3}$$

where u is the measure of unemployed workers, v is the measure of vacant firms, and μ is a scaling parameter. Define $\theta \equiv v/u$, as labor market tightness, then the probability of finding a job is given as,

$$p(\theta) \equiv \frac{m}{u} = \mu\theta^{1-\psi} \tag{2.4}$$

Workers can be in one of two states, unemployed earning unemployment benefits or employed at some wage, w. If employed, a worker is endowed with one unit of time that can be spent either in productive activities or in *on-the-job* leisure, l. Workers have preferences over consumption and leisure, $\widetilde{u}(c,l)$, where $c = (1-l)w$. For ease of presentation, we define $u(w,l) \equiv \widetilde{u}\big((1-l)w, l\big)$. We assume that u is twice continuously differentiable, that $u_2(w,0)$ exists and is finite (this makes it *possible* for workers to choose *not* to engage in on-the-job leisure even if presented with an opportunity), and $u_{22}(w,l) = \infty$. Further, we assume that $\lim\limits_{l\to 1} u_2(w,l) = -\infty$, $\lim\limits_{w\to 0} u_{12}(w,l) = \infty$, and $\lim\limits_{w\to\infty} u_{12}(w,l) = 0$. These assumptions make it so workers do at least *some* work at work and are translations of standard Inada conditions on $\widetilde{u}$.

At work, leisure opportunities arrive stochastically with probability $\Lambda(g)$, where g is a measure for the level of distractions in the economy. We assume that $\Lambda_1(g) > 0$, i.e. the probability of a leisure opportunity is increasing in the amount of distractions. If an opportunity arrives the worker takes l amount of leisure, the amount is described below in detail. Separations occur according to an exogenous function that depends on the worker's amount of leisure at work, $s(l)$. We assume that s is twice continuously differentiable and that $s'(l) > 0$, the probability of being fired is increasing in on-the-job leisure.

The value of employment for a worker is the expectation over the flow value of working with contract $x = (w, l)$ plus the discounted expected value of his future state,

$$\begin{aligned}\mathcal{V}_E(x,\theta, g) &= \Big[1 - \Lambda(g)\Big]u(w, 0) + \Lambda(g)u(w, l) \\ &+ \frac{1}{1+r}\Bigg\{\Big[\big[1 - \Lambda(g)\big]\big(1 - s(0)\big) + \Lambda(g)\big(1 - s(l)\big)\Big]\mathcal{V}_E(\cdot') \\ &+ \Big[\big[1 - \Lambda(g)\big]s(0) + \Lambda(g)s(l)\Big]\mathcal{V}_U(\theta')\Bigg\},\end{aligned} \tag{2.5}$$

where V_U is the value of unemployment defined below.

When unemployed, workers receive unemployment benefits b and search for jobs. The value of unemployment for a worker is his benefits plus his expected future state,

$$\mathcal{V}_U(\theta) = b + \frac{1}{1+r}\Big[p(\theta)\mathcal{V}_E(x', \theta', g') + (1 - p(\theta))\mathcal{V}_U(\theta')\Big]. \tag{2.6}$$

Firms consist of a single job which can either be vacant or filled. The total output of a filled job, y, depends on aggregate productivity, A and the amount of leisure taken by the worker,

$$y = A(1 - l). \tag{2.7}$$

Firms post vacancies at a flow cost of κ per period and are matched with a worker with probability $q(\theta) \equiv p(\theta)/\theta$. The value function of a vacant firm is

$$\mathcal{V}_V(\theta) = -\kappa + \frac{1}{1+r}\Big\{q(\theta)\mathcal{V}_F(A', x', \theta', g') + (1 - q(\theta))\mathcal{V}_V(\theta')\Big\}, \tag{2.8}$$

where $V_F(w, l)$ is the value of a filled job. With free entry of firms the value of a vacant job is driven to zero. The value of a filled job is the expected value of total output minus the wage paid, plus the expected future state of the job,

$$\begin{aligned}\mathcal{V}_F(A,x,\theta,g) &= [1-\Lambda(g)](A-w)+\Lambda(g)(A(1-l)-(1-l)w)\\&+\frac{1}{1+r}\Big\{\big[[1-\Lambda(g)](1-s(0))+\Lambda(g)(1-s(l))\big]\mathcal{V}_F(\cdot')\\&+\big[[1-\Lambda(g)]s(0)+\Lambda(g)s(l)\big]\mathcal{V}_V(\theta')\Big\}.\end{aligned} \tag{2.9}$$

2.4.1 Wages and Leisure

When a worker and firm meet, the wage paid and the amount of leisure on the job taken, if given an opportunity, is determined through Nash Bargaining. Wages and leisure are bargained at the beginning of every period. We assume that a firm knows that leisure opportunities exits, however it cannot monitor how much leisure a worker is taking on the job, leading to a constrained bargaining problem. The constraint is an incentive compatibility constraint for the worker, i.e., the worker does not deviate from the Nash solution for leisure on the job when an opportunity arises. That is, for any outcome of the bargained wage the outcome of the bargained leisure must give the worker at least as much value as deviating to any other amount of leisure:

$$\mathcal{V}_E\big((w,l)\cdot\big) \geq \max_{l} \mathcal{V}_E\big((w,l),\cdot\big) \tag{2.10}$$

The constrained Nash Product is thus,

$$(w^*,l^*) \in \underset{w,l}{\operatorname{argmax}}\Big[\mathcal{V}_E\big((w,l),\cdot\big)-\mathcal{V}_U(\cdot)\Big]^{\beta}\Big[\mathcal{V}_F\big((w,l),\cdot\big)-\mathcal{V}_V(\cdot)\Big]^{(1-\beta)}, \tag{2.11}$$

subject to 2.10. If the worker's incentive compatibility constraint holds with equality at *at most* one l (given w), allowing either workers to choose l^* or firms to ensure l^* is defined in the contract is equivalent. As such, the bargaining problem can be reduced to a single argument, w. Below we prove under which conditions there exists a single solution to the worker's incentive compatibility constraint.

Lemma: If there are gains to employment, i.e. $\mathcal{V}_E - \mathcal{V}_U > 0$, and $s''(l) > (1 + r)\Big[V_E(w', l') - V_U\Big]^{-1} u_{22}(w, l)$, there exists one solution, $\hat{l}(w)$ to the worker incentive compatibility constraint for each w. *Proof:* Take w as fixed. First, assuming an interior solution, take the first order condition with respect to l and rearrange,

$$u_2(w, l) = s'(l)\frac{\mathcal{V}_E(w', l') - \mathcal{V}_U}{1 + r}. \tag{2.12}$$

Since it is assumed that $u_{22}(w, l) < 0$, the left hand side (LHS) of 2.12 is decreasing in l. Differentiating the right hand side (RHS) of 2.12 with respect to l:

$$\begin{aligned}\frac{\partial RHS}{\partial l} &= s''(l)\frac{\mathcal{V}_E(w', l') - \mathcal{V}_U}{1 + r} \\ &> u_{22}(w, l) \\ &= \frac{\partial LHS}{\partial l}.\end{aligned}$$

Noting that the assumption on $s_{11}(l)$ is used to establish the inequality. Because we have assumed that $u_2(w, 0)$ exists and is finite, that $\lim_{l \to 1} u_2(w, l) = -\infty$, and that both $u(w, l)$ and $s(l)$ are twice continuously differentiable, there exists at most one point $\hat{l}(w) \in [0, 1)$ that makes the FOC hold with equality. The solution will be an interior solution on $[0, 1)$ if

$$u_2(w, 0) \geq s'(0)\frac{\mathcal{V}_E - \mathcal{V}_U}{1 + r}. \tag{2.13}$$

If 2.13 does not hold, there is a corner solution wherein workers do not find it profitable to engage in on-the-job leisure even if presented with an opportunity; in this case $\hat{l}(w) = 0$.

■

Since there exists a unique solution to 2.10 it must be that $\mathcal{V}_E\big((w,l),\cdot\big) = \max_l \mathcal{V}_E\big((w,\hat{l}(w)),\cdot\big)$. Thus the Nash Bargaining problem can be rewritten as follows:

$$w^* = \underset{w}{\operatorname{argmax}} \left[\widetilde{\mathcal{V}}_E\big(w,\theta,g\big) - \mathcal{V}_U(\theta)\right]^{\beta} \left[\widetilde{\mathcal{V}}_F\big(A,w,\theta,g\big)\right]^{1-\beta} \tag{2.14}$$

where tildes simply refer to the reduced-state value functions and where $\hat{l}(w)$ is the solution to 2.10. Then, the amount of leisure a worker takes given an opportunity is $l^* = \hat{l}(w^*)$.

2.5 Calibration

Wages are taken to be the average (per capita) real (CPI adjusted) compensation (wage and salary disbursements) of all employees indexed to unity in 1981. It is important to note that these data are *not* corrected for on-the-job leisure. Using the structure of the model, however, we are able to back out the "correct" wages by solving for the root of the following equation.

$$w_{wrong} = w\Big[1 - \Lambda(g)l^*(w)\Big] \tag{2.15}$$

The unemployment, vacancy, and separation rates are taken directly from JOLTS. F, the exogenous measure of firms, is foune using the unemployment and vacancy rates. Finally, the job finding probability p is calculated as

$$p_t = 1 - \frac{\text{unemp}_{t+1} - \text{unemp}^{st}_{t+1}}{\text{unemp}_t},$$

where unemp_t is period t's total level of unemployment and unemp_t^{st} are all short-term unemployed workers (fewer than 5 weeks).

The utility function is assumed to be quasi-linear,

$$u(w,l) = \frac{\left[w(1-l)\right]^{1-\nu} - 1}{1-\nu} + \gamma l \tag{2.16}$$

The probability of receiving a leisure opportunity is given by

$$\Lambda(g) = \Phi\Big(\eta g + \lambda\Big), \tag{2.17}$$

where Φ is the standard normal cdf. Last, the exogenous separation rate *function* is assumed to be linear.

$$s(l) = \delta_0 + \delta_1 l \tag{2.18}$$

The above assumptions allow us to solve the optimal policy for workers in closed-form.

$$l^* = \begin{cases} 1 - \left(\frac{(1+r)w^{1-\nu}}{(1+r)\gamma - \delta_1 \left[V_E(w',p',g') - V_U(w',p') \right]} \right)^{1/\nu} & \text{if positive} \\ 0 & \text{else} \end{cases} \tag{2.19}$$

The model contains a total of 12 parameters. The discount rate is set to $r = .0025$, which corresponds to a 3 percent annual discount rate. The unemployment benefit parameter is set to $b = 0.4$. ψ is set to $\psi = 0.72$. β is set equal to the elasticity of the matching function as in Hosios. κ,is calibrated such that the mean labor market tightness equals that in the data in our calibration period, 0.44. μ is chosen such that the mean monthly job finding probability is the same as in our full 1981-2015 sample, 0.358. η and λ are jointly calibrated using the g series by targeting the average extensive uptake of on-the-job leisure and the average marginal effect of distractions on the probability of obtaining such an opportunity observed in the data. Letting $\widehat{\mathbb{E}}$ denote the sample analog of the expectations operator, we can write these two moments as follows.

$$m_1 = \widehat{\mathbb{E}}\Phi\Big(\eta g + \lambda\Big) \tag{2.20}$$

$$m_2 = \widehat{\mathbb{E}}\phi\Big(\eta g + \lambda\Big) * \eta, \tag{2.21}$$

where ϕ is the standard normal pdf. The remaining four parameters are jointly calibrated to hit four targets. We target the average intensive uptake of on-the-job leisure by those who are observed to spend any time in non-work.

$$m_3 = \widehat{\mathbb{E}}l^* \tag{2.22}$$

Having accounted for both extensive and intensive margin averages, we concern ourselves with the *net* wage and unemployment effects. That is, since we found that the intensive margin dominates for both variables, we construct two moments by targeting the average net effect on the intensive uptake of on-the-job leisure. This is done not without loss of generality. While this simplification prohibits detailed analysis of the intensive-vs.-extensive margins within the model, our focus here is on the behavior of the aggregated series. The above *netted* moments include the semi-elasticity of wages on leisure and the marginal effect of unemployment on leisure, given below respectively.

$$\begin{aligned} m_4 = \widehat{\mathbb{E}}\frac{\partial l^*}{\partial \ln(w)} = \widehat{\mathbb{E}}&\frac{-(1+r)^{\frac{1-\nu}{\nu}} w^{\frac{(1-\nu)^2}{\nu}}}{\nu\Big\{(1+r)\gamma - \delta_1 V_S\Big]\Big\}^{\frac{1+\nu}{\nu}}} \times \dots \\ &\dots\Bigg\{\Big[(1+r)\gamma - \delta_1 V_S\Big](1+r)(1-\nu)w^{1-\nu} - \Big[(1+r)w^{1-\nu}\Big]\delta_1\frac{\partial V_S}{\partial w}(1+g_w)w\Bigg\} \end{aligned} \tag{2.23}$$

$$m_5 = \widehat{\mathbb{E}}\mu \frac{\partial l^*}{\partial p}\frac{\partial p}{\partial u} = \widehat{\mathbb{E}}\mu(\psi - 1)\theta^{1-\psi}\left(\frac{1}{u}\right)\frac{(1+r)w^{1-\nu}}{\nu\Big\{(1+r)\gamma - \delta_1 V_S\Big\}^{\frac{1+\nu}{\nu}}}\frac{\partial V_S}{\partial p}. \tag{2.24}$$

Finally, we target the average measure of separations observed for the time period.

$$m_6 = \widehat{\mathbb{E}}\Big[\Lambda(g)s(0) + \Big(1 - \Lambda(g)\Big)s\big(l^*\big)\Big] \tag{2.25}$$

2.6 Results

Calibration results are presented in B.3. All targets are hit, perhaps unsurprisingly to the parsimony of the model and exactly-identified nature of the exercise. Using this calibration, we then feed through observed series extending back to 1981, including g, w, and p, in order to extrapolate an extensive series (the proportion of the employed population engaging non-work) and an intensive series (the proportion of any given day spent in such activities by an average worker) of on-the-job leisure. The aggregated series is then constructed by taking the product of the extensive and intensive margins and the number of reported hours at work (hours of all nonfarm business sector).

$$OJL(w, p, g, H_{reported}) = \Lambda(g)l^*(w, p)H_{reported}, \tag{2.26}$$

This series is plotted in B.9. The top graph displays the series with its Hodrick-Prescott filtered trend, while the bottom graph plots the deviation from trend. Notable is the large increase in on-the-job leisure throughout the 1990s, driven primarily by growth in leisure-related technologies (i.e. sources for distractions). Not surprisingly, the rapid period of growth at the end of the 1990s and beginning of the 2000s generated by the model coincides with similar movements in the availability and use of cell phones and the internet.

The bottom graph of B.9 plots the deviation from trend of the produced series. Apparent here is the pro-cyclicality of on-the-job leisure. B.4 displays the standard deviations and correlations of our variables of interest. Non-work at work has a correlation coefficient of -0.59 with the unemployment rate and 0.80 with aggregate output, i.e. is pro-cyclical. Recalling the earlier regression results where it was found that the net effect of wages and the unemployment rate on non-work was positive (i.e. working against each other over the course of a business cycle as u and GDP are negatively correlated), the realized magnitudes of changes in these series over time produce an aggregated series that moves with the cycle. In other words, though the earlier estimates suggest on-the-job leisure could be counter-cyclical, the effect of wages dominates at an aggregate level.

We then use the constructed series for leisure to correct the reported series for aggregate hours, labor productivity, and real compensation for the United States. These results are presented in B.10, B.11, and B.12. Each of these graphs plots the raw series (both "reported" and "actual") along with its Hodrick-Prescott filtered trends, the associated deviations from trend, and, lastly, the year-over-year growth rates.[6] Overall, both the reported and adjusted, "actual" series are relatively parallel to one another up until the late 90s. As on-the-job leisure increases the series begin to diverge. While the most rapid divergence occurs in the late 90s, its behavior is more nuanced thereafter. The difference in trends of the actual and reported series of labor productivity and real compensation (which are integrally tied / similar to the trend of the aggregate on-the-job leisure series) are plotted in the top panel of B.13. We can see that this difference is positive and increasing from 1984-2000, but declining between the early-2000 labor market recession and the Great Recession. Starting soon after the recent recession, though,

[6]Note that the reported series are indexed to July 2009.

the trend of on-the-job leisure has returned to its earlier, upward trajectory. A similar pattern can be seen in the year-over-year growth rates. The rapid period of growth saw actual growths of labor productivity and real compensation between 1 and 2 percentage point higher than reported. More recent realizations put actual growths between 0 and 0.7 percentage points higher.

Next, we explore the higher-order moments of these series (B.4). First, note that the volatility of hours spent in on-the-job leisure is much higher than those spent working (or at work), suggesting that the leisure is an important margin of adjustment for workers and firms. As a result, total hours, labor productivity, and real compensation all exhibit higher volatilities after adjusting for on-the-job leisure.

The pro-cyclicality of the leisure series also reduces the pro-cyclicality of the hours series. As the developments over the course of a cycle enable workers the ability to enjoy more leisure at work, the increase in reported hours spent at the workplace over this time frame are diluted by this increase in non-productive time. This dilution has associated implications for the cyclicality of labor productivity and compensation. Regarding the former, much attention has been given to the decoupling of the pro-cyclical relationship between labor productivity and output during the great moderation ([59], [47]). The analysis here reconciles part of this change as stemming from issues of measurement. Correcting for on-the-job leisure, the contemporaneous correlation of labor productivity and output goes from 0 (statistically) to 0.37. Firms and workers using leisure as a margin of adjustment while keeping hours at work (relatively) constant can make notions of productivity appear to be less dynamic than they actually are. A similar story is true of real compensation. Imputed wages in the presence of non-productive time at work can distort gains accrued to non-monetary, i.e. temporal, aspects of a worker's well-being.

2.7 Conclusion

The productivity slowdown and stagnating wages have been the subject of great attention and study. We explore this topic from a slightly different perspective: one that questions whether our measure of productivity (and wages) is accurate. We find that on-the-job leisure significantly affects the bias of reported-vs.-actual labor productivity and wages, where the "actual" values are defined as output and earnings per hour *actually worked* – i.e. net of on-the-job leisure. We find that, in the aggregate, on-the-job leisure is pro-cyclical, which is qualitatively consistent with efficiency wage motives. This pro-cyclicality can partially explain the noted decline in correlation of productivity and output. Further, the high volatility of leisure time relative to time at work suggests that this is an important margin of adjustment for workers / firms and can also reconcile the decline in volatility of U.S. time series.

We find that the behavior of the leisure series is driven by three major influences. First, an (on-net) intensive increase of on-the-job leisure stemming from actual wage growth. As we model, this behavior as (observed in the data) is consistent with workers substituting away from work and towards leisure because higher wage rates allow workers the ability to achieve the same level of consumption with fewer hours of work. Second, (on-net) intensive increases in leisure stemming from increases in the unemployment rate. Here, labor hoarding motives suggest that (ceteris paribus) firms are retaining workers during periods of high unemployment so as to avoid the costs of rehiring later. Third, and finally, extensive fluctuations in on-the-job leisure are shown to be consistent with the "distraction motive," our term for the idea that productive advancements may make workers more productive, but also more likely to be observed in on-the-job leisure. Using historical patent data to proxy for productive advancements, we find evidence in the data of such a mechanism.

Our analysis not only provides evidence of the importance of on-the-job leisure to measured productivity and compensation, but also explores the structures that would lead to such observations. This can be useful for other research, where realism in the behavior of the labor input is important, and opens up new questions about the effect that such a model feature has on other variables.

Chapter 3

The Sharing Economy and Rental Markets

with Daniel Cullen

3.1 Introduction

The peer-to-peer rental market has seen rapid growth since the introduction of *Airbnb* in 2008 and *Uber* in 2009. These platforms allow individuals to share and use goods and services that might have otherwise been underutilized. In the *Airbnb* example, entire apartments, houses, or individual rooms can be rented on a short-term basis. This increasingly prominent way to interact in the economy has led to regulatory battles throughout the United States as housing affordability has become a major political issue. Much of the discussion on how to regulate the short-term rental market has centered specifically on *Airbnb*. Before regulations are implemented it is important to understand the effects these markets have on rental and housing markets, as well as the impact on local residents. Proponents of these peer-to-peer markets argue that users of these services will see many benefits, including additional income, more efficient resource allocation, and the creation of new economic activity,[1] while opponents argue that these markets avoid regulations and increase rents for local renters.

The present research contributes to this discussion by studying the effect of peer-to-peer housing technologies on traditional, *impermanent* markets for accommodation. That is, we study how rental properties affect the availability and price of hotels and long-term (annually leased) rentals. To guide our work we endeavor to address two questions, one positive and the other normative. (1) How are the number of *Airbnb* listings in an area related to the average price paid for rentals / hotels and (2) What is the optimal way to regulate the market for short-run accommodation? In this effort we construct and use a novel dataset for the Santa Barbara, California housing market. We combine hotel price and vacancy data for hotels (*Visit Santa Barbara*) with information on rental properties readily available from the U.S. Census Bureau's *American Community Survey (ACS)*. Finally, we rely on scraped *Airbnb* data collected by *Inside Airbnb* and Tom Slee.

Though the data are rich in many respects, purely reduced form analyses of such markets may suffer from an inability to isolate exogenous variation in the key covariates and identify causal relationships. Even using fixed effects and controlling for amenity heterogeneity using proxy variables, identifying causal estimates without bias is implausible. Indeed, this difficulty is inherent to identification in the housing literature because amenity values are imperfectly measured. To circumvent some of these issues we develop a structural search and matching model where property managers post vacant rooms (and their prices) and tenants direct their search to these postings. By fully defining and describing the agents, their actions, and the equilibrium, we bypass the need to directly address amenity heterogeneity and instead can use observables and the model's struc-

[1] https://blog.atairbnb.com/economic-impacts-los-angeles/

ture to disentangle the mechanisms at play.[2]. Discrete agent types and the contracts they make with one another define three separate–but endogenously related–markets for lodging. Hotels are accessible by innkeepers and visitors, short-term rentals by visitors and landlords, and long-term rentals by landlords and residents. The key feature is that, since multiple markets are available to some agents, behavior in one market may influence the outcomes in the others. For example, a landlord's decision to list a property in the short-term market negatively affects residents who are seeking long-term accommodation.

After calibrating the model we find that *Airbnb*s decrease hotel prices by about \$24 while they increase average rents by \$39 per month. The added choice afforded to visitors, though, increases their flow utility by about 3%. This is offset quantitatively to losses in welfare of residents, who have fewer rentals to search for and higher prices. We ultimately find that, with limited entry, aggregate welfare is *lower* with *Airbnb*. Search decisions by visitors and landlords do not internalize the costs to innkeepers and residents. As a result, government policy can improve efficiency. We find that the optimal policy is to set a high transient occupancy tax on short-term rentals as the lost utility to residents is quantitatively dominant.

This paper relates to a limited yet growing literature on the relationship between short-term, peer-to-peer rental markets and traditional housing and rental markets. A majority of this scholarship is case studies of individual cities. For example, [60] suggests that *Airbnb* listings are limiting the supply of rentals for long-term use and pushing up rents in the Los Angeles housing market. He goes on to recommend a set of regulations and taxes that would help lead to more affordable housing. [61] utilize data from online apartment and *Airbnb* listings to evaluate the growth of *Airbnb* on asking rents in Boston. Using a fixed effects model, they show that a one standard deviation increase in *Airbnb*

[2]To put this in a slightly different context, the model allows us to disentangle simultaneous equations that would, in a reduced form, introduce bias.

listings is associated with a 0.4% increase in asking rents in Boston.

