

Costly Commuting and the Job Ladder

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Abstract

Even though workers in the UK spent just £1,000 on commuting in 2017, the economic loss may be far higher because of the congestion externality arising from the way in which one worker's commute affects the commuting time of others. I provide empirical evidence that commuting time affects job acceptance, pointing to large indirect costs of congestion. To interpret the empirical facts and quantify the costs of congestion, I build a novel model featuring a frictional labor market within a metropolitan area. This is the first paper to endogenize commuting congestion in a labor search model, which is necessary to understand labor market responses to urban policies. Workers evaluate job offers based on their productivity and commuting costs, taking congestion as given, but by accepting and commuting to distant jobs, affect other workers' labor market outcomes. By allowing for residential and job-to-job mobility, the model highlights how moving decisions, housing rent, and wages are linked to congestion. Calibrating the model to the local labor market around London, I show that the effect of the congestion externality is to significantly decrease welfare and increase wage inequality. I quantify the effects of a congestion tax on labor market outcomes, and show that the welfare-maximizing tax has substantial negative effects on wage growth and inequality.

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1 Introduction

In the 10 most congested cities in the world, commuters spend an average of 80 hours per year in rush hour traffic, equivalent to two work weeks of lost time.¹ During rush hour, many individuals are commuting to the same place at the same time, leading to significantly longer travel times for everyone. Congestion in urban areas is an indication of a negative externality whereby the decision of one worker to commute affects the travel time of others. Taxes on commuters passing through congested areas can lead them to internalize their effect on others and improve welfare. These policies have been shown to successfully reduce congestion.² However, policies aimed at commuting and congestion can have large indirect effects because they potentially misallocate resources: more expensive commutes can stop workers from accepting productive job offers and lead them to accept less productive offers closer to home. Data from the New York Federal Reserve's Survey of Consumer Expectations shows that 13% of workers report the job's location as the main reason for rejecting an offer.³ This suggests that workers' rankings of jobs depends on the commuting costs required to get to work, and therefore varies across workers depending on where they live and work.

In order to understand the implications of congestion taxes and other urban policies on labor market outcomes, inequality, and welfare within metropolitan areas, it is necessary to consider the key margins of the labor market that respond to policy. To do so, I build a model in which the process of matching workers to jobs and commuting patterns are simultaneously determined. To the best of my knowledge, this is the first paper in which congestion arises endogenously within a frictional labor market. Workers' rankings of job offers depend on the productivity and commute required to get to a potential employer. By accepting a job offer that requires the worker to commute, she contributes to congestion which affects the labor market outcomes of others. The extent of congestion is closely tied to the frictions in the labor market, in particular how often workers receive job offers and how they rank them. In the frictionless limit, congestion will only arise if wages differ by location to fully compensate workers for their commutes. With frictions, congestion arises even though workers are not indifferent across jobs and locations. The effect of a tax is therefore not only to change the locations of workers' jobs and their commutes, but also to affect unemployment, wage growth, and inequality.

This paper makes three contributions. First, I document new facts connecting commuting and job mobility using data from the British Household Panel Survey (BHPS). Focusing specifically on the London area, one of the most congested cities in the world, I show that wage changes and job mobility are strongly linked to commuting time. In particular, workers are more likely to change jobs via a job-to-job transition the higher is their current commuting time. In addition, workers are more likely to accept wage cuts if their commuting time falls relative to their previous job.

¹Source: INRIX Global Traffic Scorecard. Rush hour is defined as the hours 6:00-9:00am and 4:00-7:00pm, Monday-Friday. Traffic congestion is defined as speeds 65% or below the free flow speed.

²For example, Singapore's electronic road pricing scheme and Stockholm's congestion tax.

³I consider the location-related reasons for rejection to be that the commute time would be too long or the job would require a relocation. See the SCE Job Search Survey codebook for further details.

Finally, using aggregate UK Census data, I show that commuting flows are positively correlated with proximity to the center of London’s economic activity, the City of London.

My main contribution is to develop a novel spatial model of job search with an externality in commuting in order to understand the forces giving rise to these patterns and quantify the effects of congestion. By combining the spatial features of an urban area with the bargaining process of Cahuc et al. (2006), the model remains tractable while matching key patterns in the data. The model is innovative in several ways, most importantly by incorporating endogenous congestion and commuting costs that affect all workers’ decisions both for job and residential mobility. The labor market is made up of a number of locations that differ in the cost of living, given by the housing rent (henceforth, rent). The value of a job reflects its productivity, rent, and commuting costs, leading to some highly productive matches being rejected when such costs are high. Commuting patterns, output, rent, and congestion are jointly determined in equilibrium. By allowing rent to adjust, the model is able to endogenously generate the pattern that the locations with the most productive jobs have both the most congestion and highest rent. By incorporating labor market frictions, the model generates the trade-offs evident in the micro data, and links these individual choices to aggregate congestion. Using tools introduced in the economic theory literature on existence of equilibria with indivisible goods, most importantly that by Kaneko and Yamamoto (1986), I prove that an equilibrium rent price exists in the steady state.⁴

I analytically show in a simple social planner’s problem, that in the presence of labor market frictions, the congestion externality is not necessarily constrained inefficient. Because moving house or remaining unemployed is costly, given the moving costs and labor market frictions it can be optimal to commute to distant jobs, even after taking into account the effect of congestion on other workers’ commuting costs. The higher is the marginal cost of congestion, the higher is the social value of reducing congestion, leading to an outcome in the decentralized economy in which congestion is inefficiently high. By making workers internalize their contribution to the externality, congestion taxes can lead some workers to move closer to their jobs, decreasing congestion for others and in turn improving welfare. Unlike models with frictionless labor markets, these taxes not only affect congestion but will also interact with job search, affecting unemployment, job mobility, and inequality.

My third contribution is quantitative. The model parameters are estimated to match features of the London labor market, taking into account productivity differentials across space by including (exogenous) agglomeration whereby the city center is most productive. Commuting costs are identified using two important moments. First, I use the share of job offers reported rejected because of the commute from the New York Federal Reserve Survey of Consumer Expectations, discussed above. Second, to pin down the effect of congestion, I use data from Google Maps of commuting times during rush hour and in low-congestion times. In this way, I disentangle the “no-traffic” cost

⁴Halket and Vasudev (2014) use similar techniques to prove existence of a spatial equilibrium, but their focus is on homeownership and the choice of housing quantity, while abstracting from search frictions in the labor market. Conversely, I am interested in the effects of commuting to work and the associated externality, and thus model a much simpler housing market and a richer labor market.

of commuting from the effect of the externality.

I use the model to estimate the effect of congestion on welfare, wage and utility dispersion across ex ante identical workers. Following [Hall and Mueller \(2018\)](#), inequality, or dispersion, is measured as the standard deviation of log wages or utility. To understand how the equilibrium interaction of the commuting amenity affects these measures, I compare the model's predictions for dispersion with and without congestion, and find that congestion accounts for roughly 14% and 5% of wage and utility dispersion, respectively. With congestion, workers have higher average commuting costs, making jobs closer to home more attractive. Thus, it is more likely that workers with long commutes renegotiate, increasing their wages relative to new hires. However, this also implies that workers with the highest wages have the highest commuting costs, resulting in low dispersion in utility, defined as the difference between the wage and commuting and rent costs. Without congestion, commuting is less costly, leading to smaller average gains from renegotiation, and decreasing wage dispersion. However, because marginal commuting costs in the center are lower without congestion, high commuting costs offset high wages by less, resulting in a smaller differential in inequality in utils between the models with and without congestion. Regarding welfare, the model predicts that congestion decreases welfare as measured by the value of workers at the time of entry into the labor force by 3.7%.

Finally, I use the model to conduct a policy exercise related to congestion taxes. Because more productive jobs are accepted even for long commutes, congestion and productivity are positively correlated, thus, the effect of the tax is to move workers from more to less productive firms. This leads to a less concentrated distribution of firms across space, causing rent to fall in the city center and rise closer to the periphery. The tax has two effects on job creation and mobility. On the one hand, by making job offers requiring a commute less attractive, the set of offers that workers would be willing to accept changes, causing the unemployment rate to increase. On the other, the tax lowers the option value of waiting for a job offer from the most productive firms which are located in the most congested areas, causing the unemployment rate to fall. The quantitative results suggest that the former effect dominates: the unemployment rate rises as the tax rate increases. For the employed, the congestion tax affects wage growth and dispersion. By reducing the variance of commuting costs, the tax significantly decreases wage growth as a function of labor market experience and decreases both wage and utility dispersion in the cross-section. In terms of magnitude, this tax is equivalent to roughly 0.6% of the monthly wage, and increases welfare by 0.5%. Due to the frictions in the labor market and substantial moving costs in my model, the welfare-maximizing tax rate and associated welfare gains are about one order of magnitude smaller than those in the baseline model of [Brinkman \(2016\)](#), discussed in the following section.