Others have explored the heterogeneous impact–both within and between cities—of these peer-to-peer technologies. [62] explore the usage of *Airbnb* across neighborhoods in New York City to look at this differential impact. Using matched census tract level data from *Airbnb* with neighborhood rent data produced by *Zillow*, they find that *Airbnb* listings have become more geographically dispersed over time. They also find that short-term rentals appear most profitable relative to long-term rentals in outlying, middle-income neighborhoods. These concerns are not only limited to the United States. [63] provide an overview of *Airbnb* in fourteen European cities. They find that the presence of *Airbnb* in a market negatively effects hotel occupancy rates, but positively effects average daily hotel rates. They also find an ambiguous impact on the rental market, suggesting that *Airbnb* may have heterogeneous effects on the rental market.

[64] investigate when and where *Airbnb* listing are offered in London and the socio-economics conditions of the areas with concentrated *Airbnb* usage. They find that *Airbnb* listings tend to be in areas that are accessible to public transit, and have residents who are young, employed, and born outside the UK. [65] study the effect of *Airbnb* listings on rental rate in Barcelona, Spain. Using multiple econometric specifications, they find that a neighborhood with the average amount of *Airbnb* activity saw rents increase by 1.9%. While neighborhoods in the top 10% percent of *Airbnb* activity, saw increased rents by 7%. Looking to French cities, [66] show that increase in *Airbnb* rentals is associated with increased rents in Lyon, Montpellier, and Paris, however *Airbnb* has no significant effect in other cities. Understanding how this heterogeneity in effect arises is an important characteristic for policy makers to study and understand.

[67] offer the most complete look at the impact of *Airbnb* listings on rent and house prices across the United States. Using an instrumental variable approach they estimate that a 1% increase in *Airbnb* listings leads to a 0.018% increase in rental prices and

a 0.026% increase in home prices. Doing a quick back-of-the-envelope calculation, this corresponds to a \$9 increase in monthly rent and \$1,800 increase in house prices. In addition they find that *Airbnb* does not impact the total supply of housing but does decrease the supply of long-term rentals. The model we write down is informed by this finding insofar as we take the supply of rental properties as given, but endogenously allow the fraction of vacancies posted in in one market or another to depend on market conditions.

Our paper also relates to a theoretical literature on search and matching in housing markets. Dating back at least as early as [68], models with search frictions have a lot of appeal in the context of buying and selling property. First, they offer a realistic and intuitive reason for vacant properties to exist in equilibrium by taking seriously the idea that markets may clear through prices *and* time. [69] use a random search framework to study buyer and seller contact hazards and time on the market. Second, models with search frictions have also had varied success in describing and explaining price dispersion ([70]). [71] and [72] think about search strategies (e.g. where to direct search, when to make an offer, etc.) and their role in the dynamism of housing markets.

Indeed, models of directed search are particularly attractive theoretically inasmuch as they seem to align with what happens in the real world. [73] develop and formalize multiple models of housing with price posting. We contribute to the above literature by applying the insights and tools of search theoretic models to *impermanent* lodging markets. More specifically, hotels and rental properties. In this effort we also seek to connect the often disjointed approach of looking at hotels and rentals separately. Finally, by explicitly modeling the endogenous relationships of key acting agents in these markets, we can therefore think in terms of normative assessments of optimal policy and address, perhaps incompletely, the discussions and debates about how peer-to-peer technologies should be governed.

In the next section we present and explore statistical facts about *Airbnb*, hotels, and rental properties in various regions. We also present and discuss some of the confounds and shortfalls of interpreting some of these results in the context of identifying the *effect* of *Airbnb* on these markets. We then develop a rich-yet-simple model of rental markets that allows us to circumvent some of these shortfalls and enables us to study the highly interrelated markets for lodging. We calibrate this model to a novel dataset that we construct for Santa Barbara, California, which we also use to assess questions of optimal policy regarding how to tax the various agents to maximize welfare. Finally, we conclude.

3.2 Empirical Regularities

In this section we present the main sources of data and establish the statistical relationship between *Airbnb* listings and the price of apartment rentals. Our empirical strategy likely does not identify the causal effect of these listings on the price of rental properties. Its purpose is to motivate the key mechanisms in our structural model of impermanent housing markets. We begin by examining the *Airbnb* data and the distribution of prices and the growth of listings in major American metro areas since 2017. From *Zillow* and the *American Community Survey* we merge the features of long-term (i.e. "traditional") rental markets: prices, stocks, and vacancies. These characteristics are then later used to calibrate the structural model.

Using this data we estimate the statistical relationship between the number of *Airbnb* listings and the median rental price using a simple fixed effects model. The implied effect is then used to compare to the results generated by the structural model. As this is the first paper to use a search and matching model in this setting, this exercise allows us to compare our results to the empirical literature.

3.2.1 Airbnb Data

The *Airbnb* data for major United States metro areas come from the free, publicly available data collected and hosted by *Inside Airbnb*[3]. Data for Santa Barbara was collected and provided publicly by Tom Slee[4] on his website. This data consists of information about the room type, price, number of reviews, and exact location of each listing. The data also consists of the availability calendar for the next year into the future. The calendar for a listing gives a price for dates that are available to book, but nights that are unavailable to book cannot be differentiated from nights that have already been booked. However we aggregate the calendar for each listing from the daily to monthly level. This means that if a listing is available for at least one day in a month the listing is considered active. We then calculate the price of a listing for the month by taking the median of its listed prices for the month.

Data are collected at *roughly* a monthly frequency, therefore we can observe many overlapping calendars for the same listing. In other words, for a listing collected in January 2017 we observe available nights for January 2017 to January 2018. When this listings data is collected again in February 2017 we observe February 2017 to February 2018, therefore we observe availability and prices for February 2017 to January 2017 twice in these two observations. This means we can observe data for a single month for a listing up to twelve times. The monthly price for a listing is calculated by finding the median monthly price in each observation then taking the maximum value across up to twelve monthly median price observations.[5]

[3]The data was sourced from publicly available information from the *Airbnb* site and cleaned and aggregated by *Inside Airbnb*. The is available under a Creative Commons CC0 1.0 Universal (CC0 1.0) "Public Domain Dedication" license at http://insideairbnb.com/get-the-data.html

[4]http://tomslee.net/airbnb-data-collection-get-the-data

[5]Doing this exercise by taking the mean or median of the observed prices does little to affect the analysis because the data is aggregated to the ZIP code level for each month and only the median monthly price for the entire ZIP code is used.

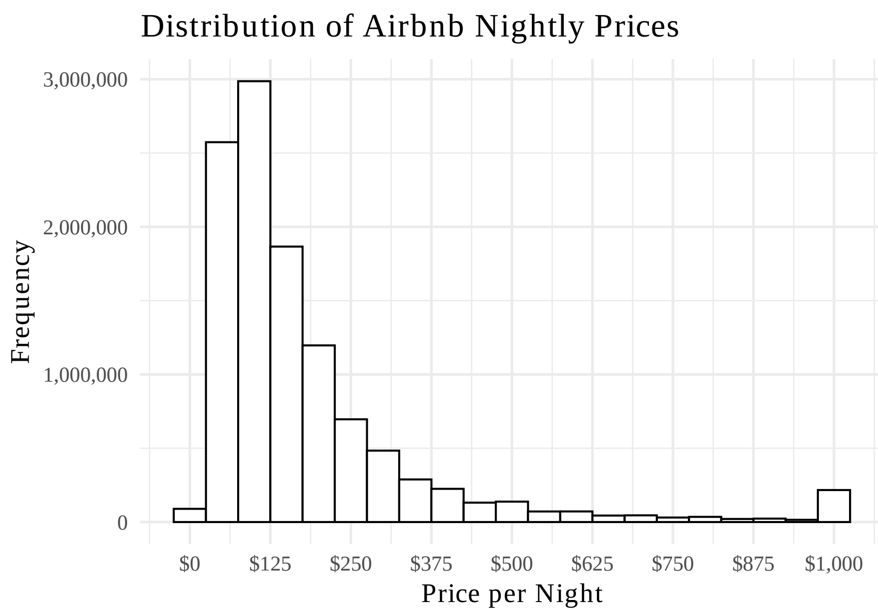


Figure 3.1: Distribution in the price of *Airbnb* listings for the entire dataset with price top coded at $1,000.

Our dataset contains listings for 12 cities: Boston, Chicago, Denver, Los Angeles, Nashville, New York City, Portland, San Diego, San Francisco, Santa Barbara, Seattle, and Washington DC. This data contains data on 477,314 unique listings for the years 2016 to 2020.[6] The distribution of *Airbnb* listing prices across the full sample can be seen in 3.1. The median price per night of an *Airbnb* listing is $125 and the majority of listings have a price between $75 and $200 per night. The median *Airbnb* nightly price is a key calibration target.

Since its introduction *Airbnb* has seen heterogeneous growth with some markets growing extremely quickly seeing growth of several hundred percent in only a few years while others have seen relatively slow growth. 3.2 presents the differences in growth between several large United States metro areas. This graph presents the time trend of the indexed number of rooms listed on *Airbnb* across from January 2017 to January 2020. We

[6]While, we use a full sample of cities for the empirical section which gives us a larger sample size and longer observation period, we calibrate the model using just data from Santa Barbara because we have richer data on the housing and hotel market available to us for that region.

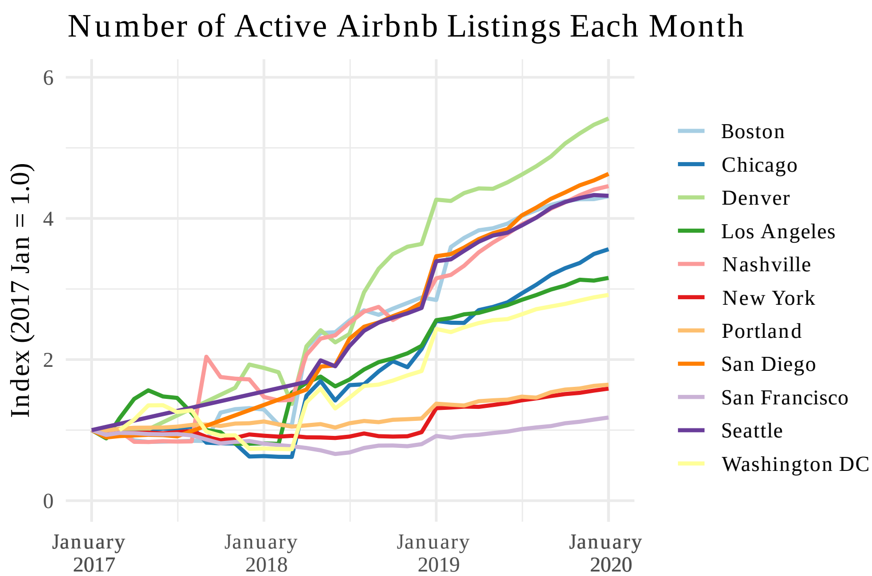


Figure 3.2: Monthly *Airbnb* listings across all room types.

can see some cities, such as Denver, are growing extremely quickly while other cities, especially those that already had a large number of *Airbnb* listings by January 2017, have seen much less growth in listings. There is also significant heterogeneity in the growth of *Airbnb* within metro areas. 3.3 shows the spatial heterogeneity in the growth in the number of rooms listed by ZIP code from January 2017 to January 2020. We can see that some area have seen much faster growth in the number of *Airbnb* listings than others.

3.2.2 Rental Market Data

Rental market price data comes from *Zillow.com*, an online real estate and rental marketplace company. *Zillow* maintains an online real estate database of over 110 million U.S. homes and estimates housing and rental prices across the United States. Because *Zillow* is used for finding houses and apartments listed for sale or rent, the price and rental rates represent the conditions in the long-term housing market. From *Zillow*, we use data on the median rental price of apartments of various sizes at the zip code level. In

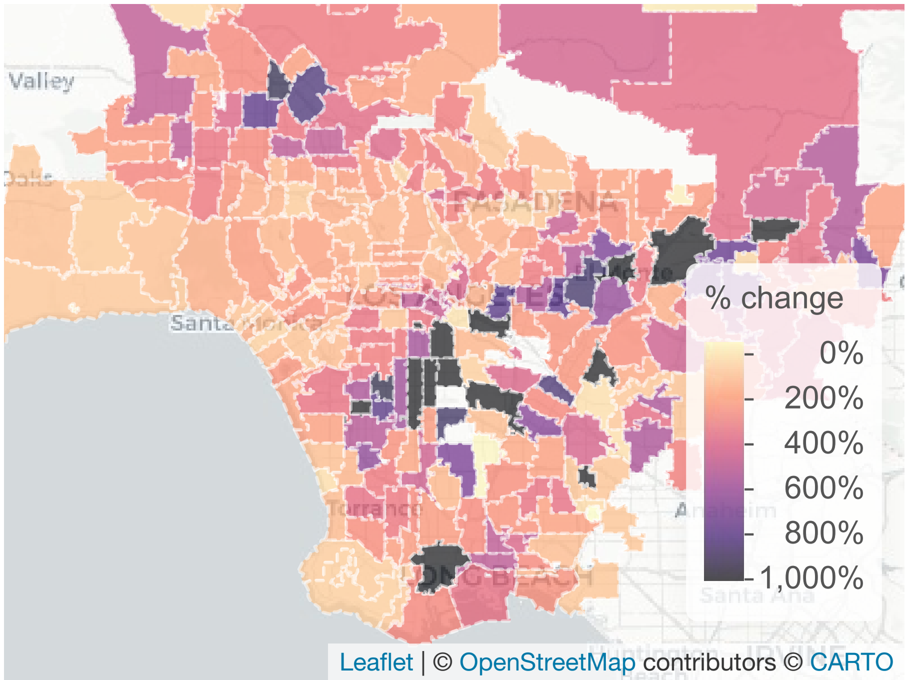


Figure 3.3: Change in the number of *Airbnb* listings from January 2017 to January 2020 by ZIP code in Los Angeles.

3.4 we see differences in the changes in the estimated price to rent a 1 bedroom apartment from January 2017 through December 2019. We can also see the heterogeneity of changes within Los Angeles in 3.5. While there isn't large change in the median rent price for a 1 bedroom apartment over this time period, there are large changes within the city.

In addition to *Zillow* housing data, additional housing data and socioeconomic variables come from the *American Community Survey* (*ACS*). From the *ACS*, we use the number of housing units, the number of occupied and vacant units, and the number of renter occupied housing units broken down by number of bedrooms at the ZIP code level for each year. This data is derived from the *ACS* 5-year estimates for the years 2014 to 2018. We use the 5-year estimates because this data offers better precision when working within geographic areas with smaller populations such as ZIP codes. The multiyear estimates are also useful for smoothing data trends over time ([74]), which we need to do because the *ACS* data is calculated at yearly frequency. We compute the monthly ZIP

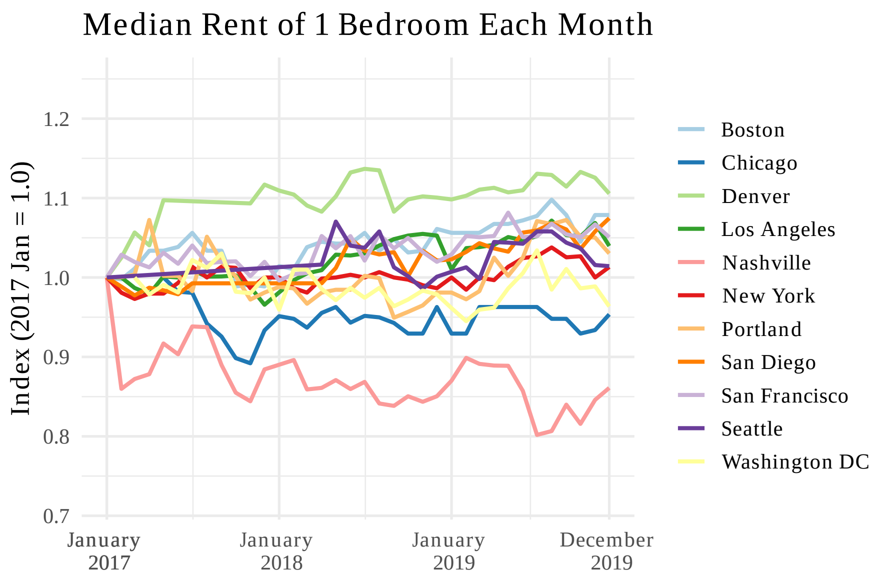


Figure 3.4: Monthly Price to Rent a 1 bedroom apartment.

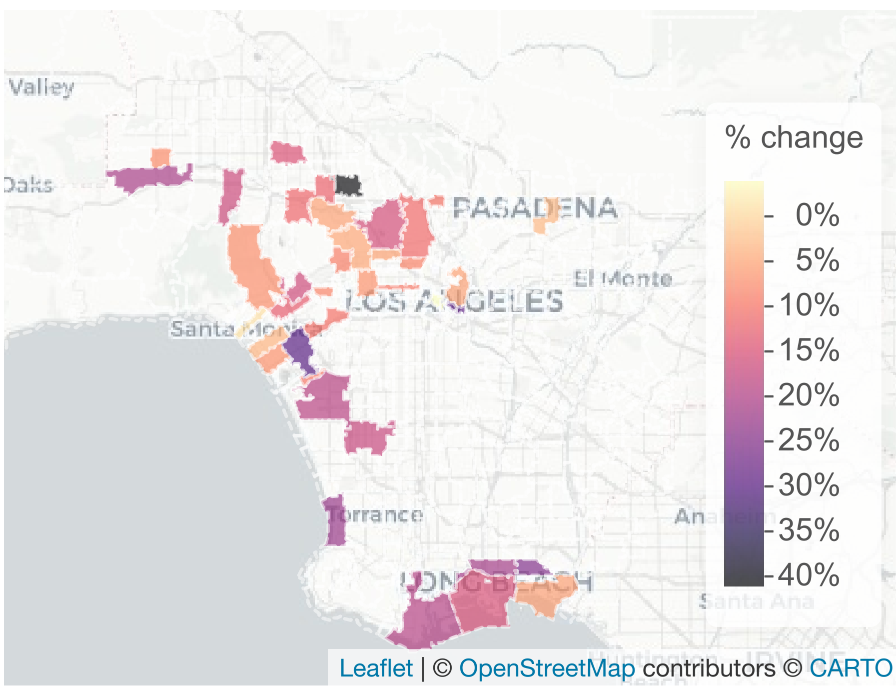


Figure 3.5: Change in the median price to Rent a 1 bedroom apartment from January 2017 through December 2019 by ZIP code in Los Angeles.

	min	p25	median	p75	max
December 2016					
Airbnb Listings	1.00	13.00	45.00	156.00	3,145.00
Housing Units	0.00	7,928.75	12,821.00	18,007.25	48,196.00
Rental Units	0.00	2,916.75	5,785.50	10,207.25	32,060.00
Vacant Units	0.00	443.25	778.50	1,253.25	9,173.00
Airbnb Price	20.00	70.94	92.73	133.06	5,000.00
Rent 1 Bd.	1,112.00	1,600.00	1,885.00	2,561.38	4,425.00
December 2018					
Airbnb Listings	1.00	21.50	81.00	250.00	2,925.00
Housing Units	0.00	8,058.75	13,120.50	18,396.25	48,359.00
Rental Units	0.00	2,715.25	5,740.00	10,192.00	32,900.00
Vacant Units	0.00	430.00	784.50	1,368.50	7,799.00
Airbnb Price	18.03	74.65	95.98	143.20	1,162.10
Rent 1 Bd.	750.00	1,525.00	1,800.00	2,405.38	4,995.00

Table 3.1: ZIP Code Level Summary Statistics

code level characteristics from the *ACS* using a cubic spline.[7] Summary statistics for the data from *Airbnb*, *Zillow* and the *ACS* are in 3.1

3.2.3 Econometric Estimation

To evaluate the relationship between the number of *Airbnb* listings and the median rental price we use the following fixed effect specification:

$$\ln(y_{zmt}) = \beta \ln(Airbnb_{zmt}) + X_{zmt}\gamma + \eta_z + \tau_t + \mu_{month} + \varepsilon_{zmt}, \tag{3.1}$$

where y_{zmt} is the median rental price of a one bedroom apartment in ZIP code z, metro m, and time t. $Airbnb_{zmt}$ is the number of rooms listed on *Airbnb* in a ZIP code in period t. X_{zmt} is a vector of observed ZIP code level characteristics including population, the

[7]Additional details can be found in the C.1.1

number of housing units, the number of vacant housing units, and the unemployment rate. We include ZIP code level fixed effects, η_z, to control for time invariant metro level characteristics and year fixed effects τ_t to control for aggregate trends. We also include month fixed effects, μ_{month}, to control for seasonality. Including these fixed effects means we are comparing the rents within a ZIP code in the same month of the year across years with different levels of *Airbnb* listings. 3.2 presents results for the regressions. Looking at column (4) we can see that the a one percent increase in the number of *Airbnb* corresponds to an increase in rent prices by 0.01%. The median ZIP code saw approximately a 36.20% year to year increase in *Airbnb* listings, which corresponds to a 0.31% increase in the price of rent. This equals a \$5.80 increase in monthly rent at the median rent in the data.

Our findings are similar to the results found in [67] which translate to a \$9 increase in monthly rent. To separate differences in effects by the size of location, we also conduct this analysis for the rental price of two bedroom and three bedroom rentals[8]. The results are presented in the second and third panel of 3.2. While these figures are similar for two bedroom rentals, they are about half the size (and estimated with less precision) for three bedroom rentals.

It is important to note that the above analysis only demonstrates the statistical relationship between the number of *Airbnb* listings in an area and the median rental price. With this fairly naive approach, we do not believe that our econometric estimation leads to a causal interpretation of the results. When investigating the impact of *Airbnb* listings on rental market or housing prices, a major issue with identification stems around isolating the impact on rental price *apart* from another factor driving both the demand for *Airbnb* and the demand for rental housing. That is, we may only be identifying

[8]The number of observations and clusters are different between each set of regressions because the *Zillow* data is available for different time frames and ZIP codes for the different variables.

	(1)	(2)	(3)	(4)
1 Bedroom				
ln(*Airbnb count*)	0.09***	0.02***	0.01***	0.01***
	(0.0099)	(0.0026)	(0.0022)	(0.0022)
Observations	10,818	10,818	10,818	10,818
Clusters	432	432	432	432
2 Bedroom				
ln(*Airbnb count*)	0.11***	0.02***	0.02***	0.01***
	(0.0088)	(0.0027)	(0.0023)	(0.0023)
Observations	12,127	12,127	12,127	12,127
Clusters	505	505	505	505
3 Bedroom				
ln(*Airbnb count*)	0.11***	0.01***	0.01***	0.005*
	(0.0119)	(0.0032)	(0.0025)	(0.0025)
Observations	5,877	5,877	5,877	5,877
Clusters	254	254	254	432
ZIP code FE		✓	✓	✓
Year FE			✓	✓
Month FE				✓

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

Table 3.2: Relationship between the Number of *Airbnb* Listings and the Median Rental Price

changing desirability or amenities in an area. Reverse causality is also a concern. As rents rise in an area it may be more likely that individuals choose to rent a room in their apartment or if they own an apartment they may choose to relocate to another area to live and rent that apartment at a higher price.

Past research controls for this endogeneity by controlling for characteristics correlated with desirability such as crime rates, new building permits, and amenities such as nearby restaurants. While these characteristics may be a proxy for amenity values in an area and controlling for them removes some of the omitted variable bias, they are not a perfect measure of amenities and the estimated coefficient may still be biased. Barron et al. create a shift-share instrument interacting the popularity of *Airbnb*, measured by the *Google* search index, with an area's attractiveness to tourists in 2010, measured by the number of establishments in the food service and accommodation industries. The argument for this approach is that an exogenous time trend (i.e. *Google* searches for *Airbnb*) will differentially impact areas based on exposure ("touristiness"). Again, while this may remove some of the concern about omitted variable bias, disentangling the impact of *Airbnb* growth and differential recoveries from the Great Recession based on amenity levels is still a concern.