Related Literature

This is the first paper to consider the interaction between commuting congestion and job search. I contribute to three main strands of the literature. First, I add to the work on frictional labor markets and commuting, explicitly modeling a congestion externality across space, a key feature

affecting commuting time in urban areas. Second, I contribute to the urban economics literature by studying the implications of this externality in a model with labor market frictions. Third, I contribute to the literature on compensating differentials by considering interactions of amenity values across workers.

The connection between jobs and locations has been acknowledged since the island model of [Lucas and Prescott \(1974\)](#). A large literature has followed, explicitly modeling the interaction of commuting and labor markets.⁵ Most theoretical models that consider commuting only allow for the unemployed to search for jobs and thus do not consider commuting's effect on the job ladder. A related literature on spatial mismatch is concerned with the effect of distance and urban structure on labor market outcomes, mostly for the unemployed.⁶ The literature has shown that spatial mismatch cannot explain the increase in unemployment during the Great Recession ([Şahin et al. 2014](#)), nor in the level of unemployment ([Marinescu and Rathelot 2018](#)). Even if unemployed workers are willing to take jobs far from home and there is little spatial mismatch, the locations of workers and jobs and the congestion arising from commuting may have large effects on workers' progress up the job ladder.

One of the few papers to consider on-the-job search and commuting is [Van Vuuren \(2018\)](#). In his model, all firms are located in the city center and in which the arrival rate of job offers is a function of distance between a worker and vacancy. His focus is on the effects of rent on the labor market outcomes of recent entrants into the labor market. My model allows for both firms and workers to be located across the city and for workers' commutes to congest one another.⁷ Another closely related paper is by [Manning and Petrongolo \(2017\)](#), who build a model of spatially directed job search by the unemployed without residential mobility. In their model, workers direct their search to jobs based on distance, taking into account how other workers' search strategies affect their job finding probability. They estimate a high cost of distance using data that covers the entire UK. This paper considers the London area, where commuting time is longer than the UK average, and therefore locally targeted policies may have larger effects. The counterfactuals considered here focus on the consequences for the local labor market due to changes in commuting and congestion in response to a congestion tax.

Commuting has long been recognized as crucial to agents' location and work decisions in urban economics.⁸ Models in this literature typically assume frictionless labor and housing markets; thus, workers are indifferent across all residential and job locations in equilibrium.⁹ [Harari \(2017\)](#)

⁵For comprehensive coverage of urban-labor models, see [Zenou \(2009\)](#). Commuting costs have been shown to be crucial determinants for a wide range of labor market outcomes, including labor supply (e.g. [Wales 1978](#), [Cogan 1981](#)), work effort (e.g. [Van Ommeren and Gutiérrez-i Puigarnau 2011](#)), and wages (e.g. [Van Der Berg 1992](#), [Van Den Berg and Gorter 1997](#), [Manning 2003](#)).

⁶e.g. [Smith and Zenou 2003](#), [Wasmer and Zenou 2006](#), [Manning and Petrongolo 2017](#). For a review, see [Gobillon et al. \(2007\)](#).

⁷An earlier, more reduced-form model is developed by [Van Ommeren et al. \(1999\)](#), who study the joint determination of job and residential locations when labor and housing markets are frictional.

⁸e.g. [Fujita 1989](#), and the seminal contributions of [Alonso 1964](#), [Mills 1967](#), and [Muth 1969](#).

⁹More recent work considers the effect of frictions in labor and housing markets. [Wasmer and Zenou \(2002\)](#) study how the spatial configuration of an urban area affects the allocation and employment status of workers. [Conley and Topa \(2002\)](#) and [Glaeser et al. \(2008\)](#) consider mechanisms that give rise to spatial concentration of unemployment.

studies how city shape can impact welfare and productivity. Recent papers by Tsivanidis (2018) and Heblich et al. (2018) consider the effects of introducing public transportation infrastructure on welfare and output. Like these papers, I build a model that captures the spatial variation in employment and residential density, but focus on how these differences interact with employment outcomes, taking the transportation technology, city shape, and city limits as given.

A related literature has focused on the importance of traffic density for travel speed and a large literature has developed to estimate the congestion externality and the tools necessary to achieve efficiency.¹⁰ A recent contribution by Brinkman (2016) builds an urban model to jointly estimate congestion and agglomeration externalities.¹¹ I model congestion similarly to his paper, as the mass of workers traveling through a location less the number of residents in that location (the “no-traffic” benchmark). I show how this congestion arises in a frictional labor market and affects the process of job search.

The literature on non-wage job characteristics and compensating differentials aims to understand how wages reflect non-wage aspects of jobs.¹² Recent work by Sorkin (2018) and Hall and Mueller (2018) take two new approaches to understand specifically how dispersion in wages reflects dispersion in non-wage values, and how dispersion in utility may differ from dispersion in wages after taking into account non-wage amenities, respectively. So far, the literature has focused on these amenities at the match level and has not considered how the interaction of amenities across matches may affect dispersion in wages and utility.¹³ This model is different from the literature studying compensating differentials through the lens of a search model because I study an amenity that gives rise to a clear externality, traffic congestion. Although the assumption of independence of amenities across jobs may be reasonable for flexible working time or having a scenic view from one’s office, it is difficult to rationalize for some amenities, especially the commute.

2 Motivating Evidence

This section discusses motivating evidence pointing to the importance of commuting for on-the-job search using two data sources from the UK. First, the UK Census Flows contain aggregate information on workers’ commuting patterns, which show the importance of the distance between workers and firms for observed job outcomes in the cross-section. Second, the British Household Panel Survey (BHPS) is an individual-level panel with information on individuals’ commute times,

¹⁰e.g. Pigou (1932), Walters (1961), Vickrey (1969).

¹¹Earlier papers that model the congestion externality include Cohen (1987), Anas and Kim (1996), Arnott et al. (1993), and Arnott (2007). Parry and Bento (2001) examine the relationship between congestion taxes and labor force participation.

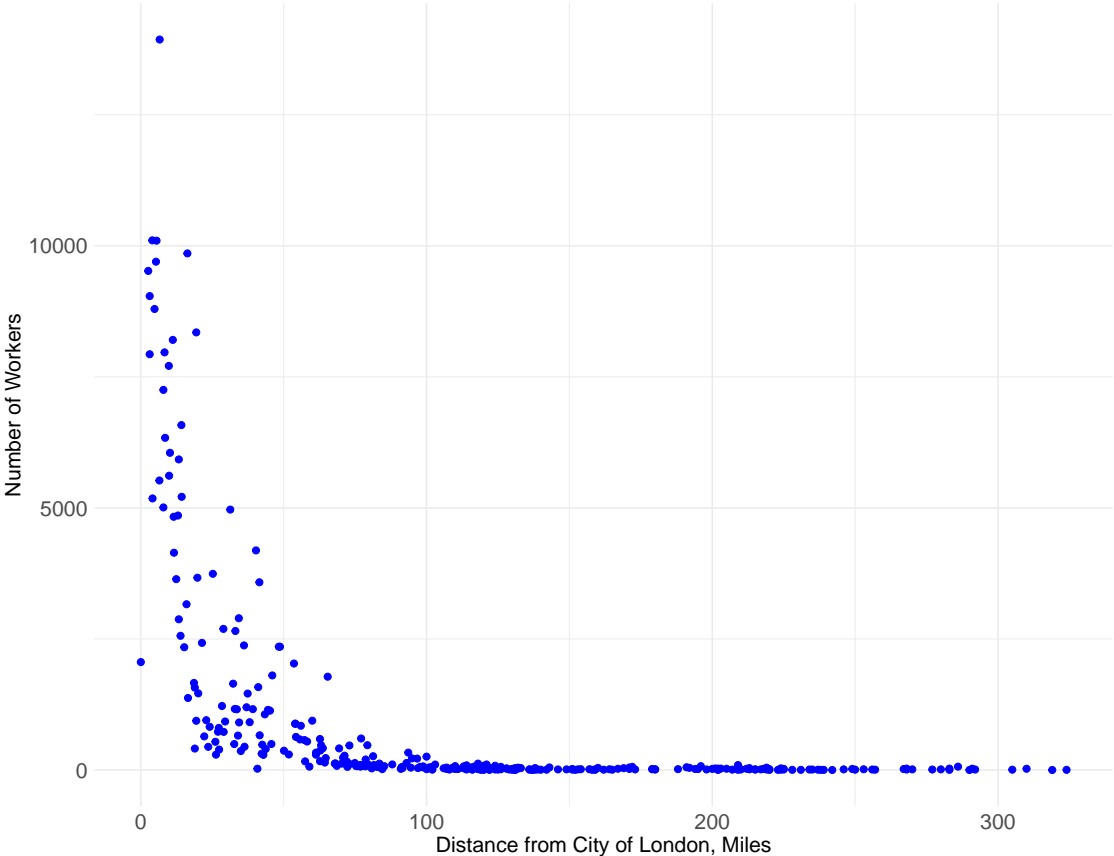
¹²Frictionless models such as Rosen (1986) predict that wages should compensate for these values, equating utility across workers. By highlighting the dynamic and frictional nature of the labor market, search theory has provided a framework through which the predictions for compensating differentials of these early models may be overturned (for instance, Hwang et al. 1998 and Bonhomme and Jolivet 2009).