In an ideal setting, one would observe two identical housing markets and have one allow *Airbnb* rentals while the other limits (i.e. bans) them in some way. Observing a natural experiment where this occurs seems unlikely as places that have passed restrictions on *Airbnb*s tend to be places worried about increasing rents and affordable housing. Without such a natural experiment, identifying the impact of *Airbnb* listings on rental prices requires a factor (instrument) that shifts the number of these listings without directly impacting rental prices. Because the decision to choose to rent a unit through *Airbnb*, as opposed to the long-term market, is one determined by profit incentives, it would seem that any factor that changes the profitability of an *Airbnb* listing might also change it in the long-term housing market.

The use of a model circumvents some of these issues by explicitly adding structure to the endogenous relationships that may confound reduced-form analyses. In particular, we specify the objectives (e.g. profit, utility, or welfare optimization), decisions (e.g. price setting, vacancy posting, where to search), and trade-offs faced by the key agents in these markets. While we abstract away from many specifics about the realities of rental markets, we carefully consider those elements to be of first-order concern, motivating further study of the nuances introduced by extensions once the groundwork has been established.

3.3 A Model of Rental Markets

In this section we formulate a model of rental markets and study its behavior. This model is then extended to evaluate the public policy and welfare implications. It features three distinct decentralized markets distinguished by the types of agents that interact within them: hotels, short-term rentals, and long-term rentals. We think of long-term renters as annual leasers. Peer-to-peer technologies allow some property managers to compete with hotels for those looking for short-term stays. Property managers publish prices and potential tenants direct their search to these postings. Prices and queue times are determined endogenously with market utilities taken as given by these managers, making the equilibrium competitive. Importantly, the three markets are endogenously linked which allows us to investigate policy spillovers.

3.3.1 Environment

Time is continuous, infinite, and agents discount the future at a rate r. To find, purchase, and sell lodging services, property managers and tenants interact in three distinct, frictional dwelling markets. Both property managers and tenants are one of two types, and these types exist in fixed measures. Property managers are either innkeepers ($\mathcal{I}$) or landlords ($\mathcal{L}$) and are endowed with a single dwelling unit that can be vacant and searching for a tenant, or occupied and receiving a flow payment p. Tenants are either visitors ($\mathcal{V}$) or residents ($\mathcal{R}$). If the tenant is accommodated, she receives flow utility $w-p$, otherwise they search for lodging and receive flow utility b, where w and b may vary by type of tenant. Further, an agent's type affects which of the three dwelling markets are available to them. Hotels (H) are available to innkeepers and visitors; short-term rentals (S) are available to landlords and visitors; and long-term rentals (L) are available to landlords and residents. The key feature in the above structure is that residents and innkeepers may only participate in one market, but landlords and visitors may participate in multiple, allowing the behavior in one market to influence outcomes in the others.[9]

Within each dwelling market (indexed by i) there is a continuum of sub-markets differentiated by price (indexed by j). Each agent may only participate in one of these sub-markets, which are separate in the sense that search in the ij^{th} sub-market can only produce matches with other agents in that sub-market. Search is assumed to be directed as in [75] and [76]. Tenants observe all prices and choose where to search, but within a sub-market search is random. These stochastic, bilateral meetings are governed by a technology that maps the measures of unaccommodated tenants and vacant dwellings into matches: $m^i(u^{ij}, v^{ij})$. m^i is assumed to be increasing, concave with continuous derivatives, and satisfy constant returns. We allow the function (namely its parameterization) to vary by market. Further, let $m^i(u^{ij}, v^{ij})/u^{ij} = m^i(1, \theta^{ij}) \equiv \lambda^i(\theta^{ij}) \equiv \lambda^{ij}$ denote the

[9]Importantly, these markets are *not* necessarily distinguished by location. Rather, we define markets by the types of agents that interact within them. One can think of hotels and rental properties as being spatially distinct and separate, but we abstract from any quality differences that may exist between hotels and short-term markets (and within hotels and rental properties more generally). This is done *not* without loss of generality, but to make the model as simple as possible to highlight the first-order effects of the peer-to-peer rental economy on the existing markets.

rate at which a property manager meets an unaccommodated tenant, where $\theta^{ij} \equiv v^{ij}/u^{ij}$ is the "tightness" of sub-market ij, and that $\lim_{\theta \to 0} \lambda(\theta) = \infty$ and $\lim_{\theta \to \infty} \lambda(\theta) = 0$. From the perspective of an unaccommodated tenant, the rate at which she finds a vacant dwelling is given by $m^i(u^{ij}, v^{ij})/v^{ij} = m^i(1/\theta^{ij}, 1) = \theta^{ij}\lambda^i(\theta^{ij})$.

We follow the literature in assuming that sub-markets are formed by a market maker who posts p^{ij} for each sub-market. Then, both property managers and tenants choose which sub-market to search in. Any sub-market that fails to attract tenants or managers is assumed to be costlessly shut down. As noted in [37], the assumption of a market maker is a convenience and isomorphic to assuming that one side of the market posts prices and the other side directs to these postings. To post a vacancy in any sub-market j within market i, property managers must pay a flow cost κ^i. In the abstract we interpret these costs as reflecting all technologies (e.g. physical, digital, or legal) that allows certain land to be sold to individuals for (temporary) residence. More concretely, we interpret differences in this cost by market as capturing differences in in the regulatory structure associated with allowing a property to be sold to a tenant. Matches, i.e. tenant-manager pairs, are assumed to dissolve at a rates $\delta^{\mathcal{V}}$ and $\delta^{\mathcal{R}}$ for visitors and residents, respectively. Capturing differences in preferences between the two groups, it is assumed that $\delta^{\mathcal{V}} > \delta^{\mathcal{R}}$. A visual schematic of the environment is given in 3.6.

3.3.2 Value Functions

In this section we recursively formulate the asset values for each agent type ($\mathcal{R}$, $\mathcal{V}$, $\mathcal{I}$, $\mathcal{L}$) in submarket ij depending on whether or not they are currently matched $\{0, 1\}$. First consider a resident searching for accommodation. Residents may only search for long-term rentals, but choose which sub-market j to search in. While searching she receives

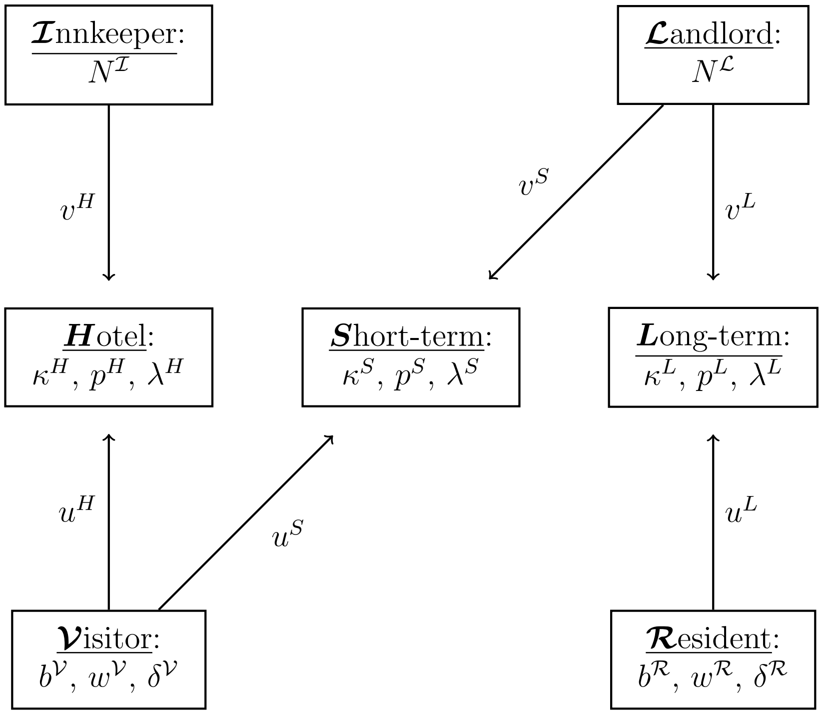


Figure 3.6: Schematic summary of the model.

flow utility $b^{\mathcal{R}}$ plus the expected gain from locating a dwelling.

$$r\mathcal{R}_0^j = b^{\mathcal{R}} + \theta^{Lj}\lambda^{Lj}\Big[\mathcal{R}_1^j(p^{Lj}) - \mathcal{R}_0^j\Big] \tag{3.2}$$

An accommodated resident receives flow utility $w^{\mathcal{R}} - p^{Lj}$ plus the expected loss from separating.

$$r\mathcal{R}_1^j(p^{Lj}) = w^{\mathcal{R}} - p^{Lj} + \delta^{\mathcal{R}}\Big[\mathcal{R}_0^j - \mathcal{R}_1^j(p^{Lj})\Big] \tag{3.3}$$

It will prove useful to substitute 3.3 for $\mathcal{R}_1^j(p^{Lj})$ in 3.4 and simplify.

$$r\mathcal{R}_0^j = \frac{b^{\mathcal{R}}(r+\delta^{\mathcal{R}}) + \theta^{Lj}\lambda^{Lj}(w^{\mathcal{R}} - p^{Lj})}{r + \delta^{\mathcal{R}} + \theta^{Lj}\lambda^{Lj}} \tag{3.4}$$

for $p^{Lj} \leq w^{\mathcal{R}} - b^{\mathcal{R}}$. If the price is higher than the gain from finding lodging, the resident does not search and receives expected utility $b^{\mathcal{R}}/r$.

Visitors may search in either the hotel or short-term rental market, $i \in \{H, S\}$. Given this choice, they also choose which sub-market j to search for. The asset values for unaccommodated and accommodated visitors are given by the following.

$$r\mathcal{V}_0^{ij} = b^{\mathcal{V}} + \theta^{ij}\lambda^{ij}\left[\mathcal{V}_1^{ij}(p^{ij}) - \mathcal{V}_0^{ij}\right] \tag{3.5}$$

$$r\mathcal{V}_1^{ij}(p^{ij}) = w^{\mathcal{V}} - p^{ij} + \delta^{\mathcal{V}}\left[\mathcal{V}_0^{ij} - \mathcal{V}_1^{ij}(p^{ij})\right]. \tag{3.6}$$

As with residents, if no price induces visitors to search, they receive utility $b^{\mathcal{V}}/r$. Substituting out the value of being accommodated produces

$$r\mathcal{V}_0^{ij} = \frac{b^{\mathcal{V}}(r + \delta^{\mathcal{V}}) + \theta^{ij}\lambda^{ij}(w^{\mathcal{V}} - p^{ij})}{r + \delta^{\mathcal{V}} + \theta^{ij}\lambda^{ij}} \tag{3.7}$$

for $p^{ij} \leq w^{\mathcal{V}} - b^{\mathcal{V}}$.

Innkeepers manage property in the hotel market. When searching for a tenant, they must incur a flow cost κ^H but receive an expected gain when the vacancy is filled.

$$r\mathcal{I}_0^j = -\kappa^H + \lambda^{Hj}\left[\mathcal{I}_1^j(p^{Hj}) - \mathcal{I}_0^j\right] \tag{3.8}$$

When occupied, the innkeeper receives p^{Hj} plus the expected loss from separation.

$$r\mathcal{I}_1^j(p^{Hj}) = p^{Hj} + \delta^{\mathcal{V}}\left[\mathcal{I}_0^j - \mathcal{I}_1^j(p^{Hj})\right] \tag{3.9}$$

for $p^{Hj} \geq 0$. If the price is negative we assume that the dwelling remains indefinitely vacant. Combining the above we have

$$r\mathcal{I}_0^j = \frac{-\kappa^H(r + \delta^{\mathcal{V}}) + \lambda^{Hj}p^{Hj}}{r + \delta^{\mathcal{V}} + \lambda^{Hj}}. \tag{3.10}$$

Finally, landlords may participate in either the short-term or long-term rental markets, $i \in \{S, L\}$, and then additionally choose a sub-market j.

$$r\mathcal{L}_0^{ij} = -\kappa^i + \lambda^{ij}\left[\mathcal{L}_1^{ij}(p^{ij}) - \mathcal{L}_0^{ij}\right] \tag{3.11}$$

$$r\mathcal{L}_1^{ij}(p^{ij}) = p^{ij} + \delta^i\left[\mathcal{L}_0^{ij} - \mathcal{L}_1^{ij}(p^{ij})\right] \tag{3.12}$$

for $p^{ij} \geq 0$ and where $\delta^i = \delta^{\mathcal{V}}$ if $i = S$ and $\delta^i = \delta^{\mathcal{R}}$ if $i = L$. Eliminating 3.12 we have

$$r\mathcal{L}_0^{ij} = \frac{-\kappa^i(r + \delta^i) + \lambda^i p^{ij}}{r + \delta^i + \lambda^{ij}}. \tag{3.13}$$

3.3.3 Equilibrium

In this section we establish and characterize the model's equilibrium, focusing in particular on the notion of *competitive search equilibria*.[10] One can solve for such an equilibrium by maximizing property managers' profits subject to tenants receiving some fixed level of utility. Since tenants are homogeneous within type, any sub-market that a positive measure of tenants searches in must pay them the same utility called their *market utility*. Agents in the economy take this level of utility as given, but it is determined endogenously in equilibrium.

Consider a resident searching for accommodation and denote her market utility as $\mathcal{R}_0$ where it must be that $r\mathcal{R}_0 \geq b^{\mathcal{R}}$. Plugging this into 3.4 and rearranging gives us the following expression for the relationship she faces between accommodation finding and

[10] The term "competitive search" equilibrium comes from [76] and, as explained by [37], can be thought of as the combination of directed search and price posting. As noted earlier, posting with directed search can be made outcome-equivalent to assuming a third type of agent (or fifth in this paper), a market maker, sets up the sub-markets to attract both property managers and tenants.

price for some given level of utility.

$$\theta^{Lj}\lambda^{Lj} = \frac{(r+\delta^{\mathcal{R}})(r\mathcal{R}_0 - b^{\mathcal{R}})}{w^{\mathcal{R}} - p^{Lj} - r\mathcal{R}_0} \tag{3.14}$$

From the above we can see that a searching resident must pay a high price to achieve a high finding rate and receive the market utility $\mathcal{R}_0$. In other words, 3.14 describes her indifference curve. Further, the RHS is continuous and strictly increasing in both p^{Lj} and $\mathcal{R}_0$ on $p^{Lj} \in (-\infty, w^{\mathcal{R}} - r\mathcal{R}_0)$. As the price approaches $w^{\mathcal{R}} - r\mathcal{R}_0$, the gain from finding accommodation goes to zero, and the sub-market tightness goes to infinity. If the price is above $w^{\mathcal{R}} - r\mathcal{R}_0$, no resident searches and the sub-market shuts down. A similar argument with similar conditions can be made for a searching visitor. Here, though, her market utility is not only equal for all j within a given market, but also between markets $i \in \{H, S\}$.

$$\theta^{ij}\lambda^{ij} = \frac{(r+\delta^{\mathcal{V}})(r\mathcal{V}_0 - b^{\mathcal{V}})}{w^{\mathcal{V}} - p^{ij} - r\mathcal{V}_0} \tag{3.15}$$

We can thus think of the problems faced by property managers as a choice of sub-market with price p and tightness θ such that the (p, θ) relationships of 3.14 and 3.15 deliver searching tenants their market utility, where this market utility is taken as given. Letting $\theta^H(p^H; \mathcal{V}_0)$ describe this relationship for the hotel market, $\theta^S(p^S; \mathcal{V}_0)$ for the short-term market, and $\theta^L(p^L; \mathcal{R}_0)$ for the long-term market, the problems of property managers can be written as a (profit) maximization problem in θ *or* p given this market utility. In addition to visitors receiving $\mathcal{V}_0$ in both the hotel and short-term markets, landlords must also be indifferent to posting vacancies in the short and long-term markets.

$$\max_{p^H} \mathcal{I}_0\big(p^H, \theta^H(p^H; \mathcal{V}_0)\big) \tag{3.16}$$

$$\max_{p^S} \mathcal{L}_0\big(p^S, \theta^S(p^S; \mathcal{V}_0)\big) = \max_{p^L} \mathcal{L}_0\big(p^L, \theta^L(p^L; \mathcal{R}_0)\big) \tag{3.17}$$

The following lemma establishes that the above is well-defined.

Lemma 1 *Let* $\widetilde{\mathcal{I}}_0 \equiv \sup_{p^H} \mathcal{I}_0\big(p^H, \theta^H(p^H; \mathcal{V}_0)\big)$, $\widetilde{\mathcal{L}}_0^S \equiv \sup_{p^S} \mathcal{L}_0\big(p^S, \theta^S(p^S; \mathcal{V}_0)\big)$, *and* $\widetilde{\mathcal{L}}_0^L \equiv \sup_{p^L} \mathcal{L}_0\big(p^L, \theta^L(p^L; \mathcal{R}_0)\big)$, *where* $\widetilde{\mathcal{L}}_0^S = \widetilde{\mathcal{L}}_0^L = \widetilde{\mathcal{L}}_0$. *Further, assume that* $\widetilde{\mathcal{I}}_0 \geq 0$ *and* $\widetilde{\mathcal{L}}_0 \geq 0$. *Then the property managers' problems are well defined and the argmax in the price domain is achieved in* $[0, w^{\mathcal{V}} - r\mathcal{V}_0)$ *for the hotel and short-term markets, and in* $[0, w^{\mathcal{R}} - r\mathcal{R}_0)$ *for the long-term market.*

Proof: *See Appendix C.1.2.* ■

Notably, the solutions to the problems defined by 3.16, 3.17 are not necessarily unique. Put differently, many combinations of prices and finding rates may deliver tenants their market utility and maximize managers' profits. Given our assumptions on the matching technology, though, the following lemma establishes that there is no price dispersion *within* a market.

Lemma 2 *All property managers within market* $i \in \{H, S, L\}$ *choose the same price, and this price is a weighted average of each agent's gain from market participation.*

$$p^H = \eta_H(\theta^H)\big(w^{\mathcal{V}} - r\mathcal{V}_0\big) + \big(1 - \eta_H(\theta^H)\big)r\mathcal{I}_0 \tag{3.18}$$

$$p^S = \eta_S(\theta^S)\big(w^{\mathcal{V}} - r\mathcal{V}_0\big) + \big(1 - \eta_S(\theta^S)\big)r\mathcal{L}_0 \tag{3.19}$$

$$p^L = \eta_L(\theta^L)\big(w^{\mathcal{R}} - r\mathcal{R}_0\big) + \big(1 - \eta_L(\theta^L)\big)r\mathcal{L}_0, \tag{3.20}$$

where $\theta \frac{d\lambda}{d\theta}/\lambda \equiv \eta(\theta) - 1$ *is the elasticity of the filling rate with respect to* θ *(and is a number between* 0 *and* 1*). Equivalently,* $\eta(\theta)$ *is the elasticity of the finding rate with respect to* θ.

Proof: *See Appendix C.1.3.* ■

The equilibrium pricing equations 3.18, 3.19, and 3.20 make clear the endogenous relationship between the three dwelling markets. The existence of a technology allowing landlords to compete with innkeepers makes visitors weakly better off (an increase $\mathcal{V}_0$). Given that innkeepers may lose customers, prices and profits in the hotel market will decline. Residents, too, are affected by this technology. With this additional renting channel, profits for landlords are weakly higher and may induce more of the fixed stock of rental units to be posted for short-term stays. This has upward pressure on prices in the long-term market. The introduction of this peer-to-peer technology has unclear welfare effects: though innkeepers and residents are worse off, landlords and visitors are better off. Resolving whether the aggregate welfare effect is positive or negative is therefore a quantitative exercise.

Turning to solve the model, we start by expressing equilibrium market tightnesses as implicit functions of a vacancy's value. Put differently, we derive the demand for vacancies per searcher as functions of their *cost*–i.e. the expected profits that a vacancy commands. Below, we formalize that this relationship is decreasing.

Lemma 3 *Let $\theta^H = \zeta_H(\mathcal{I}_0)$, $\theta^S = \zeta_S(\mathcal{L}_0)$, and $\theta^L = \zeta_L(\mathcal{L}_0)$ be functions that map the expected profits of a vacant dwelling into market tightnesses. In equilibrium, we have that*

$$\frac{d\zeta_H}{d\mathcal{I}_0} < 0, \qquad \frac{d\zeta_S}{d\mathcal{L}_0} < 0, \qquad \frac{d\zeta_L}{d\mathcal{L}_0} < 0.$$

Proof: See Appendix C.1.4. ■

To close the model we consider the steady state: the inflows into accommodation equal the outflows from it. Let $u^{\mathcal{V}}$ and $u^{\mathcal{R}}$ be the positive, exogenous measures of visitors and residents, respectively. Further, let $N^{\mathcal{I}}$ and $N^{\mathcal{L}}$ be the positive, exogenous measures of hotels and rentals, respectively. Starting with the hotel market, the measure of innkeeper-managed properties equals the sum of all vacant properties and those accommodating visitors: $N^{\mathcal{I}} = v^{\mathcal{I}} + a^{\mathcal{I}}$. In the steady state, the flows into and out of accommodation must be equal. That is $u^{\mathcal{I}}\theta^H\lambda^H = \delta^{\mathcal{V}}a^{\mathcal{I}}$. For ease of notation, define $\widetilde{\lambda} \equiv \theta\lambda$ and let $\chi = u^H/u^{\mathcal{V}}$ be the fraction of visitors searching in the hotel market. We then have

$$\begin{aligned} & N^{\mathcal{I}} = v^{\mathcal{I}} + \frac{\chi u^{\mathcal{V}}\widetilde{\lambda}^H}{\delta^{\mathcal{V}}} \\ \iff \quad & N^{\mathcal{I}} = \chi u^{\mathcal{V}}\Big[\zeta_H(\mathcal{I}_0) + \frac{\widetilde{\lambda}\circ\zeta_H(\mathcal{I}_0)}{\delta^{\mathcal{V}}}\Big], \end{aligned} \tag{3.21}$$

noting the substitution of $\theta^H = \zeta_H(\mathcal{I}_0)$.

In the rental market the measure of landlord-managed properties must equal the sum of all vacant properties and those accommodating visitors *and* residents: $N^{\mathcal{L}} = v^{\mathcal{L}} + a^{\mathcal{L}}$. Use the steady state conditions for both short and long-term markets and substituting for θ^S and θ^L.

$$\begin{aligned} & N^{\mathcal{L}} = v^{\mathcal{L}} + \frac{(1-\chi)u^{\mathcal{V}}\widetilde{\lambda}^S}{\delta^{\mathcal{V}}} + \frac{u^{\mathcal{R}}\widetilde{\lambda}^L}{\delta^{\mathcal{R}}} \\ \iff \quad & N^{\mathcal{L}} = (1-\chi)u^{\mathcal{V}}\theta^S + u^{\mathcal{R}}\theta^L - \frac{(1-\chi)u^{\mathcal{V}}\widetilde{\lambda}^S}{\delta^{\mathcal{V}}} + \frac{u^{\mathcal{R}}\widetilde{\lambda}^L}{\delta^{\mathcal{R}}} \\ \iff \quad & N^{\mathcal{L}} = (1-\chi)u^{\mathcal{V}}\Big[\zeta_S(\mathcal{L}_0) + \frac{\widetilde{\lambda}\circ\zeta_S(\mathcal{L}_0)}{\delta^{\mathcal{V}}}\Big] + u^{\mathcal{R}}\Big[\zeta_L(\mathcal{L}_0) + \frac{\widetilde{\lambda}\circ\zeta_L(\mathcal{L}_0)}{\delta^{\mathcal{R}}}\Big] \qquad (3.22) \\ & \qquad (3.23) \end{aligned}$$

The above two conditions describe the steady state equilibrium conditions for properties managed by innkeepers and landlords. These two equations, though, are functions of three endogenous variables: $\mathcal{I}_0$, $\mathcal{L}_0$, and χ. Recalling that χ is the share of searching visitors in the hotel market, we pin down its value with the indifference condition of visitors–i.e. that visitors are indifferent between search in the hotel and short-term markets. To do so, separately rearrange 3.13 for p^S and p^L. Plugging these into 3.7 and equating them between markets, we have

$$\frac{b^{\mathcal{V}}(r+\delta^{\mathcal{V}})+\theta^H\lambda^H(w^{\mathcal{V}}-r\mathcal{I}_0)-\theta^H(r+\delta^{\mathcal{V}})(r\mathcal{I}_0+\kappa^H)}{r+\delta^{\mathcal{V}}+\theta^H\lambda^H} = \frac{b^{\mathcal{V}}(r+\delta^{\mathcal{V}})+\theta^S\lambda^S(w^{\mathcal{V}}-r\mathcal{L}_0)-\theta^S(r+\delta^{\mathcal{V}})(r\mathcal{L}_0+\kappa^S)}{r+\delta^{\mathcal{V}}+\theta^S\lambda^S}.$$

This describes an implicit relationship between market θs that we write as $\xi_H(\theta^H;\mathcal{I}_0) = \xi_S(\theta^S;\mathcal{L}_0)$. Rewriting θ^H in terms of known quantities and χ and substituting for θ^S,

$$\xi_H \circ \frac{\delta^{\mathcal{V}}N^{\mathcal{I}} - \chi u^{\mathcal{V}}\widetilde{\lambda}\circ\zeta_H(\mathcal{I}_0)}{\delta^{\mathcal{V}}\chi u^{\mathcal{V}}} = \xi_S\circ\zeta_S(\mathcal{L}_0). \tag{3.24}$$

Definition 1 *A steady state, competitive search equilibrium is a set of values* $\{\mathcal{V}_0,\mathcal{R}_0,\mathcal{I}_0,\mathcal{L}_0\}$, *prices* $\{p^H,p^S,p^L\}$, *and quantities* $\{\theta^H,\theta^S,\theta^L,\chi\}$ *that solve the following equations.*

$$N^{\mathcal{I}} = \chi u^{\mathcal{V}}\Big[\theta^H + \frac{\theta^H\lambda^H}{\delta^{\mathcal{V}}}\Big] \tag{3.25}$$

$$N^{\mathcal{L}} = (1-\chi)u^{\mathcal{V}}\Big[\theta^S + \frac{\theta^S\lambda^S}{\delta^{\mathcal{V}}}\Big] + u^{\mathcal{R}}\Big[\theta^L + \frac{\theta^L\lambda^L}{\delta^{\mathcal{R}}}\Big] \tag{3.26}$$

$$r\mathcal{V}_0 = \xi_H \circ \frac{\delta^{\mathcal{V}}N^{\mathcal{I}} - \chi u^{\mathcal{V}}\theta^H\lambda^H}{\delta^{\mathcal{V}}\chi u^{\mathcal{V}}} = \xi_S\big(\theta^S\big) \tag{3.27}$$

$$r\mathcal{R}_0 = \frac{b^{\mathcal{R}}(r+\delta^{\mathcal{R}}) + \theta^L\lambda^L(w^{\mathcal{R}} - p^L)}{r + \delta^{\mathcal{R}} + \theta^L\lambda^L} \tag{3.28}$$

$$\theta^H = \zeta_H(\mathcal{I}_0) \tag{3.29}$$

$$\theta^S = \zeta_S(\mathcal{L}_0) \tag{3.30}$$

$$\theta^L = \zeta_L(\mathcal{L}_0) \tag{3.31}$$

$$p^H = \eta_H(\theta^H)\big(w^{\mathcal{V}} - r\mathcal{V}_0\big) + \big(1 - \eta_H(\theta^H)\big)r\mathcal{I}_0 \tag{3.32}$$

$$p^S = \eta_S(\theta^S)\big(w^{\mathcal{V}} - r\mathcal{V}_0\big) + \big(1 - \eta_S(\theta^S)\big)r\mathcal{L}_0 \tag{3.33}$$

$$p^L = \eta_L(\theta^L)\big(w^{\mathcal{R}} - r\mathcal{R}_0\big) + \big(1 - \eta_L(\theta^L)\big)r\mathcal{L}_0 \tag{3.34}$$

A graphical representation of the equilibrium is presented in 3.7. In the center column we describe the indifference relation of visitors (top) and residents (bottom). Tenants receive their market utility, paying relatively low prices and finding accommodation slowly, or high prices and finding it quickly. The equilibrium lies along these indifference curves where property managers maximize the expected profits of a vacancy. For innkeepers this is straightforward. For landlords there is the added condition that the expected profits in both short and long-term markets is equal. This highlights the interconnectedness of the three markets. For example, changes that affect residents therefore alter the problems faced by landlords. This affects profit maximization in the short-term markets, and therefore visitors and innkeepers.

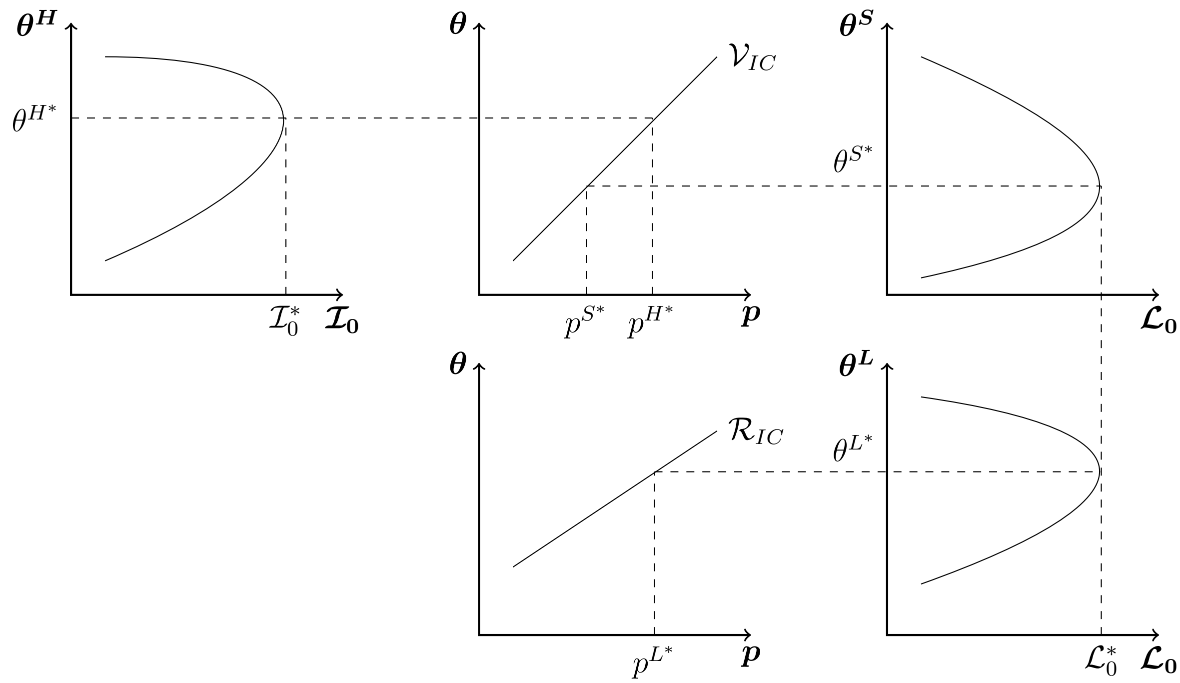


Figure 3.7: Graphical representation of the model's equilibrium.

3.3.4 Comparative Statics

We next present and discuss several exercises moving towards understanding the model laid out above. Though the model is reasonably simple, the interrelatedness of the three markets makes analytic comparative static exercises difficult, if not impossible. We thus rely on the computer to solve and disentangle it. Since the primary focus of this paper surrounds the existence (effect) of peer-to-peer technologies on traditional, lodging markets, we highlight the vacancy posting costs as convenient levers with which to pull. Namely, we can think of taking $\kappa^S \to \infty$ as reflecting the case when peer-to-peer meetings are impossible (or, rather, negligibly rare). When finite, we will later interpret the κ's as the *choices* of a government agent with its own objective function. For now we look at the effects of changes in κ^i on the model's endogenous variables holding all κ^j, $j \neq i$, constant. We report the results of this exercise in 3.3.

	$\mathcal{V}_0$	$\mathcal{R}_0$	$\mathcal{I}_0$	$\mathcal{L}_0$	p^H	p^S	p^L	θ^H	θ^S	θ^L
$\uparrow \kappa^H$	$+$	$+$	$-$	$-$	$-$	$-$	$-$	$-$	$+$	$+$
$\uparrow \kappa^S$	$-$	$+$	$+$	$-$	$+$	$+$	$-$	$-$	$-$	$+$
$\uparrow \kappa^L$	$+$	$+$	$-$	$-$	$-$	$-$	$-$	$+$	$+$	$-$

Table 3.3: Comparative Statics

First consider raising the posting cost of innkeepers, κ^H. This lowers the value of hotel vacancies and, recalling that the equilibrium price is an increasing function of $\mathcal{I}_0$, puts downward pressure on p^H. More visitors are inclined to search for hotels, decreasing the vacancy-to-searcher ratio in H (and increasing it in S). For landlords, the higher market utility enjoyed by visitors hurts them insofar as they must deliver tenants a combination of lower prices and higher finding rates. In response to the lowered profitability in the short-term market, more landlords post in the long-term market (partially undoing the increased tightness in S). Residents thus benefit as they more easily find accommodation at lower prices.

Next, assume that the cost of posting vacancies for short-term rentals, κ^S, increases. The value of unoccupied rentals declines and leads landlords to post more vacancies in the long-term market. This makes residents better off, as there are more vacancies vying for their business at lower prices. Visitors, on the other hand, are made worse off. More are pushed into the hotel market where innkeepers can raise prices alongside filling rates, increasing the value of a vacant hotel room. The fall in market utility for visitors is found to be large enough such that prices in the short-term market actually *increase*. Recalling the equilibrium pricing equation 3.19, the fall in market utility makes the gain from accommodation higher. Though the value of a vacancy drops, the net effect is that visitors must pay more and find accommodation more slowly.

Last, consider raising costs for long-term rentals, κ^L. Profits for landlords are reduced and pushes more to list their vacancies in the short-term market. Because these markets are competitive, p^S and p^L fall. This unambiguously makes visitors better off who enjoy lower prices and faster finding. For residents, the effect is slightly less clear. Accommodation is harder to find, but prices are lower. Though, because accommodation finding is relatively fast, we find that the lowered prices are quantitatively dominant and result in raised resident market utilities.[11] Finally, the value of unoccupied hotel rooms falls as innkeepers must deliver visitors a higher market utility.

Overall, the above exercises demonstrate the importance of modeling all three markets. In models with only two of the three markets, much can be lost when failing to consider the spillovers associated with affecting any one type of agents' decisions. Further, these considerations may also impact notions of optimal policy concerning how short-term accommodation is governed. For example, thinking of changes in κ^H as a government's transient occupancy tax (TOT) policy, the above suggests that increases in this rate *could* benefit residents through multiple channels. Increased TOT revenues may be distributed directly, while indirectly benefiting them by reducing prices, raising finding rates, and lifting market utilities. This of course comes at the cost of property managers (both innkeepers and landlords). κ^S can similarly be thought of the fees charged to *Airbnb*. A lot of discussion has centered around whether or not these peer-to-peer websites should be allowed to operate in certain areas. A "ban" would correspond to $\kappa^S \to \infty$. What the optimal fees should be in each market, what the funds are used for or given to, and what the government's objective function is are all explored in the

[11] This result holds for a large portion of the parameter space, and all regions where this model makes sense qualitatively and quantitatively.

next section.

At this point it is important to discuss the assumption of a perfectly inelastic supply of dwellings. Some obvious detractions are that we know that properties are being developed for housing accommodation over time, and that decisions to develop are inherently tied to their profitability. Notwithstanding, we argue that the largest hold-up for new buildings centers around issues of permitting rather than, say, small changes in a TOT. In this respect, the model should be thought of in a static, short-run context. *Static* because we look at steady states, and *short-run* because of time-to-build restrictions on the construction of new lodging. Put differently, the results concerning the model's policy implications are conditional on there being no entry (or exit) response. Using a previous example, the identifying assumption requires that changes in the TOT do not affect the supply of hotels or rentals.

3.4 Calibration

We calibrate the model using Santa Barbara, California data. We do this for several reasons. The first is that we have detailed data on prices for hotels, *Airbnb*s, and rentals for the region. *Visit Santa Barbara*[12] provides data on hotel prices and vacancies. They report a sample of 75% of the rooms across their jurisdiction (Santa Barbara, Goleta, Montecito and Summerland), and therefore are estimates with a slight margin of error. These data are provided by "STR" and do not include hostels, vacation rentals or long-term rentals. Also, because these only show hotel room consumption, they do not represent any indicator of total visitor volume (it doesn't include day visitors from our surrounding area). We plot time series of monthly hotel demand in 3.8. We rely on data from *Zillow* for information on rental properties. For comparison with hotel demand,

[12] https://santabarbaraca.com/

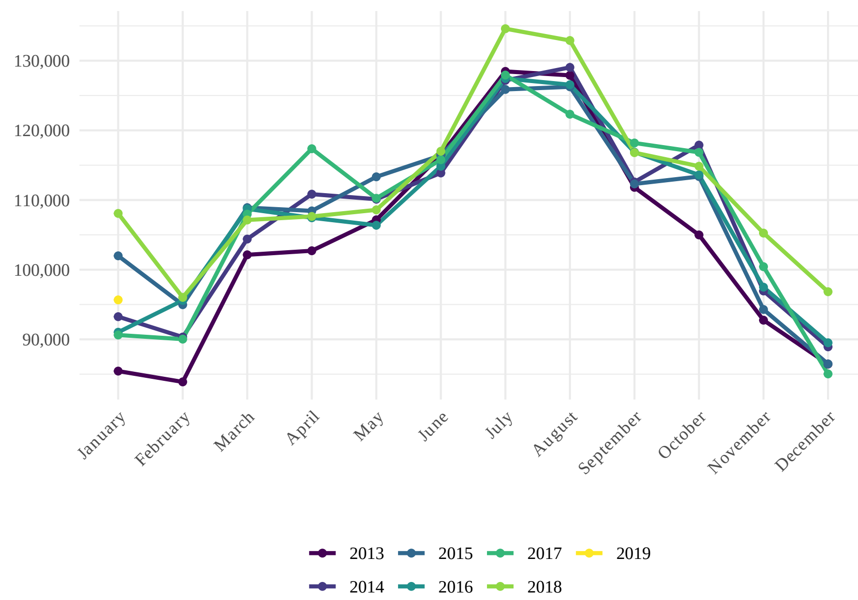


Figure 3.8: Monthly Demand for Hotels in Santa Barbara

we plot trends in the median rental prices in 3.9. We use *Inside Airbnb* and Tom Slee for data on *Airbnb* listings. We plot the change median prices in these listed short-term rentals for the Santa Barbara area in 3.10.

The second reason we calibrate to this region is that the Santa Barbara Coast is fairly isolated along the central coast of California, with very limited expansion potential. Inland mountains prevent building away from the coast, while the coastal commission (paired with what one may call NIMBY sentiments) greatly hinders vertical construction. Since entry is impossible in the model, we view this as a near-ideal scenario to study and assess the policy and welfare implications of peer-to-peer technologies on communities. Indeed, the concern for affordable housing is an important topic for Santa Barbara residents and is a key topic for local politicians. We hope that the following exercises will provide insights into notions of optimal policy regarding the effects of *Airbnb* and traditional lodging markets.

To calibrate the model we must make some functional form assumptions on the match-

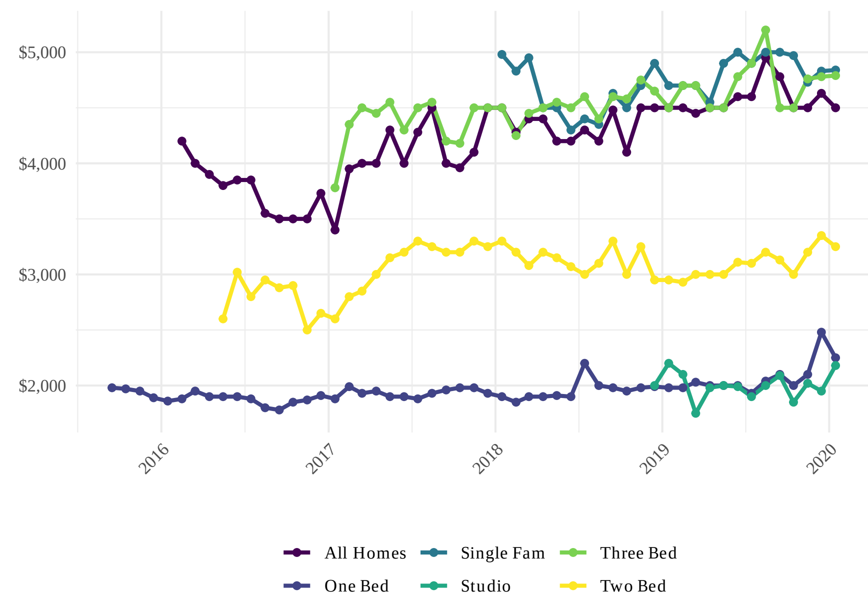


Figure 3.9: Price to Rent in Santa Barbara

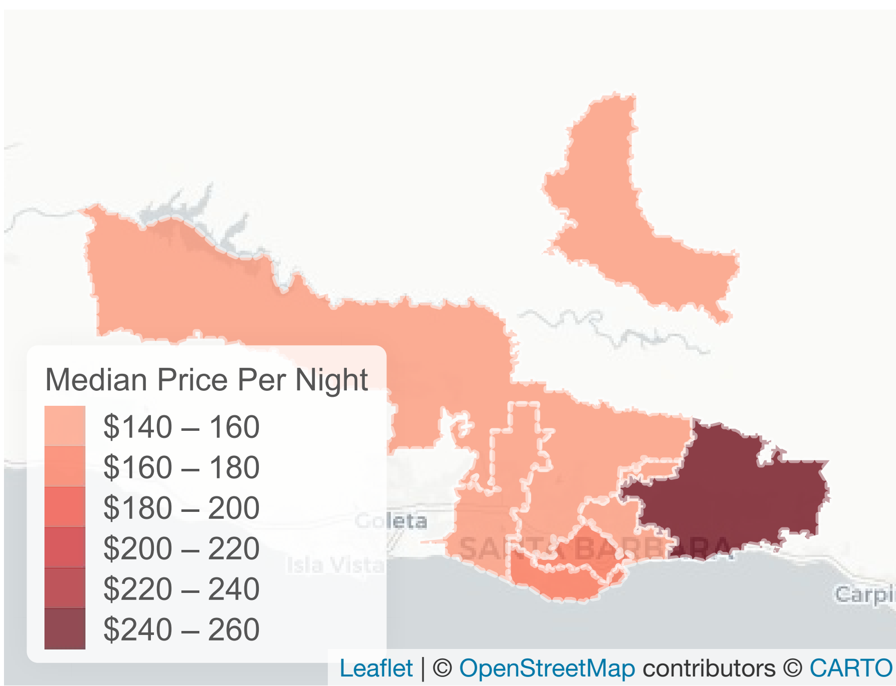


Figure 3.10: Median Price of *Airbnb* listings from January 2017 to July 2017 by ZIP code in Santa Barbara.

ing function. We assume that m^i is isoelastic and parameterized by $\eta^{\mathcal{I}}$ and $\eta^{\mathcal{L}}$ for each respective property manager. This assumption is attractive for two reasons. First, it reflects the idea that similar increases in the vacancy-to-searcher ratio may differentially impact vacancy filling for innkeepers or landlords. Second, it is quantitatively necessary to generate the price dispersion observed in data. Recalling the equilibrium pricing equations 3.18 - 3.20, a structurally rigid assumption of uniform elasticities *across* markets can produce only small differences in market prices faced by visitors. In total there are 16 parameters, 10 we set directly and 6 we jointly calibrate. We group these parameters into those related to preferences (r, $w^{\mathcal{V}}$, $w^{\mathcal{R}}$, $b^{\mathcal{V}}$, $b^{\mathcal{R}}$, $\delta^{\mathcal{V}}$, $\delta^{\mathcal{R}}$), search ($\eta^{\mathcal{I}}$, $\eta^{\mathcal{L}}$, $u^{\mathcal{V}}$, $u^{\mathcal{R}}$, κ^H, κ^S, κ^L), and the stock of lodgings ($N^{\mathcal{I}}$, $N^{\mathcal{L}}$).

To begin with the preference parameters, we calibrate the model to the daily frequency with discount rate r of 0.00013, corresponding to an annual discount rate of 5%. $\delta^{\mathcal{V}}$ and $\delta^{\mathcal{R}}$ are set so that the average stay for a visitor and residents, respectively, match what is observed in the data. According to *Visit Santa Barbara*, the average length-of-stay for tourists in 2017 was 2.8 days. The associated daily separation probability is therefore 1/2.8. Converting this to a rate, we set $\delta^{\mathcal{V}} = 0.442$. For residents we assume annual leases, implying a separation rate of $\delta^{\mathcal{R}} = 0.0027$. Flow utilities for unaccommodation, $b^{\mathcal{V}}$ and $b^{\mathcal{R}}$, are unidentified and therefore normalized to zero. Those for accommodation, $w^{\mathcal{V}}$ and $w^{\mathcal{R}}$, are jointly calibrated such that prices paid by visitors and residents match the data. Utilizing January 2017 through July 2017 data, the median (nominal) price for an *Airbnb* in Santa Barbara is \$158.83 (*Tom Slee*). For the same time period, the median price for a hotel room was \$245.14 (Visit SB). Finally, Using *Zillow* listings for two bedroom apartments, the median per-room rental price is \$49.29.

Moving on to the search parameters, the matching function is characterized by $\eta^{\mathcal{I}}$ and $\eta^{\mathcal{L}}$. Unlike in the labor market context, there is a dearth of scholarship on the finding and filling rates of rental properties (or their elasticities w.r.t. market tightnesses). As a result, we reduce the number of parameters to calibrate by letting $\eta^{\mathcal{I}} = 0.5 + \eta$ and $\eta^{\mathcal{L}} = 0.5 - \eta$ so that we capture the *spread* in elasticities with a single parameter. Since these are free parameters (here centered at 0.5), we later evaluate our results' sensitivity to them and find that they are quantitatively robust for reasonable values. Because *both* hotels and *Airbnb*s pay transient occupancy taxes, we calibrate κ^H and κ^S so that they correspond to the 12% TOT in Santa Barbara. Since TOTs are paid as a rate for the whole stay–and in the model they are paid in flow prior to the stay–we thus calculate the expected cost of search relative to the expected gain from filling a vacancy. In the model the total cost of a vacancy is κ/λ and the flow revenue is given by p/δ. Thus we have $\kappa\delta/\lambda p = 0.12$ for both the H and S markets. Rental properties do not pay any tax (other than property taxes), so we set $\kappa^L = 0$.

The final four parameters ($u^{\mathcal{V}}$, $u^{\mathcal{R}}$, $N^{\mathcal{I}}$, $N^{\mathcal{L}}$) are calibrated to match observed populations of rental market participation observed in data. We normalize the total measure of dwellings to equal 100. The fraction of innkeepers and landlords is then directly calculated using *ACS* and *Visit Santa Barbara* estimates on the total number of rental and hotel properties, respectively. From January through July 2017, there were 4,657 hotel rooms and 50,874 rental units, so $N^{\mathcal{I}} = 8.39$ and $N^{\mathcal{L}} = 91.61$. $u^{\mathcal{V}}$ and $u^{\mathcal{R}}$ are jointly calibrated to target the average measures of hotel and rental vacancies, respectively. Using the same data sources as before, there are an average of 1,075 unoccupied hotels and 4,601 vacant rental units ($v^H = 1.94$ and $v^{\mathcal{L}} = 8.29$). The careful reader will have noticed that there is one more moment than jointly calibrated parameters above. To make this exercise exactly identified, we lastly use the number of *Airbnb* vacancies from Tom Slee's data, which find an average of 394 listings ($v^S = 0.71$). A summary of the calibration, and its results, are presented in 3.4.