¹³Most models in this literature consider all non-wage amenities rather than focusing on one, with three exceptions being Dey and Flinn (2005), who focus on access to health care, and Pinheiro and Visschers (2015) and Jarosch (2016) who consider job security.

employment histories, housing, and wages, which I use to document within-worker patterns relating to commuting, wages, and on-the-job search.

I present several facts. First, in the Census data, there is a decreasing pattern between commuting flows and distance between workers and firms. Second, commuting time positively affects individual workers' probabilities of future job-to-job transitions as well as the share of workers accepting wage cuts, showing the importance of commuting for outcomes related to on-the-job search. Finally, I provide evidence for the importance of congestion by comparing commuting time at different levels of congestion using data from Google Maps.

Figure 1: Number of Commuters to City of London by Distance



Data: UK Census Flow Data 2001, Special Workplace Statistics (Level 1). Number of workers commuting to the City of London as a function of driving distance in miles computed by Google Maps. Map data: Google, DigitalGlobe.

Census Flows

The model presented in the next section considers a “local labor market” that I will define for the quantitative analysis as the London metropolitan area. Using the 2001 Census data, Figure 1 shows the number of residents in each Local Authority District (LAD) working in the City of

London as a function of distance between the residence and the City in miles.^{14,15} The distance is computed using Google Maps, with the location automatically selected by Google for each LAD, where distance is defined as the shortest driving distance between the two locations.^{16,17}

On-the-Job Search

To provide evidence on the relationship between job search and commutes, I use data from the BHPS between 1992 and 2008. The BHPS is an annual panel survey with information on individuals' commute times, employment histories, housing, and wages. I restrict the sample in several ways. First, I drop all LADs for which there are fewer than 50 observations or that are more than 100 miles driving distance from the City to focus on daily commuters.¹⁸ I restrict attention to full-time workers between 24 and 55 (inclusive), and consider the period 1992-2008 to exclude any effect of the Global Financial Crisis on the commuting-wage trade-off. I include workers reporting net monthly labor income within 3 standard deviations of the mean and a one-way commute up to 90 minutes, to exclude individuals with so-called "mega-commutes".^{19,20} Reported one-way commutes are multiplied by 2 to determine the daily round-trip commute. Labor income is deflated by annual CPI in the UK from the Office for National Statistics. I exclude workers who are self-employed. The results presented in this section correspond to the unweighted sample; estimates using longitudinal weights are quantitatively similar and can be found in Appendix A.

Table 1 reports the marginal effects from a probit regression in which the dependent variable is equal to 1 if the individual made at least one job-to-job transition in the past year and 0 if she remained employed in the same job according to her self-reported employment history.²¹ The first column regresses the job-to-job transition probability on the commute and wage in the previous year and region, time, commute method, industry, and occupation fixed effects. The second column repeats the regression including a large set of individual characteristics. The estimates suggest that the commute in year $t - 1$ has a positive relationship with the probability of a job-to-job transition between years $t - 1$ and t even after controlling for the wage in $t - 1$. The results in column 2 can

¹⁴Data used in Figure 1 is the 2001 Census: Special Workplace Statistics (Level 1), available through the UK Data Service's WICID. For each pair of locations i and j , the flow data contains the number of individuals whose usual residence is in i and usual place of work is in j .

¹⁵LADs are a unit of regional classification, with populations ranging from 2,300 to 1 million, and land area between 1 and 1,936 square miles.