Parameter	Value	Description	Target
Preferences			
r	0.00013	discount rate	5% annual discount rate
$w^{\mathcal{V}}$	1,345.72	visitor's flow utility of accomm.	price of hotels / Airbnbs ($\star$)
$w^{\mathcal{R}}$	8,201.30	resident's flow utility of accomm.	price of long-term rentals ($\star$)
$b^{\mathcal{V}}$	0.0	visitor's flow utility of search	unidentified, normalization
$b^{\mathcal{R}}$	0.0	resident's flow utility of search	unidentified, normalization
$\delta^{\mathcal{V}}$	0.442	visitor's separation rate	average stay of 2.8 days
$\delta^{\mathcal{R}}$	0.0027	resident's separation rate	annual lease
Search & Matching			
η	0.072	spread in matching elasticities	price dispersion ($\star$)
$u^{\mathcal{V}}$	0.34	measure of searching visitors	1,075 hotel vacancies ($\star$)
$u^{\mathcal{R}}$	0.03	measure of searching residents	4,601 rental vacancies ($\star$)
κ^{H}	17.14	hotel vacancy posting cost	12% TOT ($\star$)
κ^{S}	8.69	short-term vacancy posting cost	12% TOT ($\star$)
κ^{L}	0.0	long-term vacancy posting cost	No TOT equivalent
Stock of Lodging			
$N^{\mathcal{I}}$	8.39	measure of hotel units	4,657 hotels
$N^{\mathcal{L}}$	91.61	measure of rental units	50,874 rental units

Moment	Data	Model
average per day hotel price	\$209.50	\$209.50
average per day Airbnb price	\$158.83	\$158.83
average annual rent (per day)	\$49.29	\$49.29
hotel TOT	0.12	0.12
Airbnb TOT	0.12	0.12
number of Airbnb listings	0.709 (394 listings)	0.709
average long-term vacancy filling rate	0.011 (3 months)	0.062

Table 3.4: Results of the calibration. The top panel displays the parameters and the bottom reports the moments targeted in the joint exercise. Jointly calibrated parameters are "starred" in the top panel.

3.5 The Effect of Airbnb on Rental Markets

In this section we use the calibrated model to explore the effect of peer-to-peer rentals, namely *Airbnb*, on rental markets. To do so we compare two economies, the calibrated economy from the previous section and one where we let $\kappa^S \to \infty$. As discussed earlier, the case when κ^S is high can be thought of as a situation where *Airbnb*s are too costly to operate or, equivalently, that peer-to-peer technologies are not yet feasible. In the context of equilibrium quantities in the model, as we let $\kappa^S \to \infty$, χ becomes arbitrarily close to 1. We summarize the steady state equilibria in both models in 3.5. We report prices, the share of visitors in the hotel market (χ), the measure of vacancies that landlords post in the long-term market ($\equiv \gamma$), market utilities, and aggregate welfare measures (for specifics about the precise welfare function we use, see Section 3.6).

	Prices			**Search**	
	p^H	p^S	p^L	χ	γ
Benchmark	\$209.50	\$158.83	\$49.29	0.87	0.84
No Airbnb	\$233.25	∞	\$48.11	1.00	1.00

	Values				**Welfare**	
	$r\mathcal{V}_0$	$r\mathcal{R}_0$	$r\mathcal{I}_0$	$r\mathcal{L}_0$	$r\mathcal{G}$	$r\mathcal{W} \times E5$
Benchmark	1,037.4	8,149.12	45.98	47.14	92.04	7.17
No Airbnb	1,006.7	8,150.33	77.33	45.98	83.48	7.24

Table 3.5: Equilibrium outcomes in the same economy with and without peer-to-peer rentals.

From the benchmark model, note that the prices are the same (i.e. reproduced from) the calibration exercise. In this regime 87% of visitors search for hotels (13% for *Airbnb*s), and 84% of vacant rental properties are listed in the long-term market. As we squeeze the short-term market into nonexistence, we find some intuitive qualitative results. The presence of *Airbnb* depresses hotel prices as innkeepers must compete with them. Further, prices for long-term rentals increase as landlords must be adequately compensated for not listing in the short-term market. Quantitatively we find modest effects on prices. The average price for a hotel is about $24.00 (per night) *less* expensive with *Airbnb*. The average room in a rental property is $1.28 *more* expensive per day (about $39 more per month). For visitors, added choice in search and lower prices make them better off by about 3% with *Airbnb* competition. Residents, however, are worse off. Property manager vacancy profits mimic these results: landlords are better off, innkeepers worse off.

To make these numbers comparable to the empirical literature, we use the model to "translate" the above results. In particular, we convert the model's results in terms of an elasticity: "a percent change in the number of *Airbnb* listings is associated with an X% change in Y." One difficulty in directly making this calculation, though, is that the number of *Airbnb*s in the model is endogenous, so directly manipulating the number of listed short-term rentals is difficult (read *impossible*). Instead we vary κ^S and solve for the model's equilibrium each time. We then use this collection of equilibria to construct a mapping from v^S to equilibrium outcomes. Interpolation of this discrete mapping allows us to uncover the desired statistics. It should be noted, though, that because v^S is varied *through* κ^S for this exercise, we cannot comment on the effect of changes in *Airbnb* listings on the price of *Airbnb*.[13] Results are displayed in 3.11. In the left plot we display the effects on prices; values are displayed on the right. We graphically report the effect for -10% to 10% changes in posted vacancies. A 1% increase in the number of *Airbnb* listings

. . .

[13]Instead, the exercise produces the effect of changes in the posting cost of *Airbnb*s on *Airbnb* prices.

increases	rents	0.023%
	visitor utilities	0.022%
	the value of a vacant rental	0.024%
decreases	hotel prices	0.086%
	resident utilities	0.0001%
	the value of a vacant hotel	0.138%.

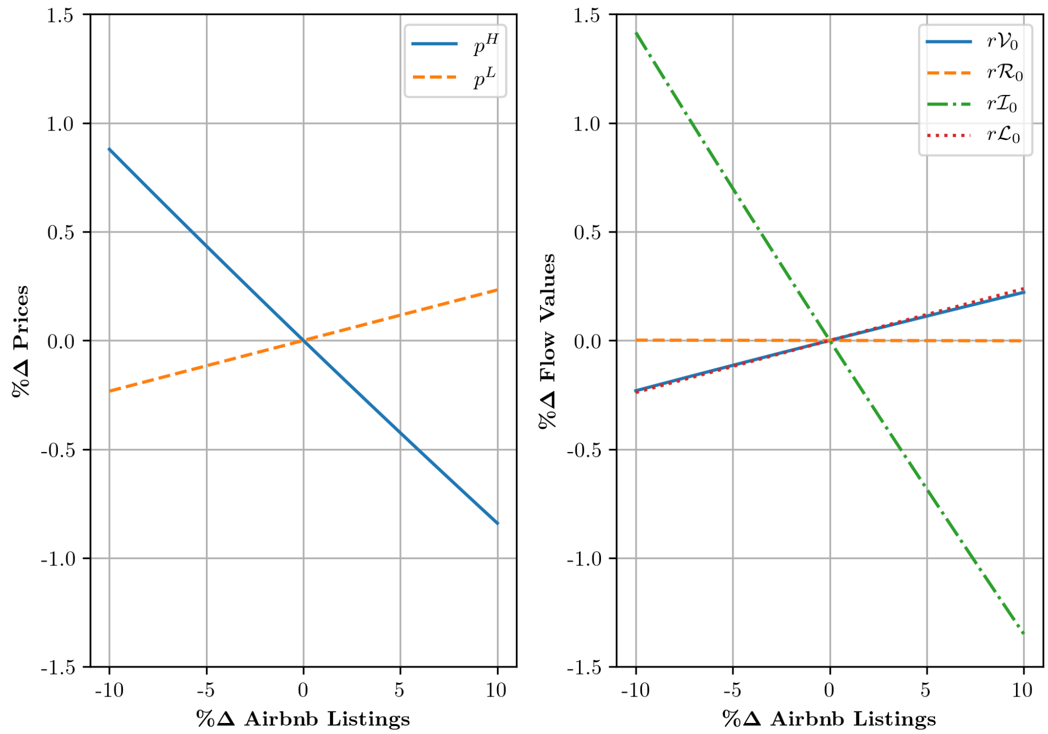


Figure 3.11: Percentage change in equilibrium values from a percentage change in the number of *Airbnb* listings.

The model numbers are larger than what are found in our reduced-form analyses: the regression results found an effect of 0.01% on the price of rentals. However, they are closer to estimates found in [67] which suggest an effect of 0.018%. Their paper utilizes data for the entire United States, so quantitative differences may stem from Santa

Barbara's relatively unique isolation and development constraints. More broadly this raises questions about the importance of building constraints in generating heterogeneous effects of *Airbnb*. This important extension is left for future research.

Notwithstanding, the model generally produces effects larger than what is found in empirical studies that we feel the need to comment on. While our structural approach avoids issues of measurement error and reverse-causation, for example, it does abstract in some key ways that might be important. Most notably there is no heterogeneity in quality. In reality we know that there are at least some key differences in most short and long-term rentals. Traditional (long-term) rentals are typically unfurnished, while *Airbnb*s are. If we think that *Airbnb*s attract furnished (or some notion of higher quality) properties, we *a priori* predict that that the above price effects would be smaller. Further, we might expect peer-to-peer markets to cater towards medium length–as opposed to short–stays. We have modeled both short-term rentals and hotels to be perfect compliments. Relaxing this might keep hotel prices from dropping as much as we vary the availability of *Airbnb*.

We argue that these results offer a starting point to exploring the general equilibrium effects of peer-to-peer technologies on existing, traditional markets. In addition, we find a relatively surprising normative result regarding *aggregate* welfare: the economy is worse off with *Airbnb*. Phrased differently, what are the sources of inefficiency that can generate lower welfare with *more* choice? In the next section we more formally define the welfare problem and think of this question in the context of optimal policy.

3.6 Policy and Welfare

Now we extend the model above to address questions of public policy and welfare. We interpret the κ's as elements in the choice set of governing agent $\mathcal{G}$. Let $\kappa^i = \kappa + \widetilde{\tau}^i$,

$i \in \{H, S, L\}$, where κ is a flow cost charged to properties in all markets.[14]. Because of linear production and utility, we normalize κ to zero. $\widetilde{\tau}^i$ are fees paid to operate in market $i \in \{H, S, L\}$. $\widetilde{\tau}^H$ and τ^S model TOT fees, while τ^L are hypothetical fees placed on traditional rentals.

The government's objective is to maximize aggregate welfare using one of several policies. The different policies limit which markets the government can tax. For example, in one policy we suppose that the government cannot tax traditional rentals, but is free to tax hotels and *Airbnb*s. Deviations away from the unlimited policy (i.e. can levy fees on all markets) are *constrained optimal* and interpreted as "politically feasible" options. Letting $\boldsymbol{\tau} = [\widetilde{\tau}^H, \widetilde{\tau}^S, \widetilde{\tau}^L]'$, the government's objective is to maximize

$$\begin{aligned}
\mathcal{W} = \max_{\boldsymbol{\tau}} \Bigg\{ & u^{\mathcal{V}}\mathcal{V}_0(\boldsymbol{\tau}) + u^{\mathcal{R}}\mathcal{R}_0(\boldsymbol{\tau}) + v^{\mathcal{I}}(\boldsymbol{\tau})\mathcal{I}_0(\boldsymbol{\tau}) + v^{\mathcal{L}}(\boldsymbol{\tau})\mathcal{L}_0(\boldsymbol{\tau}) \\
& + \frac{\chi(\boldsymbol{\tau})u^{\mathcal{V}}\widetilde{\lambda}^H(\boldsymbol{\tau})}{\delta^{\mathcal{V}}}\Big[\mathcal{V}_1(p^H;\boldsymbol{\tau}) + \mathcal{I}_1(p^H;\boldsymbol{\tau})\Big] \\
& + \frac{(1-\chi(\boldsymbol{\tau}))u^{\mathcal{V}}\widetilde{\lambda}^S(\boldsymbol{\tau})}{\delta^{\mathcal{V}}}\Big[\mathcal{V}_1(p^S;\boldsymbol{\tau}) + \mathcal{L}_1(p^S;\boldsymbol{\tau})\Big] \\
& + \frac{u^{\mathcal{R}}\widetilde{\lambda}^L(\boldsymbol{\tau})}{\delta^{\mathcal{R}}}\Big[\mathcal{R}_1(p^L;\boldsymbol{\tau}) + \mathcal{L}_1(p^L;\boldsymbol{\tau})\Big] \\
& + \mathcal{G}(\boldsymbol{\tau}) \Bigg\},
\end{aligned} \tag{3.35}$$

where $r\mathcal{G}(\boldsymbol{\tau}) = v^H(\boldsymbol{\tau})\widetilde{\tau}^H + v^S(\boldsymbol{\tau})\widetilde{\tau}^S + v^L(\boldsymbol{\tau})\widetilde{\tau}^L$. In the above we make clear the dependence of the model's endogenous variables upon $\boldsymbol{\tau}$ through prices, values, and search.

In total there are eight welfare exercises whose outcomes are summarized in 3.6 along with the benchmark economy from the calibration. For ease of comparison, we report the policies as tax rates of total revenues ($\tau = \kappa\delta/\lambda p$) and summarize the steady state search behavior with the share of visitors searching for hotels (χ) and the share of vacant

[14]This, for example, includes property taxes which are paid on all types of property

rental properties posted in the long-term market (γ). We group and order the exercises by how many markets are allowed to be taxed, beginning with a no-tax case. In this environment there are no government revenues, prices paid by visitors are lower, and prices paid by residents are higher relative to the calibrated benchmark. The short-term market is more attractive for both visitors and landlords, and so a larger proportion redirect their search away from the hotel and long-term market, respectively. A notable theme that will arise in the results to follow is that aggregate welfare can be improved by government intervention. Put differently, the no-tax case does *not* produce a socially optimal allocation of search effort and vacancy posting. Briefly, though search is directed and competitive, barriers to entry result in positive profits for posted vacancies. This opens up the possibility for agent decisions (to search in another market) to not fully internalize their effects on other agents.

Consider the government having access to tax revenues from each market separately. That is, one-by-one we set $\tau^j = 0.0$ for all markets $j \neq i$. When taxing hotels the government sets a high tax rate (49%) to maximize aggregate welfare. Since hotels must compete with each other *and* landlords, hotel prices fall, more visitors search in the hotel market, and market utilities rise. Indeed, they also rise for residents who enjoy lower prices and faster finding rates as landlords shift some vacancies to the long-term market. Here, visitor decisions to search for *Airbnb*s do not adequately compensate innkeepers for the lower filling rates. The government can improve aggregate welfare by taxing hotels to lower prices and induce these visitors back into the hotel market, where tax revenues can be distributed to hotels to compensate for the lost revenues. In the absence of these taxes, individual innkeepers take market utilities as given and so do not have incentives to lower prices and induce more visitors to search in the hotel market. In contrast the governing agent *can* affect market utilities. In this sense one may think of this inefficiency as a coordination problem in the price / market utility space. An atomistic innkeeper cannot improve visitor utility to induce enough short-term searchers to change their search behavior.

A similar intuition also follows when the government can only tax short-term rentals– though through a slightly different channel. Noting from above that visitors are inefficiently searching for *Airbnb*s, landlords also inefficiently re-direct vacancy postings from residents to this market. Since residents have no outside occupancy options (and because they are a large portion of the population) lost utility from lower finding rates and higher prices add up quickly and have large effects on aggregate welfare. Increasing fees in the short-term market can kill both of these birds (with one stone). Higher fees reduces landlords profits and leads more to advertise their vacant rentals to residents. Since both markets are available to landlords, in order to keep at least some posting in the short-term market, p^S must *increase*.[15] These higher prices lead more visitors to search for hotels. Since this policy addresses two sources of inefficiency, aggregate welfare is higher than when only taxing innkeepers. Further, due to the *Airbnb* market being relatively small, this welfare improvement is achieved with very little redistribution.

The last, single-market tax exercise is the long-term market. Very straightforwardly, we find that the optimal fee to place is 0.00 as one of the main sources of inefficiency involves not enough vacancies for residents. This can also be seen in the two-market exercise where the governing agent may tax hotels and long-term rentals. We find no tax should be levied in L, and the high, 49% tax should be imposed in H to reallocate search effort. When taxing the two visitor markets, we find a slightly more "balanced" optimal policy wherein *Airbnb* taxes are slightly lower (though virtually identical after rounding) and hotel taxes are present, but small. Finally, the welfare maximizing policy can be achieved by taxing *only* landlords. Here, the government sets taxes on *Airbnb*s

[15] This differs from the case above because innkeepers do not have an outside option to lodge non-visitors.

so high (71%) that they are effectively nonexistent, bringing back the economy to one where peer-to-peer rentals do not exist. In addition, since all agents have limited choice sets (i.e. no outside option for visitors or landlords), the government can levy a small, redistributive tax on long-term rentals à la the single-market hotel tax case. Because the search externalities can be corrected primarily with the high tax in the short-term market, there is no need to tax the hotel market.

$\mathcal{G}$ Choice Set			Policy			Prices			Search		Welfare	
H	S	L	τ^H	τ^S	τ^L	p^H	p^S	p^L	χ	γ	$r\mathcal{G}$	$r\mathcal{W}$ ($\times E5$)
X	X	X	0.00	0.00	0.00	\$204.21	\$154.14	\$50.56	0.77	0.71	0.00	7.09
✓	X	X	0.49	0.00	0.00	\$184.48	\$150.95	\$48.74	0.94	0.91	311.48	7.20
X	✓	X	0.00	0.33	0.00	\$239.64	\$172.71	\$48.40	0.96	0.96	5.21	7.22
X	X	✓	0.00	0.00	0.00	\$204.21	\$154.14	\$50.56	0.77	0.71	0.00	7.09
X	✓	✓	0.00	0.71	0.03	\$246.57	\$164.40	\$27.20	1.00	1.00	82.60	7.24
✓	X	✓	0.49	0.00	0.00	\$184.48	\$150.95	\$48.74	0.94	0.91	311.48	7.20
✓	✓	X	0.06	0.33	0.00	\$236.71	\$172.38	\$48.18	0.99	0.99	52.72	7.23
✓	✓	✓	0.00	0.71	0.03	\$246.57	\$164.40	\$27.20	1.00	1.00	82.60	7.24
Benchmark			0.12	0.12	0.00	\$209.50	\$158.83	\$49.29	0.87	0.84	92.04	7.17

Table 3.6: Policy experiment results.

3.7 Conclusion

In this paper, we examine the impact of the presence of *Airbnb* listings on the price of long-term rentals and hotels. We do this by developing a structural search and matching model where property managers post vacant rooms and tenants direct their search to these postings. In our model we have three separate but interconnected markets, the hotel market accessible to innkeepers and visitors, the short-term rental market accessible to landlords and visitors, and the long-term rental market accessible to landlords and residents. We then apply our model using a novel dataset for the Santa Barbara, California, housing and hotel markets combining data from several sources including *Visit Santa Barbara*, the *American Community Survey*, *Zillow*, and scraped *Airbnb* listings.

Our results suggest that *Airbnb*s decrease hotel prices by about $24 per night while increasing average rents by $39 per month. While the presence of *Airbnb* creates added choice in accommodation for visitors, increases their flow utility by about 3%, this welfare gain is more than offset by the reduction in welfare for residents due to fewer rentals to search for and higher prices. Overall, we find that with limited entry, aggregate welfare is reduced by the presence of *Airbnb*. As a result, a government policy to set a high transient occupancy tax on short-term rentals would increase aggregate welfare.

While this paper addresses the impact of *Airbnb*s on renters, there are other impacts of *Airbnb* on housing markets that are not accounted for, such as the effect on the price of owning a home. Furthermore, we do not explore the impacts of allowing for the development of new properties.

Appendix A

Job Finding (mis)Perceptions and Where Searchers Look for Work

A.1 Job Finding Beliefs by Demographic Groups

	Believed Prob.	Realized Prob.	Difference	Ratio
male	0.443	0.363	0.081	1.414
female	0.503	0.365	0.138	1.554
young: $[25, 45]$	0.572	0.349	0.223	1.893
old: $(45, 65]$	0.424	0.373	0.051	1.265
High School	0.472	0.367	0.105	1.410
Some College	0.484	0.361	0.123	1.564
College	0.482	0.364	0.118	1.554
HH inc. $<$ 50k	0.462	0.366	0.097	1.462
HH inc. 50k to 100k	0.567	0.367	0.200	1.661
HH inc. $>$ 100k	0.474	0.344	0.131	1.537

(Back to Empirical Regularities 1.3.2)

A.2 Proof of Lemma 1

The proof of this lemma relates the conjugate property of the beta distribution for the likelihood function of a Bernoulli random variable, namely the outcome of job search. Additionally, in the application to a setting with endogenous job finding probabilities that may change over time, a prior mean belief of μ (in addition to α and γ) is necessary to initiate the learning mechanism. First observe that *(i)* is established by noting that the mean of $f \sim \text{Beta}(\alpha, \gamma)$, $\alpha \in \mathbb{R}_+$ and $\gamma \in \mathbb{R}_+$, is $\hat{f} = \alpha/(\alpha + \gamma) \in (0, 1)$. This mean is increasing (decreasing) in α (γ), and so given $\hat{f}$ there exists a (non-unique) pair (α, γ) that produces it. Bayes' formula establishes *(ii)*. Letting $B(\cdot)$ denote the beta function and $p(\cdot)$ denote the appropriate probability functions, we have

$$\begin{aligned} p(f|y) &= \frac{p(y|f)p(f)}{p(y)} \\ &= \frac{f^y(1-f)^{1-y}\left[B^{-1}(\alpha,\gamma)f^{\alpha-1}(1-f)^{\gamma-1}\right]}{B^{-1}(\alpha,\gamma)\displaystyle\int f^{y+\alpha-1}(1-f)^{\gamma-y}df} \\ &= B^{-1}(\alpha_y,\gamma_y)f^{\alpha_y-1}(1-f)^{\gamma_y-1}, \end{aligned} \tag{A.1}$$

where $\alpha_y = \alpha + y$ and $\gamma_y = \gamma + 1 - y$. Finally, *(iii)* may be backed out from the expression for the posterior mean of f.

$$\begin{aligned} \hat{f}' &= \frac{\alpha_y}{\alpha_y + \gamma_y} \\ \hat{\mu}_y\hat{\theta}^\eta &= \frac{\alpha + y}{\alpha + \gamma + 1} \\ \hat{\mu}_y &= \left(\frac{\alpha + y}{\alpha + \gamma + 1}\right)\hat{\theta}^{-\eta} \end{aligned} \tag{A.2}$$

(Back to Model 1.4.1)

A.3 Proof of Theorem 1

Let $\mathcal{V} : \{0,1\} \times \mathbb{R}^3_+ \times \Psi \to \mathbb{R}$ be a function defined such that $\mathcal{V}(0, \hat{\mu}, e, \psi) = \mathcal{V}_U(\hat{\mu}, e, \psi)$ and $\mathcal{V}(1, \hat{\mu}, e, \psi) = \mathcal{V}_E(\hat{\mu}, e, \psi)$. 1.3, and 1.4 can then be rewritten as

$$\begin{aligned} \mathcal{V}(a, \hat{\mu}, e, \psi) = a &\left[A + \beta \mathbb{E}_{\psi'|\psi} \max_s \left\{ s\mathcal{V}(0, \hat{\mu}, e, \psi') + (1-s)\mathcal{V}(1, \hat{\mu}, e, \psi') \right\} \right] \\ +(1-a) &\left[b + \beta \mathbb{E}_{\psi'|\psi} \max_x \left\{ \hat{f}_{x,e,\psi} x + \left(1 - \hat{f}_{x,e,\psi}\right) \mathcal{V}(0, \hat{\mu}_0, e+1, \psi') \right\} \right]. \end{aligned} \tag{A.3}$$

Next, note that the worker's choice of x can be written in terms of $\hat{\theta}$, $\hat{\mu}$, e, and ψ using 1.5 as $x(\hat{\theta}, \hat{\mu}, e, \psi) = \mathbb{E}_{\psi'|\psi} \mathcal{V}(1, \hat{\mu}_1, e+1, \psi') - \frac{\kappa}{q}$. As in [11], x cannot be uniquely expressed as a function of market tightness and the state variables in sub-markets with $\hat{\theta}_{x,e,\psi} = 0$. However, this is irrelevant insofar as the worker never expects to find a job in these sub-markets. As such, it can be assumed w.l.o.g. that those sub-markets with $\hat{\theta} = 0$ have values given by the above. Different than [11] is that $\hat{\theta}$ does not necessarily equal θ. As can be observed in 1.4, though,

$$\hat{\theta}_{x,e,\psi} = \left(\frac{\mu}{\hat{\mu}} \right)^{\frac{1}{1-\eta}} \theta_{x,e,\psi}, \tag{A.4}$$

so $\hat{\theta} = 0$ if and only if $\theta = 0$, and vice versa. Therefore this assumption can be extended w.l.o.g. to θ. Now substitute $x(\hat{\theta}, \hat{\mu}, e, \psi)$ for x and $\hat{\theta}$ for $\hat{\theta}_{x,e,\psi}$ in A.3 and write the problem as follows.

$$\begin{aligned}\mathcal{V}(a,\hat{\mu},e,\psi) = a&\left[A+\beta\mathbb{E}_{\psi'|\psi}\max_{s}\left\{s\mathcal{V}(0,\hat{\mu},e,\psi')+(1-s)\mathcal{V}(1,\hat{\mu},e,\psi')\right\}\right]\\ +(1-a)&\left[b+\beta\mathbb{E}_{\psi'|\psi}\max_{\hat{\theta}}\left\{\hat{\mu}\hat{\theta}^{\eta}\mathcal{V}(1,\hat{\mu}_1,e+1,\psi')-\kappa\hat{\theta}+\right.\right.\\ &\left.\left.\left(1-\hat{\mu}\hat{\theta}^{\eta}\right)\mathcal{V}(0,\hat{\mu}_0,e+1,\psi')\right\}\right].\end{aligned} \tag{A.5}$$

Let $\Omega = \{0,1\}\times\mathbb{R}^3_+\times\Psi$ and let $C(\Omega)$ denote the space of bounded continuous functions $R:\Omega\to\mathbb{R}$, with the sup norm. Let $T: C(\Omega)\to C(\Omega)$ be the operator associated with A.5. The following can be easily established.

(i) T is monotonic: for $R_1, R_2 \in C(\Omega)$ where $R_1 \le R_2$ w.l.o.g., $T(R_1)\le T(R_2)$.

(ii) T discounts: for $R\in C(\Omega)$ and $c\in\mathbb{R}_+$, $T(R+c) = TR+\beta c$.

Thus, by Blackwell's sufficiency conditions, we have that the operator T is a contraction mapping and there exists a unique fixed point $\mathcal{V}$. Next, it is also easy to see that R depends on ψ' only through A'. It is thus also the case that $T(R)$ depends on ψ only through A. This logic similarly applies to the agents' policy functions. Thus the value and policy functions only depend on the aggregate state through realizations of the aggregate shock, A, and not on the distribution of workers (and their résumés) across employment states. (Back to Model 1.4.3)

A.4 Bilaterally Efficient Contract with Constant Wages

Suppose a worker finds a job that pays a fixed, non-changing wage w each period with separation contingency specified in the employment contract given by s. Her lifetime utility can be written as

$$\begin{aligned}\mathcal{V}_W(w;\hat{\mu},e,\psi) = w + \beta\mathbb{E}_{\psi'|\psi}\Big[&s(\hat{\mu},e,\psi')\mathcal{V}_U(\hat{\mu},e,\psi') \\ &+ (1-s(\hat{\mu},e,\psi'))\mathcal{V}_W(w;\hat{\mu},e,\psi')\Big].\end{aligned} \tag{A.6}$$

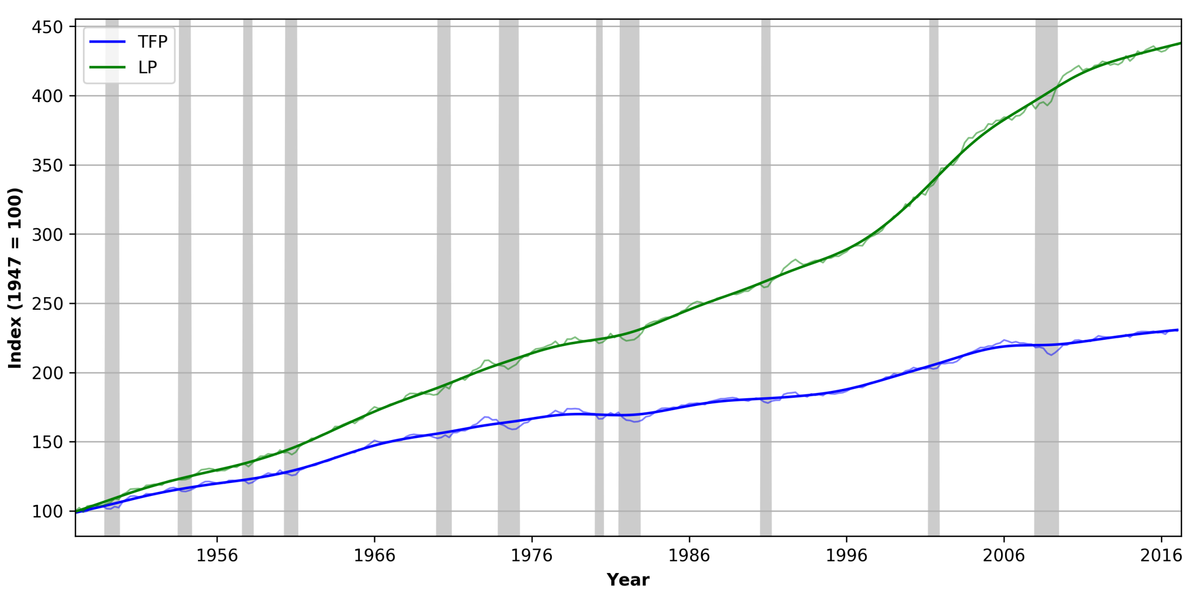
The fixed-wage is given by the solution to the above when $x = \mathcal{V}_W(w;\hat{\mu},e,\psi)$, where x is the value promised by the firm to the worker when the contract was signed. It should also be noted that all block recursive results established above also apply here. That is, $\mathcal{V}_W$ can be shown to depend on ψ only through A. For a formal treatment of fixed-wage (and other) contracts in directed search, block recursive environments, see [9]. (Back to Calibration 1.5)

Appendix B

On-the-Job Leisure

B.1 Tables and Figures

Figure B.1: United States Productivity Series



Notes: The TFP series was accessed through Fernald's TFP data set at the FRBSF. Labor productivity is accessed through FRED.

Table B.1: Summary Statistics

	Means			
Variable	Unconditional	OJL=1	OJL=0	Difference
Prop. of Nonwork	0.067	0.099	0.000	***
OJL	0.681	1.000	0.000	–
Unemp. Rate	6.419	6.422	6.412	
Unemp. Rate (3mo. ave.)	6.425	6.428	6.419	
Real Wage (base = 2009)	19.504	19.115	20.337	***
Usual Weekly Hours	41.33	41.492	40.985	***
Time at Work (diary day)	8.463	8.952	7.419	***
Experience (potential)	20.489	20.720	19.995	***
Female	0.459	0.451	0.478	***
Married	0.539	0.538	0.540	
Black	0.113	0.123	0.092	***
Hispanic	0.156	0.174	0.119	***
Educ. ≤ 12 Years	0.292	0.312	0.250	***
Educ. $13 - 15$ Years	0.275	0.273	0.279	
Educ. 16 Years	0.214	0.200	0.244	***
Educ. ≥ 16 Years	0.030	0.025	0.039	***
Metropolitan	0.844	0.843	0.845	
N	46,314	30,670	15,644	

*Notes: ATUS final weights are used. The last column reports the significance level of the p-values for a test of the difference in conditional means: *** p<0.01, ** p<0.05, * p<0.1.*

Table B.2: Regression Results

	OLS				Probit	
	Prop. Nonwork				OJL	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Real Wage)	-0.0002	-0.0004	0.0045***	0.0048***	-0.0235***	-0.0264***
	(0.0013)	(0.0014)	(0.0017)	(0.0017)	(0.0054)	(0.0057)
UE Rate	0.0007*	0.0008	0.0017***	0.0023***	-0.0025*	-0.0066***
	(0.0004)	(0.0006)	(0.0005)	(0.0007)	(0.0015)	(0.0020)
<u>Patent Growths</u>:						
Total		-0.2037		0.1836		-3.8585***
		(0.2281)		(0.2518)		(0.9122)
Communication		0.1218		0.2287		-0.5697
		(0.1505)		(0.1727)		(0.6138)
Comp. Hard/Software		-0.1152		-0.1828		1.2808*
		(0.1871)		(0.2221)		(0.7628)
Comp. Peripherals		0.0414		-0.0671		0.8725***
		(0.0761)		(0.0865)		(0.3284)
Amusement Devices		0.0505		-0.0967		1.0925***
		(0.0757)		(0.0846)		(0.3178)
Other Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓	✓	✓
Sample Restriction	NA	'03-'14	OJL=1	OJL=1, '03-'14	NA	'03-'14
N	45,924	40,820	30,442	27,087	45,924	40,820
R^2	0.0763	0.0740	0.3249	0.3236	0.1179	0.1190

*Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust SEs are given in parentheses. Probit estimates are average marginal effects, with SEs calculated using the delta method. The real wage is measured in 2009 dollars. As noted earlier, the unemployment rate is the 3-mo. average leading up to a respondent's interview. Patent growth rates are calculated as the 12-mo. percentage change of patents in-force. Occupation, industry, state, and month fixed effects are included. Other controls include all other listed variables in B.1, including a female-by-married interaction and quadratic terms in age, experience, usual weekly hours, and total time at work. All specifications use ATUS final weights.*

Table B.3: Calibration

Parameter	Value	Description	Source
γ	1.110	utility function value of leisure	jointly calibrated
δ_0	0.034	sep. prob. function intercept	jointly calibrated
δ_1	0.006	sep. prob. function slope	jointly calibrated
η	6.044	prob. of leisure opp.	jointly calibrated
λ	0.203	prob. of leisure opp.	jointly calibrated
μ	0.447	matching function scale	mean p of 0.358
ν	1.021	utility function curvature	jointly calibrated
ψ	0.72	matching function elasticity	[77]
β	0.72	bargaining parameter	Hosios
κ	24.90	vacancy posting cost	mean θ of 0.44
b	0.4	unemployment benefits	[77]
r	0.0025	discount rate	3% annual discount
g_w	0.0	expected wage growth	behavioral assumption
Moment	**Value: (Model, Data)**	**Description**	
1	$(0.685, 0.685)$	eq. prob. of leisure opp.	
2	$(2.146, 2.146)$	ave. marg. effect of distractions on prob. of leisure opp.	
3	$(0.099, 0.099)$	eq. prop. of non-work	
4	$(0.0019, 0.0019)$	semi-elasticity of wages on leisure	
5	$(0.0014, 0.0014)$	marg. effect of unemployment rate on leisure	
6	$(0.034, 0.034)$	ave. measure of separations	

Table B.4: Second Order Moments

	St. Dev.	Correlation	
		u	GDP
u	0.0157	1.00	-0.58
		(0)	(0.00)
GDP	0.0111	-0.58	1.00
		(0.00)	(0)
hours_{ojl}	0.0322	-0.59	0.80
		(0.00)	(0.00)
$\text{hours}_{reported}$	0.0177	-0.64	0.88
		(0.00)	(0.00)
hours_{actual}	0.0143	-0.62	0.84
		(0.00)	(0.00)
$\text{lprod}_{reported}$	0.0085	0.28	-0.04
		(0.00)	(0.65)
lprod_{actual}	0.0085	-0.02	0.37
		(0.92)	(0.00)
$\text{rcomp}_{reported}$	0.0110	0.08	-0.06
		(0.36)	(0.48)
rcomp_{actual}	0.0120	-0.14	0.23
		(0.11)	(0.00)

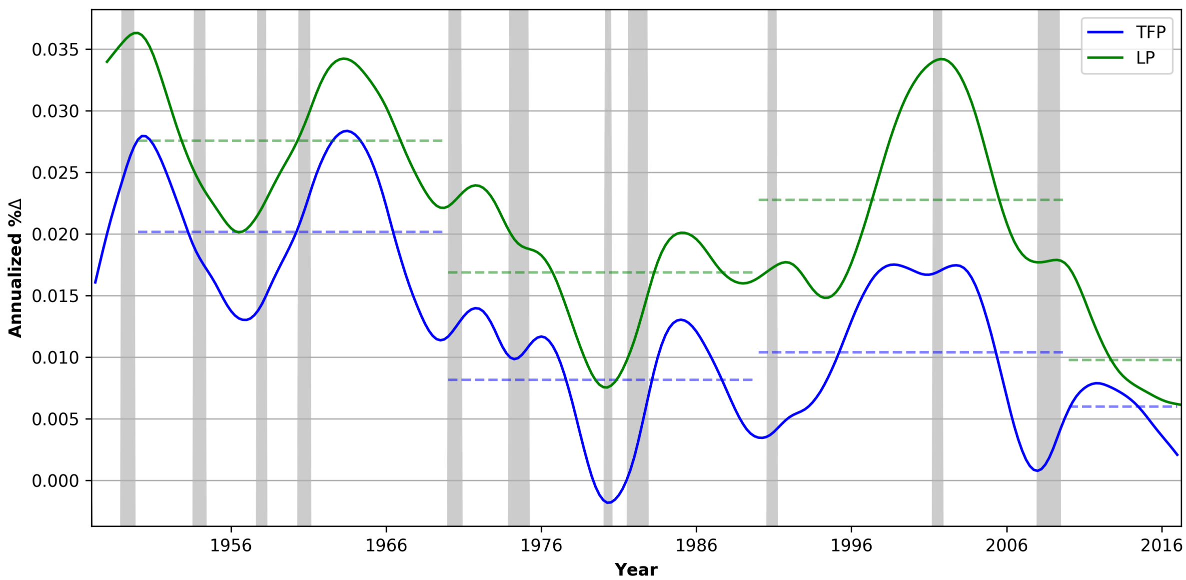
Notes: Hours, labor productivity, and real compensation are logged and detrended prior to calculation of the above standard deviations and correlations. p-values for a test of non-correlation are given in parentheses.

Table B.5: Growth Rates By Period

	Cycle				Period	
	'83-'89	*'92-'00*	*'03-'07*	*'09-'15*	*'83-'02*	*'03-'15*
Hours						
actual	3.09	2.46	1.51	2.07	1.53	1.51
reported	3.14	2.51	1.6	2.02	2.33	1.47
Labor Prod.						
actual	1.88	2.03	1.61	0.61	2.33	1.47
reported	1.84	1.98	1.51	0.65	2.31	1.48
Real Comp.						
actual	0.82	1.23	1.31	0.19	1.26	1.31
reported	0.77	1.18	1.22	0.24	1.24	1.22

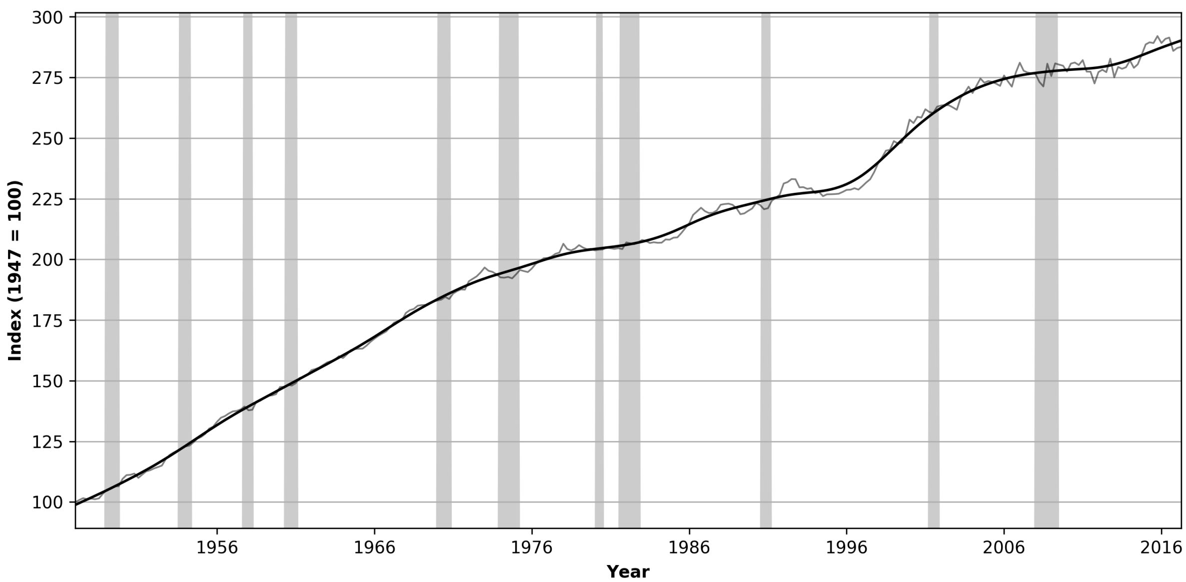
Notes: Calculated above are average annualized quarterly growth rates of the indicated reported series, the corrected "actual" series, and the difference.

Figure B.2: United States Productivity Growth



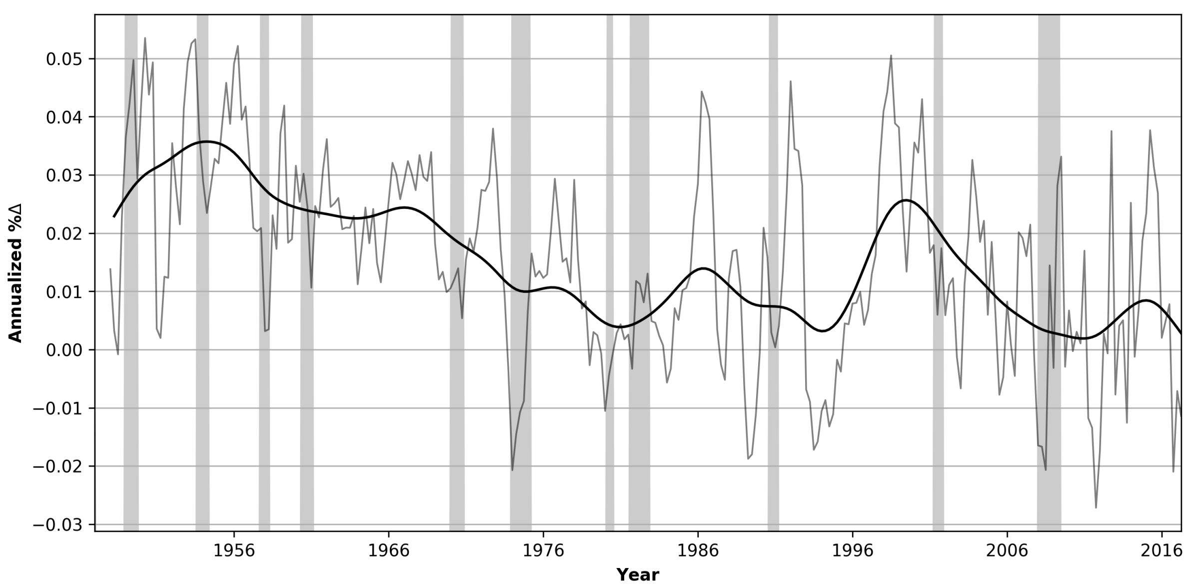
Notes: The TFP series was accessed through Fernald's TFP data set at the FRBSF. Labor productivity is accessed through FRED. We graph the trend of the annualized percentage change and give the means over the 1950-1970, 1970-1990, 1990-2010, and 2010-present time frames.

Figure B.3: United States Real Compensation



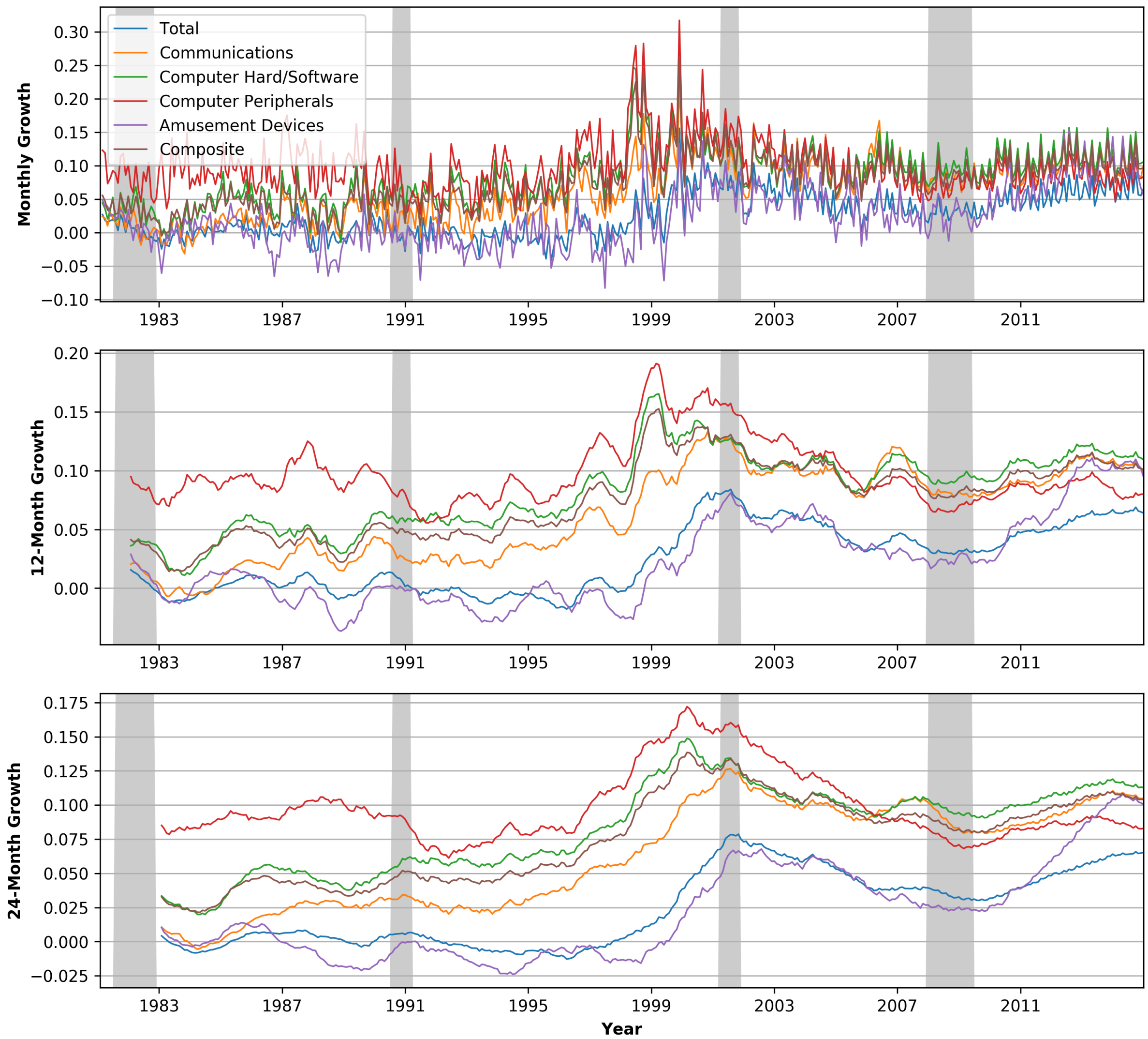
Notes: The above series is the real compensation per hour of the nonfarm business sector, accessed through FRED.