¹⁶For instance, a Google Maps search for directions from Kensington to the City of London returns directions leaving from 112 Kensington High St, Kensington, London and arriving at 21 Bloomberg Arcade, London.

¹⁷For similar figures with distance in terms of commuting time and the commuters as a share of the LAD population, see Appendix A.

¹⁸About 5% of LADs in the sample have fewer than 50 observations, results when including these LADs are similar and are available upon request. For the full sample, there are 12,510 individuals; when restricting the sample to individuals living within 100 miles from the City, this falls to 4,276.

¹⁹I include workers reporting a commute of 0 minutes to take into consideration people working from home. Restricting the sample to those reporting a strictly positive commute or allowing for workers with wages outside 3 standard deviations of the mean does not significantly change the results.

²⁰The Census Bureau defines a "mega-commuter" as a worker traveling more than 90 minutes to work, one-way, see Rapino and Fields (2013). In the BHPS data, these individuals represent less than 0.6% of the sample.

²¹I define a job-to-job transition as one with no more than 30 days of nonemployment between two employment spells. Results are similar if the nonemployment duration is limited to 0 days between the two spells.

Table 1: Marginal Effects of Lagged Commute and Wage on Job-to-Job Transition Probability

	J2J _t	J2J _t
Commute _{t-1} × 30	0.015*** (0.003)	0.011*** (0.003)
Real log Wage _{t-1}	-0.035*** (0.006)	-0.041*** (0.008)
Individual Characteristics		✓
Region, Time, Commute Method Industry & Occ FE	✓	✓
Pseudo R ²	.067	.124
N obs	7,310	6,528

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time in year t . Estimated marginal effects from a probit regression of J2J_t, which is a dummy equal to one if a worker made a job-to-job transition in the past year and 0 if she remained in the same job, on commute time and wages in the previous year. Individual characteristics include the annual regional house price index, a quadratic term in labor market experience, age, education, marital status, and number of children, 1-year lagged tenure, 1-year lagged dummies for outright homeownership, mortgage holding, whether the individual moved in the past year, real housing expenditures, whether the worker was unemployed in the past year, the number of employment spells, whether the spouse or partner was employed last year, a government job dummy, and union status. All regressions include region, month, year, 1-digit industry and occupation fixed effects. Robust standard errors are reported in parentheses. * denotes $p < .1$, ** $p < .05$, and *** $p < .01$.

be interpreted as follows: a 30 minute increase in last year’s commute is associated with about a 1 percentage point increase in the probability of making a job-to-job transition in the current year.

The results in Table 1 potentially suffer from endogeneity as they may be driven by unobservable heterogeneity in workers: those who commute more today could be more diligent workers, leading them to be more likely to switch jobs. Conversely, it is possible that the workers who commute more and earn lower wages are less motivated and therefore may switch jobs more often because they are more likely to be unsuitable for any job. To consider this possibility, I run similar regressions using a linear probability model with individual fixed effects. The results are similar and can be found in Appendix A.

Table 2 shows that decreases in commuting time explain the prevalence of wage cuts following job-to-job transitions. To construct the table, I compare wages and commutes in the years before and after a job-to-job transition took place. “Up” and “Down” indicate differences from the last reported wage or commute of more than 5%, and “Same” indicates differences less than 5%.²² Each column of the table shows, for a given accepted wage which was higher, lower, or the same as her previous wage, the share of workers whose commute was higher, lower, or the same as her previous commute. N indicates the total number of wage cuts, no change, or wage increases. If commuting were irrelevant in workers’ decisions to make job-to-job transitions, we would expect the share of

²²The median wage cut in the sample is 6.3% of the real monthly wage (£116) and the median commuting decrease in the sample is 33% of commuting time (20 minutes).

workers taking commuting increases and decreases would be equal for each column.