Figure B.4: United States Real Compensation Growth



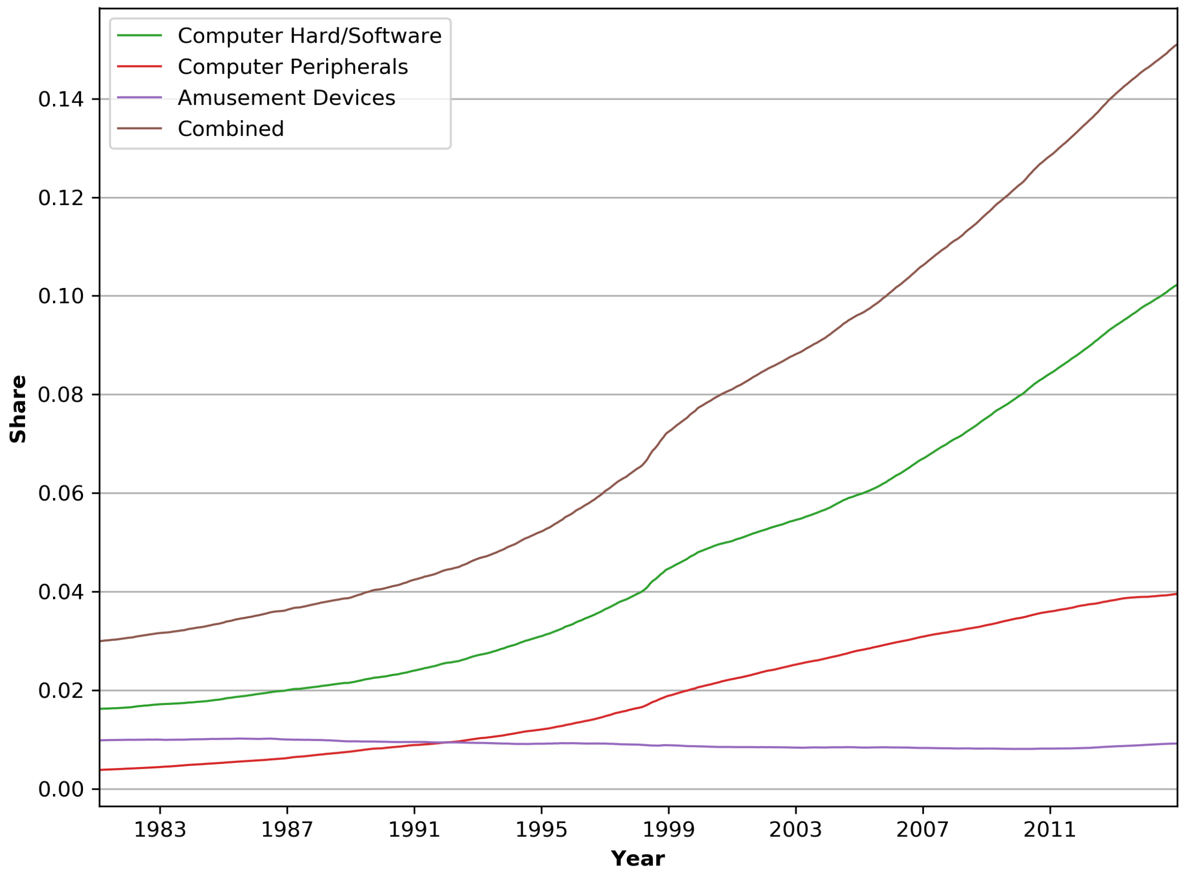
Notes: The above series is the annualized growth in real compensation per hour of the nonfarm business sector, accessed through FRED.

Figure B.5: United States In-Force Patents – Growths



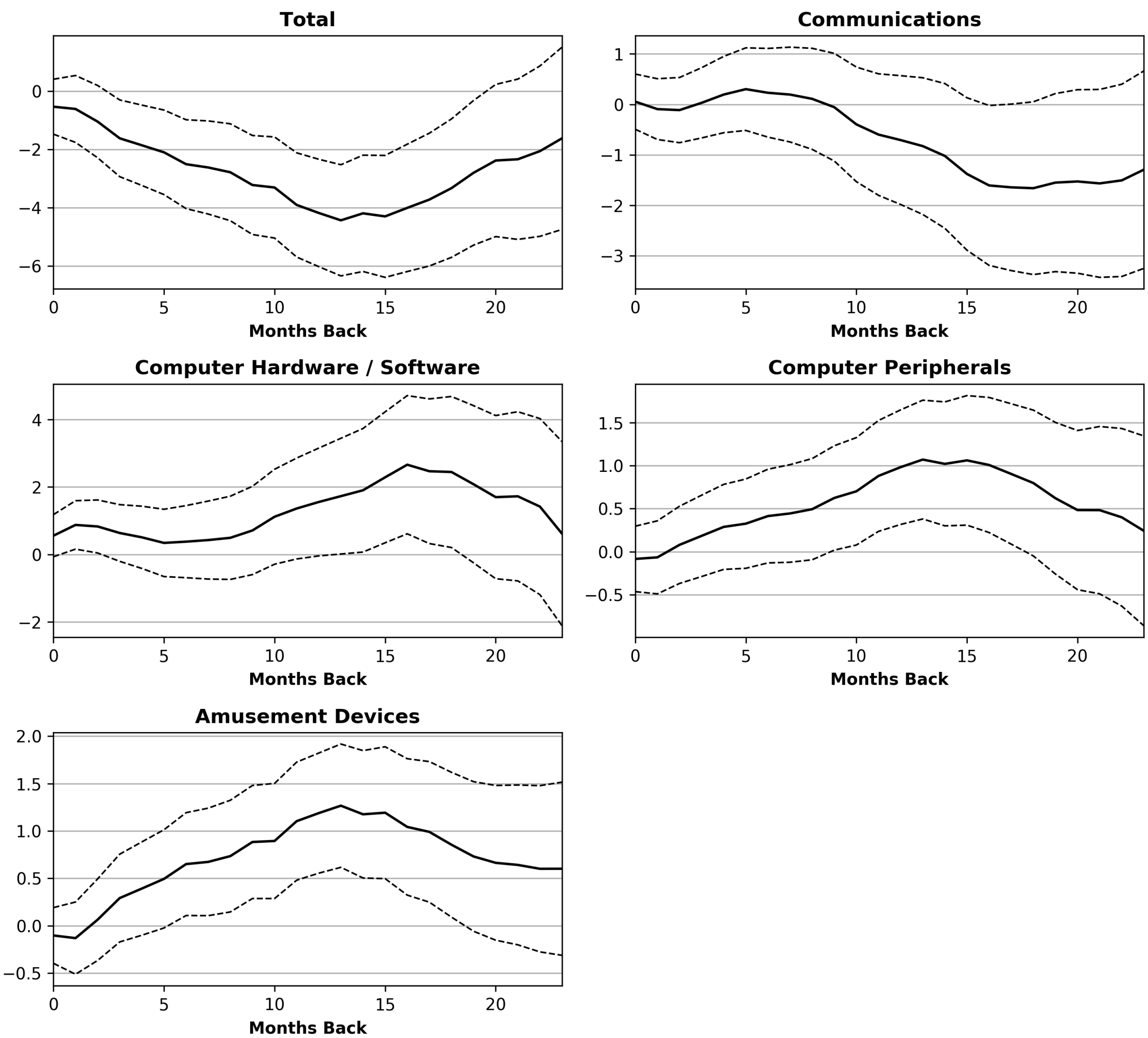
Notes: These data come from the United States Patent and Trademark Office. Graphed are the annualized monthly, 12-month, and 24-month growth rates of total patents along with categories plausibly associated with on-the-job leisure. Namely, the communications, computer hard/software, computer peripherals, and amusement devices categories (NBER categories 21-23 and 62). The composite category, used for calibration, combines the computer hard/software, computer peripherals, and amusement devices.

Figure B.6: United States In-Force Patents – Shares of Total



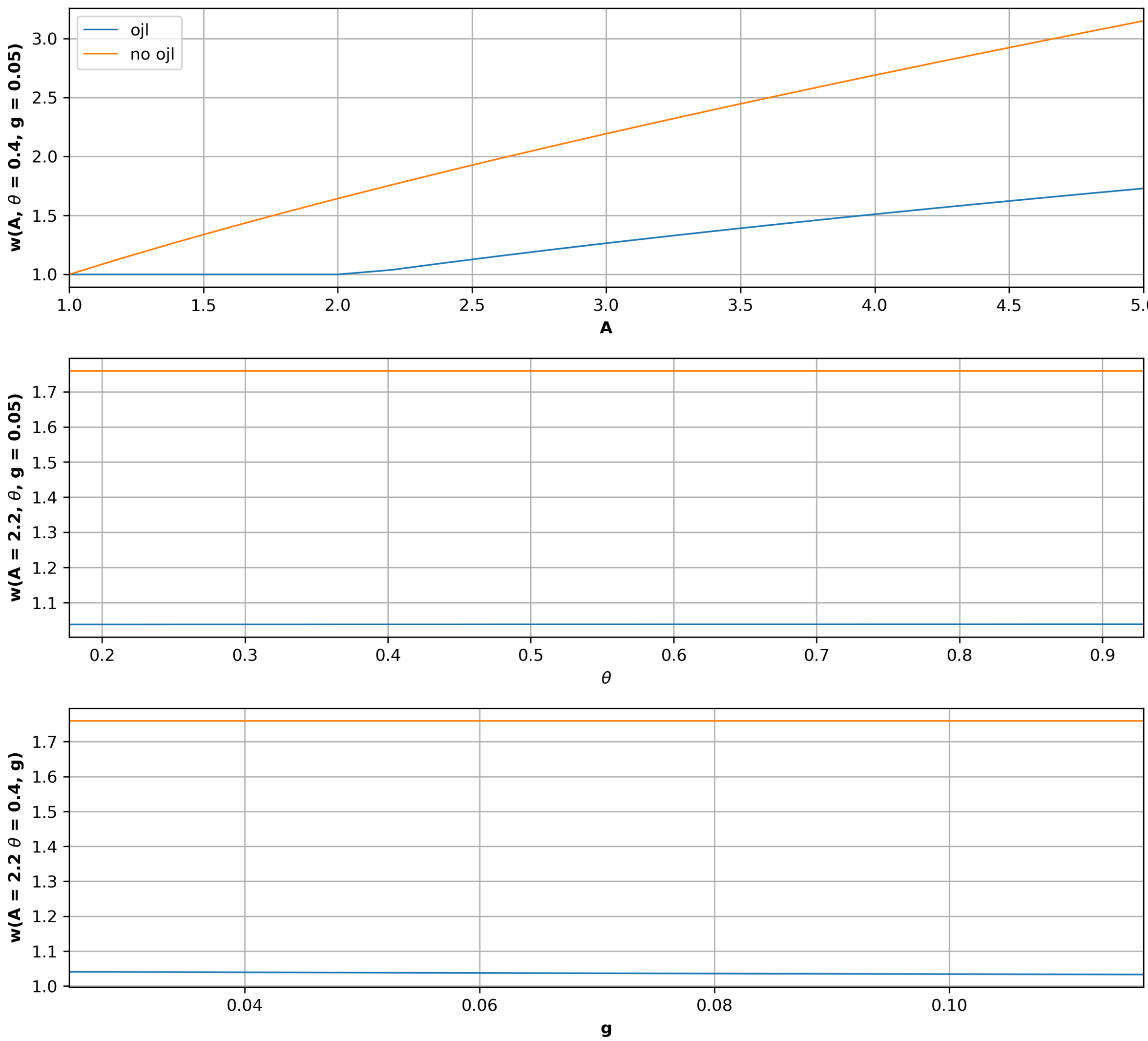
Notes: These data come from the United States Patent and Trademark Office.

Figure B.7: Innovation Coefficients



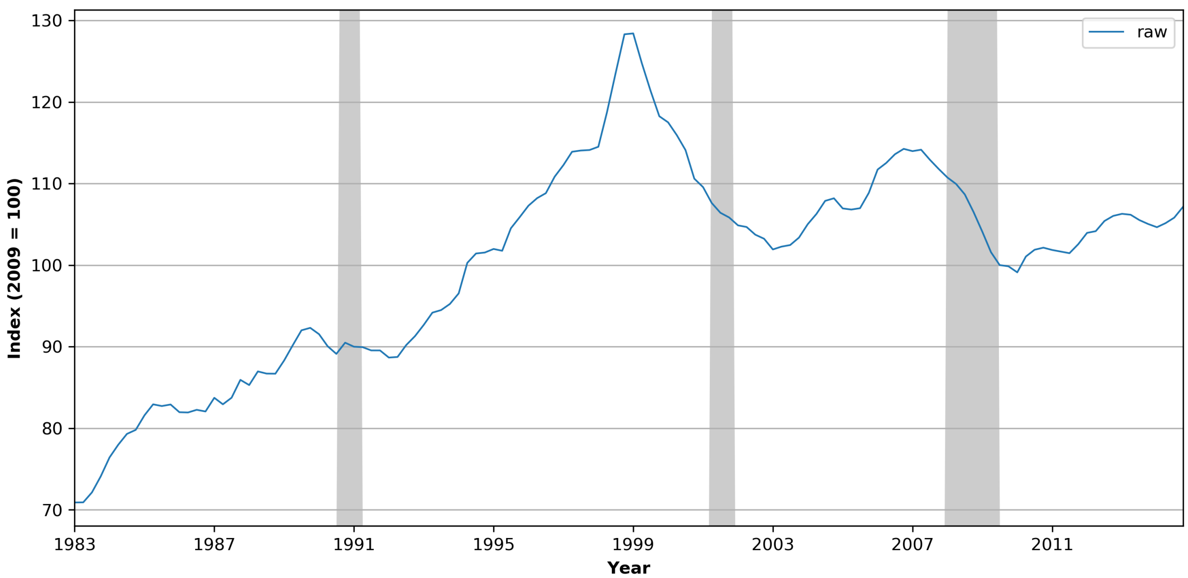
Notes: Above are plots of the Probit derivatives (and 95% confidence bands calculated numerically with the delta method) on the patent growth variables from the Probit regressions for different horizons. That is, each point is the average percentage point effect of increasing the annualized t-month growth rate of a given category by 1pp, holding all other categories constant.

Figure B.8: Wage Formation



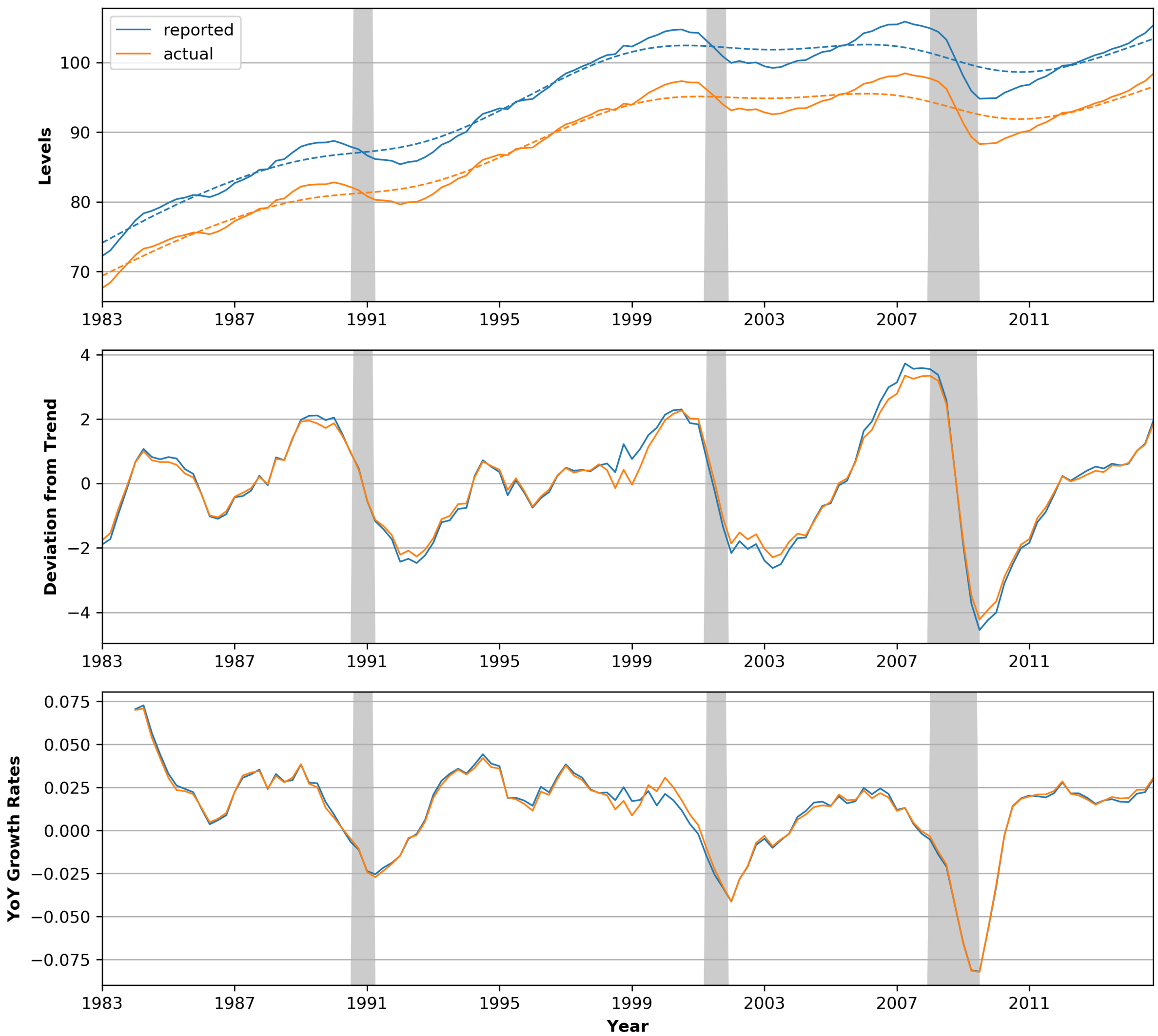
Notes: Plotted above is a comparison of equilibrium wages in the paper's model and an otherwise similar model, differing only in that no on-the-job leisure is permitted: $l^* = 0$. *The results use our later calibration. Each plot graphs equilibrium wages over grids of other variables, fixing other variables to the center of their grids.*

Figure B.9: U.S. On-the-Job Leisure



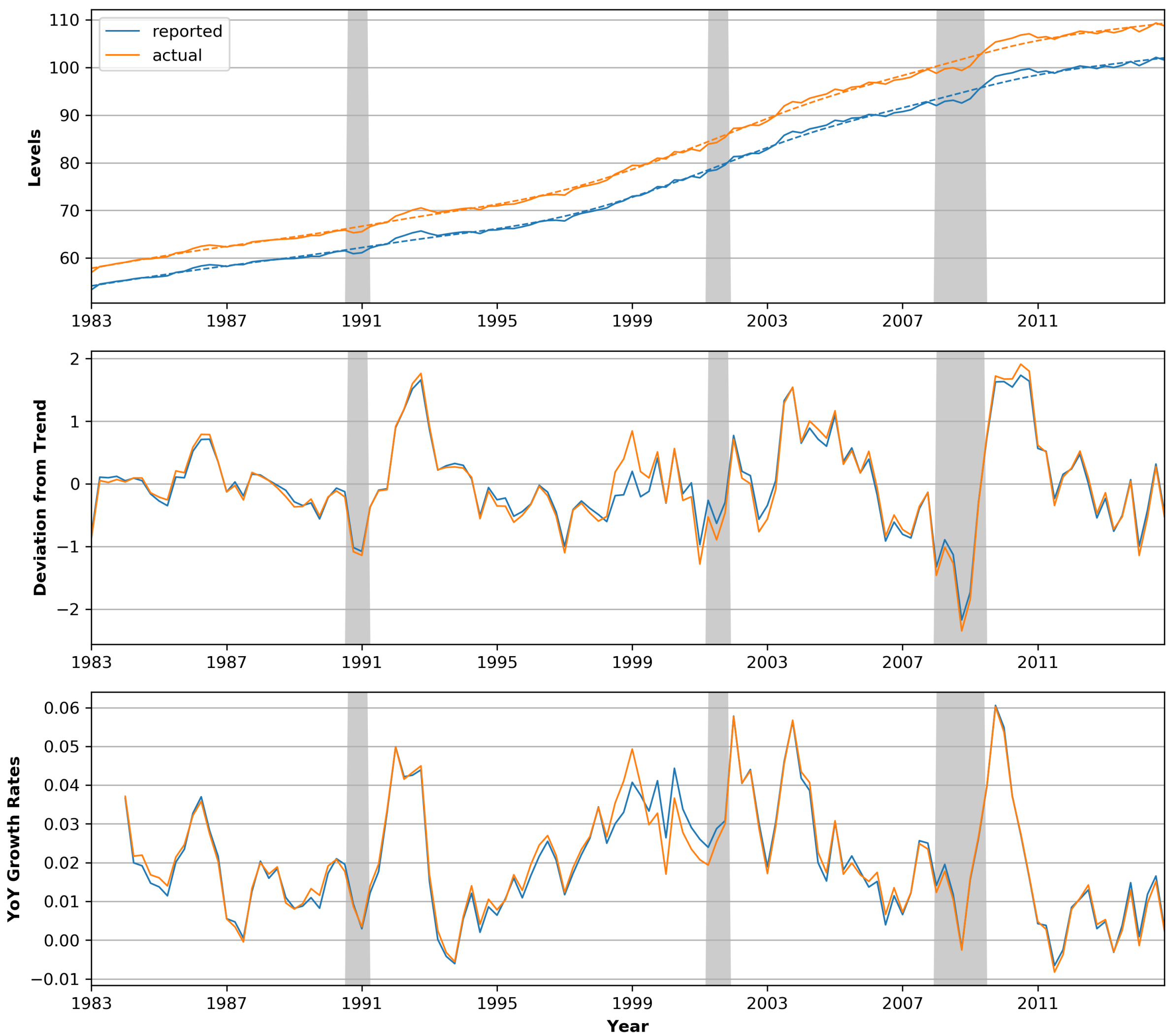
Notes: Plotted in the top graph is the aggregate on-the-job leisure series produced by the model along with its Hodrick-Prescott filtered trend. The bottom graph displays the associated deviation from trend.