Table 2: After Job-to-Job Transition

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.50	0.44	0.34
	Same	0.19	0.18	0.25
	Up	0.31	0.38	0.41
	N	157	103	437

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

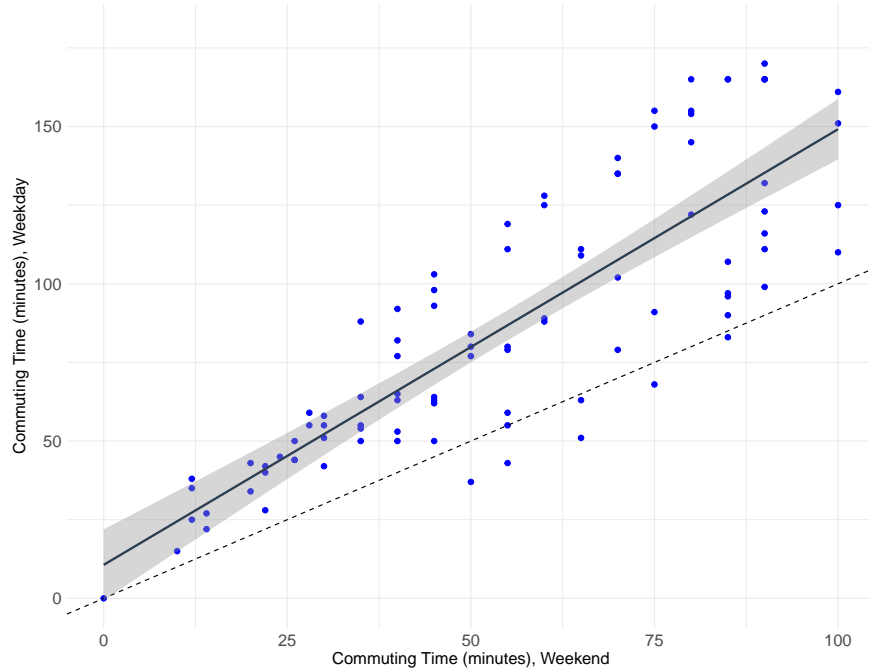
Models with renegotiation such as Cahuc et al. (2006) generate wage cuts when workers move to more productive jobs with a high future value. Workers are willing to take wage cuts because they expect to extract more of the surplus through future renegotiation of their wages. Other models explain wage cuts as the result of an unobserved advance notice of a separation: when workers know that their job will be destroyed, they are forced to accept any offer that is better than unemployment. This paper follows the literature on non-wage amenities and argues that wage cuts can be due to increases in the non-wage value of the job. In general, these amenities are difficult to measure or are subjective (e.g. measures of job satisfaction). One benefit of studying commuting using the BHPS is the availability of time use data on workers' daily commutes. Assuming that the amenity value is monotonic in the time spent commuting, the data provides an objective measure of the commuting amenity.

The table shows that half of all workers reporting wage cuts in the year in which a job-to-job transition takes place also report decreases in their commuting time relative to the previous year. The relationship is roughly symmetric: a larger share of wage increases are accompanied by increases in commuting time. Thus, the wage-commuting trade-off can help to explain the existence of wage cuts in the data. Appendix A contains similar tables showing that this pattern is robust: the share of workers taking wage cuts and commuting cuts is stable across genders, occupation switchers, residential movers, and marital status. The results are also robust to defining a commuting change in terms of minutes rather than percent and restricting the definition of a job-to-job transition to have zero days of nonemployment between employment spells.

Congestion

Finally, I show that congestion is important for commuting time by comparing travel time at rush hour and on weekends. Though I do not consider mode of transportation here, which clearly affects travel time, the regressions using BHPS data presented above and in Appendix A do control for workers' commuting method as well as time. Because the BHPS does not contain information on

Figure 2: Commuting Time to City of London: Effect of Congestion



Notes: Map data: Google, DigitalGlobe. Horizontal axis: average one-way commuting time in minutes from each LAD to the City of London on a weekend. Vertical axis: average one-way commuting time in minutes from each LAD to the City of London on a weekday. Commuting times are predicted for Saturday, July 14 and Thursday, July 19, 2018.

firms' locations, I use Google Maps to estimate the underlying relationship between travel time from each LAD to the City of London, which I will consider to be the city center when estimating commuting costs in the model. To do so, I compute the minimum commuting time required to arrive by 9am on an arbitrary weekday and Saturday from the location selected by Google for each LAD as described above, using Google Maps' recommended travel mode option. Figure 2 shows results for each of the LADs in the Census Flow data for which a positive number of residents commute to the City, with a distance of at most 100 miles. The difference between the observation and the 45 degree line is the additional time required to arrive in the City if traveling on a weekday relative to traveling at the same time of day on the weekend. The data shows that on average, it takes 50% more time to travel into the City during periods of high congestion.