Figure B.10: Adjusted Aggregate Hours



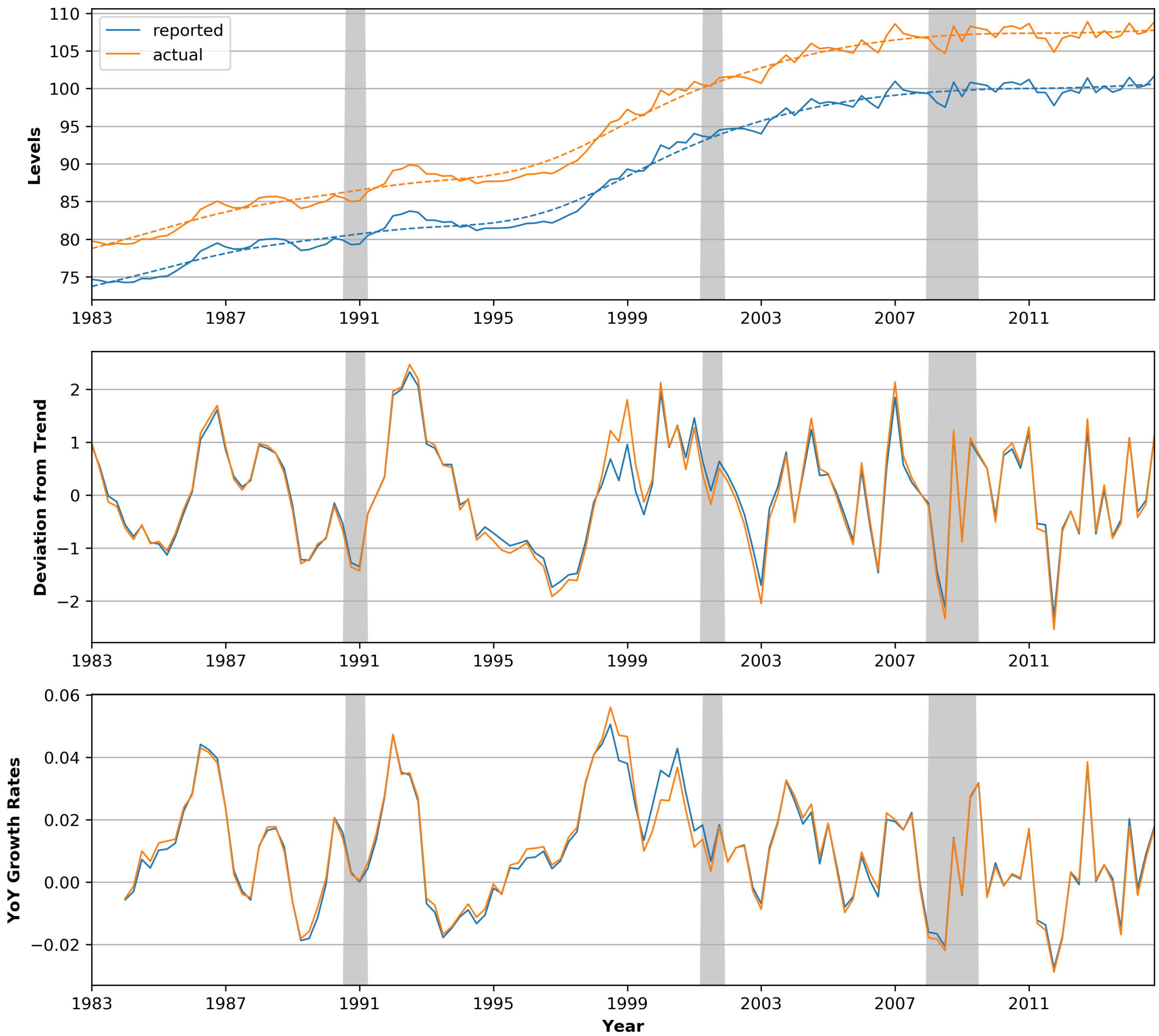
Notes: The top graph plots the observed, i.e. published by the BLS, nonfarm business sector hours in the U.S. economy and the leisure-corrected, "actual" series (and their HP filtered trends) using the model's produced on-the-job leisure series. The middle and bottom graphs plot the differences from trend and year-over-year growth rates of these series.

Figure B.11: Adjusted Labor Productivity



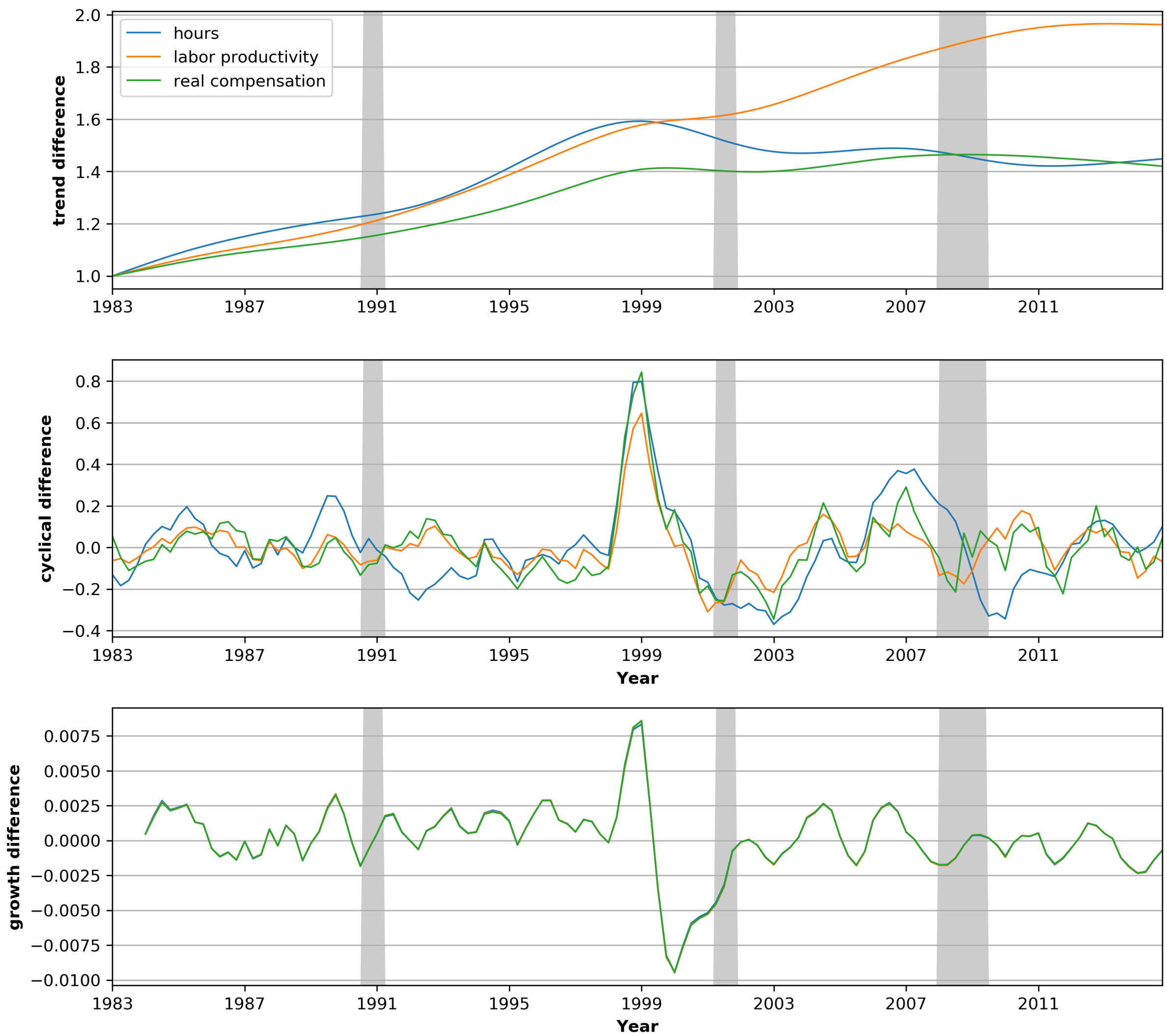
Notes: The top graph plots the observed, i.e. published by the BLS, nonfarm business sector real output per hour of all persons in the U.S. economy and the leisure-corrected, "actual" series (and their HP filtered trends) using the model's produced on-the-job leisure series. The middle and bottom graphs plot the differences from trend and year-over-year growth rates of these series.

Figure B.12: Adjusted Real Compensation



Notes: The top graph plots the observed, i.e. published by the BLS, nonfarm business sector real compensation per hour of all persons in the U.S. economy and the leisure-corrected, "actual" series (and their HP filtered trends) using the model's produced on-the-job leisure series. The middle and bottom graphs plot the differences from trend and year-over-year growth rates of these series.

Figure B.13: Differences in Actual and Reported Series



Notes: The top graph plots the differences in trends of the "actual" and "reported" series for hours, labor productivity, and real compensation. The middle and bottom graphs similarly plot these differences for the cyclical components and year-over-year growth rates of these series.

Appendix C

The Sharing Economy and Rental Markets

C.1 Appendix

C.1.1 Interpolation of American Communities Survey Data

In our empirical analysis we wish to control for trends in housing and demographic using data taken from the *American Community Survey* (*ACS*). The *ACS* collects demographic and housing data on a continuous basis from a national sample. Due to the nature of the collection of the data, the *ACS* estimates describe conditions over the time period during which the data was collected. Using the 5-year estimates means that about four-fifths of the data for one year overlaps with the data of the following year. That means comparing estimates from one year 5-year dataset to the next will not allow you to isolate the differences in the two estimates. The 5-year estimates however are useful for representing long run trends in the data.

The *Airbnb* listings data and the *Zillow* housing data are both available at the monthly ZIP code level, however the *ACS* data is only at the yearly ZIP code level. Therefore, we wish to interpolate the *ACS* data to the monthly level. To do this we assign the month of December[1] to each reported value from the *ACS* then use a cubic spline to fill in the data for the remaining month between the observed years. The interpolated data for select ZIP codes can be seen in C.1.

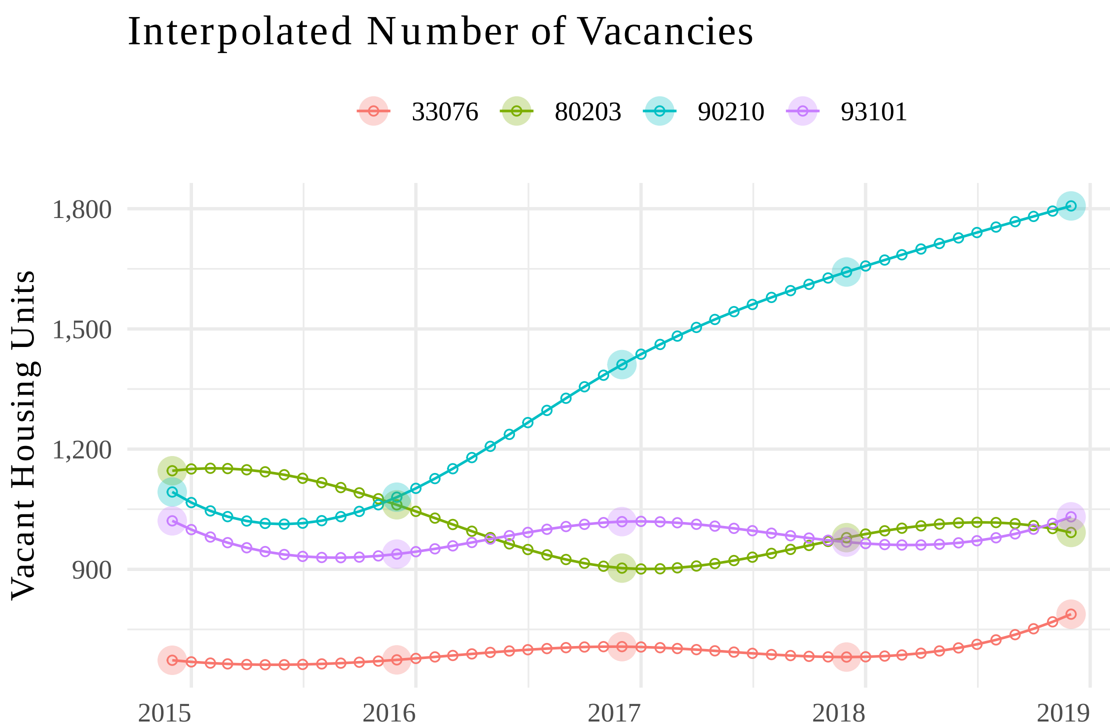


Figure C.1: Interpolated number of vacancies for select ZIP codes. Large circles represent *ACS* data points and small circles represent interpolated points.

C.1.2 Proof of Lemma 1

Proof:

Consider the problem faced by innkeepers and define $\widehat{\mathcal{I}}_0(p^H, \mathcal{V}_0) \equiv \mathcal{I}_0\big(p^H, \theta^H(p^H; \mathcal{V}_0)\big)$

[1]Varying the month of the year the *ACS* estimate is assigned has little impact of the results of the analysis.

for $0 \leq p^H < w^{\mathcal{V}} - r\mathcal{V}_0$ and $\widehat{\mathcal{I}}_0(w^{\mathcal{V}} - r\mathcal{V}_0, \mathcal{V}_0) = -\kappa^H$. It is easy to see that 3.10 is continuous in p^H at $w^{\mathcal{V}} - r\mathcal{V}_0$ and so $\widehat{\mathcal{I}}_0$ is continuous across its domain. Noting also that $\widehat{\mathcal{I}}_0(0, \mathcal{V}_0) = -\kappa^H$, the innkeeper's problem is well defined and must achieve a maximum on the interval $[0, w^{\mathcal{V}} - r\mathcal{V}_0)$ since we have assumed $\widetilde{\mathcal{I}}_0 \geq 0$.

The problem faced by landlords in the short and long-term markets is structurally similar and, for brevity, not included. Since we have assumed that participation is weakly profitable, the short-term market's argmax, like that of the hotel market, must be in the interval $[0, w^{\mathcal{V}} - r\mathcal{V}_0)$, and the long-term market's in the interval $[0, w^{\mathcal{R}} - r\mathcal{R}_0)$.

■

(Back to Model)

C.1.3 Proof of Lemma 2

Proof:

It is sufficient to show that the first order conditions of property managers have unique solutions. First, consider an innkeeper who has entered the hotel market and is choosing which price to post. She maximizes 3.10 subject to 3.15. Rearranging the constraint for p^H, we have

$$p^H = w^{\mathcal{V}} - r\mathcal{V}_0 - \frac{(r + \delta^{\mathcal{V}})(r\mathcal{V}_0 - b^{\mathcal{V}})}{\theta^H \lambda^H}. \tag{C.1}$$

Substituting the above into 3.16, we can write the problem of innkeepers as a choice of θ^H.

$$\max_{\theta^H} \left[-\kappa^H + \lambda^H \left(\frac{w^{\mathcal{V}} - r\mathcal{V}_0 - r\mathcal{I}_0}{r + \delta^{\mathcal{V}}} \right) - \frac{1}{\theta^H} \big(r\mathcal{V}_0 - b^{\mathcal{V}} \big) \right] \tag{C.2}$$

The first order condition is given by

$$-(\theta^H)^2 \frac{d\lambda^H}{d\theta^H} \big(w^{\mathcal{V}} - r\mathcal{V}_0 - r\mathcal{I}_0 \big) = (r + \delta^{\mathcal{V}})(r\mathcal{V}_0 - b^{\mathcal{V}}) \tag{C.3}$$

which, given our assumptions on the matching function, has a unique solution. Thus, all innkeepers choose to search in a sub-market with the same market tightness, and because of the one-to-one relationship, the same price. By plugging C.3 into C.1 and simplifying, we uncover a classic competitive search result that the total surplus is split according to the elasticity of matching with respect to their participation. The problem in the short-term and long-term markets is structurally similar. The first order conditions are

$$-(\theta^S)^2 \frac{d\lambda^S}{d\theta^S}\big(w^{\mathcal{V}} - r\mathcal{V}_0 - r\mathcal{L}_0\big) = (r+\delta^{\mathcal{V}})(r\mathcal{V}_0 - b^{\mathcal{V}}) \tag{C.4}$$

$$-(\theta^L)^2 \frac{d\lambda^L}{d\theta^L}\big(w^{\mathcal{R}} - r\mathcal{R}_0 - r\mathcal{L}_0\big) = (r+\delta^{\mathcal{R}})(r\mathcal{R}_0 - b^{\mathcal{R}}). \tag{C.5}$$

■

(Back to Model)

C.1.4 Proof of Lemma 3

Proof:

To begin we derive the (implicit) demand functions, starting with the hotel market. First rearrange 3.10 for p^H.

$$p^H = r\mathcal{I}_0 + \frac{(r+\delta^{\mathcal{V}})(r\mathcal{I}_0 + \kappa^H)}{\lambda^H}. \tag{C.6}$$

Combining this with 3.7, C.3, and simplifying we have

$$
\begin{aligned}
&-(\theta^H)^2\frac{d\lambda^H}{d\theta^H}\left[w^{\mathcal{V}}-r\mathcal{I}_0-\frac{b^{\mathcal{V}}(r+\delta^{\mathcal{V}})+\theta^H\lambda^H(w^{\mathcal{V}}-r\mathcal{I}_0)-\theta^H(r+\delta^{\mathcal{V}})(r\mathcal{I}_0+\kappa^H)}{r+\delta^{\mathcal{V}}+\theta^H\lambda^H}\right]\\
&\qquad=(r+\delta^{\mathcal{V}})\left[\frac{b^{\mathcal{V}}(r+\delta^{\mathcal{V}})+\theta^H\lambda^H(w^{\mathcal{V}}-r\mathcal{I}_0)-\theta^H(r+\delta^{\mathcal{V}})(r\mathcal{I}_0+\kappa^H)}{r+\delta^{\mathcal{V}}+\theta^H\lambda^H}-b^{\mathcal{V}}\right]\\
&-(\theta^H)^2\frac{d\lambda^H}{d\theta^H}\left[\frac{w^{\mathcal{V}}-r\mathcal{I}_0-b^{\mathcal{V}}+\theta^H(r\mathcal{I}_0+\kappa^H)}{\lambda^H}\right]\\
&\qquad=\frac{\lambda^H(w^{\mathcal{V}}-b^{\mathcal{V}}-r\mathcal{I}_0)-(r+\delta^{\mathcal{V}})(r\mathcal{I}_0+\kappa^H)}{\lambda^H}\\
&\left[r+\delta^{\mathcal{V}}+\big(1-\eta_H(\theta^H)\big)\theta^H\right](r\mathcal{I}_0+\kappa^H)=\eta_H(\theta^H)\big(w^{\mathcal{V}}-b^{\mathcal{V}}-r\mathcal{I}_0\big).
\end{aligned}
\tag{C.7}
$$

C.7 describes an implicit function for the equilibrium demand for vacancies, θ^H, in terms of their cost, $\mathcal{I}_0$, which we write as $\theta^H=\zeta_H(\mathcal{I}_0)$. Next, differentiate w.r.t. $\mathcal{I}_0$.

$$
\frac{d\zeta^H}{d\mathcal{I}_0}=\frac{-r\left[r+\delta^{\mathcal{V}}+\eta_H(\theta^H)+\big(1-\eta_H(\theta^H)\big)\theta^H\right]}{(r\mathcal{I}_0+\kappa^H)\left[1-\eta_H(\theta^H)-\theta^H\frac{d\eta_H(\theta^H)}{d\theta^H}\right]-(w^{\mathcal{V}}-b^{\mathcal{V}}-r\mathcal{I}_0)\frac{d\eta_H(\theta^H)}{d\theta^H}}
\tag{C.8}
$$

The above is strictly negative iff

$$
\frac{d\eta_H(\theta^H)}{d\theta^H}<\frac{\big(1-\eta_H(\theta^H)\big)(r\mathcal{I}_0+\kappa^H)}{(w^{\mathcal{V}}-b^{\mathcal{V}}-r\mathcal{I}_0)+\theta^H(r\mathcal{I}_0+\kappa^H)}.
\tag{C.9}
$$

That is, if the marginal effect of market tightness on the filling rate elasticity is not *too* high, the demand for hotel vacancies is declining in $\mathcal{I}_0$. Given our standard assumptions on the matching function, $\frac{d\eta(\theta)}{d\theta}\leq 0$ so this condition is necessarily met. Under an isoelastic function, i.e. a Cobb-Douglas matching function,

$$
\frac{d\zeta^H}{d\theta^H}=\frac{-r\left[r+\delta^{\mathcal{V}}+\eta_H+(1-\eta_H)\theta^H\right]}{(1-\eta_H)(r\mathcal{I}_0+\kappa^H)}<0.
\tag{C.10}
$$

A similar set of steps establishes this result for the short and long-term markets. The implicit demand curves $\theta^S = \zeta_S(\mathcal{L}_0)$ and $\theta^L = \zeta_L(\mathcal{L}_0)$ are reproduced below.

$$\left[r + \delta^{\mathcal{V}} + \left(1 - \eta_S(\theta^S)\right)\theta^S\right](r\mathcal{L}_0 + \kappa^S) = \eta_S(\theta^S)\left(w^{\mathcal{V}} - b^{\mathcal{V}} - r\mathcal{L}_0\right) \tag{C.11}$$

$$\left[r + \delta^{\mathcal{R}} + \left(1 - \eta_L(\theta^L)\right)\theta^L\right](r\mathcal{L}_0 + \kappa^L) = \eta_L(\theta^L)\left(w^{\mathcal{R}} - b^{\mathcal{R}} - r\mathcal{L}_0\right) \tag{C.12}$$

■

(Back to Model)

C.1.5 More Comparative Static Results

In C.1 we report more comparative static results for completeness. These parameters do not as easily map into policy choices, but also provide some interesting model insights. First consider the flow values of unaccommodation. As they are increased, residents and visitors are made directly better off when searching for accommodation. Because property managers must deliver higher market utilities, they are made worse off. Increases in $b^{\mathcal{V}}$, ceteris paribus, increase finding rates for residents, while similar increases in $b^{\mathcal{R}}$, increase finding rates for visitors as landlords adjust vacancy posting strategies.

Increases in the flow value of being accommodated has similar effects. By making accommodation more attractive, market utility increases and prices rise. Increases in $w^{\mathcal{V}}$ hurts residents in terms of value and finding rates as landlords increase posting in the short-term market. The opposite holds when $w^{\mathcal{R}}$ increases. Interestingly, increases in $b^{\mathcal{V}}$ do negatively affect $\mathcal{R}_0$ like increases in $w^{\mathcal{V}}$ do (and the mirrored scenario). The key distinction is that increases in the flow value of searching effectively amount to better outside options. This pushes some landlords to post in the long-term market in the case of $b^{\mathcal{V}}$ increasing (and the short-term market in the when $b^{\mathcal{R}}$ increases). In other words, increases in one type's b directly increases their utility, while it indirectly improves the other by incentivizing landlords to the other market.

When δ increases, more properties are vacant in the steady state, increasing market tightnesses across the board and lowering vacancy values. If $\delta^{\mathcal{R}}$ increases, all prices fall with the value of the vacancies. In contrast, if $\delta^{\mathcal{V}}$ increases landlords can mitigate lost values by posting more in the short-term market and raising prices (which feeds through to the hotel market). Last, the results for increasing the number of searchers and properties are reported in the bottom of the table. Briefly, more tenants benefits property managers, and more properties benefit tenants.

	$\mathcal{V}_0$	$\mathcal{R}_0$	$\mathcal{I}_0$	$\mathcal{L}_0$	p^H	p^S	p^L	θ^H	θ^S	θ^L
$\uparrow b^{\mathcal{V}}$	+	+	−	−	−	−	−	−	−	+
$\uparrow b^{\mathcal{R}}$	+	+	−	−	−	−	−	+	+	−
$\uparrow w^{\mathcal{V}}$	+	−	+	+	+	+	+	+	+	−
$\uparrow w^{\mathcal{R}}$	−	−	+	+	+	+	+	−	−	+
$\uparrow \delta^{\mathcal{V}}$	−	+	−	−	+	+	−	+	+	+
$\uparrow \delta^{\mathcal{R}}$	+	+	−	−	−	−	−	+	+	+
$\uparrow u^{\mathcal{V}}$	−	−	+	+	+	+	+	−	−	−
$\uparrow u^{\mathcal{R}}$	−	−	+	+	+	+	+	−	−	−
$\uparrow N^{\mathcal{I}}$	+	+	−	−	−	−	−	+	+	+
$\uparrow N^{\mathcal{L}}$	+	+	−	−	−	−	−	+	+	+

Table C.1: More Comparative Statics

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