3 Model

I build a spatial random search model where commuting costs are an important determinant of match surplus. The goal of the model presented here is to consider how workers' employment patterns and wages are affected by the spatial configuration of the labor market and how externalities in commuting shape equilibrium outcomes. I take rent in each location as given and assume that land supply is perfectly elastic. In Section 4 I assume land is scarce and introduce a land market

through which rent is endogenously determined.

3.1 Set-up

Time is continuous and agents are infinitely lived. The economy is populated by a continuum of workers of measure one and a continuum of firms of a positive measure. A firm in the model is simply a job, and I will use these terms interchangeably. Workers exit the labor market at rate $\chi > 0$, and new workers enter at the same rate. All agents share a common discount rate ρ and are risk neutral.

There is a single labor market within which all workers and firms are located. The labor market is defined by $2N + 1$ locations, $\ell \in \mathcal{L} \equiv \{1, \dots, N + 1, \dots, 2N + 1\}$, with location $N + 1$ defining the city center. Each worker and each filled job is located in a “residence” of size 1. For simplicity, all residences are assumed to be rented. Both workers and filled jobs pay rent in their location, $r(\ell)$, which is exogenous.

Workers differ in their location ℓ and may be employed or unemployed. Unemployed (employed) workers draw job offers at rate λ_0 (λ_1). A job offer is a pair (ℓ_F, y) drawn from exogenous distribution G , where $\ell_F \in \mathcal{L}$ is the location of the job and y is the match-specific productivity drawn from a finite set Y . Thus, search is random in both the spatial and productivity dimensions. Both ℓ_F and y are fixed for the duration of the match. Firms have access to a constant returns to scale technology where employed workers supply their labor inelastically and match output is given by y . Employed workers receive a wage w and unemployed workers receive their value of home production, b .

In order to earn her wage, an employed worker must pay an out-of-pocket flow commuting cost $T(\ell, \ell_F, \Omega)$, increasing in the commuting distance and travel time. Commuting does not affect the output of a match; it is assumed that firms are rigid about the hours that workers must be present at the firm (full-time), and that commuting therefore provides disutility to the worker but does not directly affect output. The worker’s commuting distance $d(\ell, \ell_F)$ is determined by the location of the worker’s residence and of her workplace, ℓ and ℓ_F , respectively. Travel time is affected by the extent of the congestion externality, which is determined by the distribution of workers Ω and is discussed in detail in Section 3.5.

A worker may choose a new location in which to live by paying a fixed moving cost k_M . To allow workers to move for reasons other than the job, employed workers face moving shocks at rate φ , which trigger a draw of the worker’s location from exogenous distribution $\Pi(\ell)$, where $\pi(\ell)$ denotes the probability that the worker draws $\ell \in \mathcal{L}$.²³

When a worker is employed, she consumes her wage net of commuting and rental costs. Matches are destroyed exogenously at rate δ . When a match is destroyed, the worker becomes unemployed and the firm exits. Unemployed workers consume the flow value of home production less rental

²³For simplicity I assume that unemployed workers cannot change their location. It is straightforward to allow for this extension; with moving costs of the magnitude calibrated below this assumption is insignificant for the quantitative results.

costs. All workers have the outside option of leaving the labor market and consuming \bar{u} , which is normalized to zero.

3.2 Wage Determination

Employment contracts consist of a wage and worker location, (w, ℓ_e) . Wages are renegotiated with the agreement of both parties, following [Dey and Flinn \(2005\)](#) and [Cahuc et al. \(2006\)](#). The outcome of this game is identical to the generalized Nash-bargaining solution, where the worker's bargaining power is given by β . Similar to search intensity in [Bagger and Lentz \(Forthcoming\)](#), I assume that the worker's location is contractible at the time of matching, to ensure that the equilibrium can be characterized independently of the split of the surplus between firm and worker.²⁴ This assumption is further discussed at the end of the next section.

All value functions depend on the endogenous distributions due to the effect of congestion on commuting costs and through job search. As I will be solving the model in steady state, I omit dependence on these distributions for notational convenience. For a given location ℓ , define the value of unemployment as $U(\ell)$. For a given firm location and productivity (ℓ_F, y) , worker location ℓ , and wage w , denote the value of an employed worker as $W(w, \ell_F, y, \ell)$. This value takes into account the worker's contracted location ℓ_e :

$$W(w, \ell_F, y, \ell) = \tilde{W}(w, \ell_F, y, \ell_e) - k_M \mathbb{1}\{\ell \neq \ell_e\} \quad (1)$$

where variables with a tilde denote those taking the worker's location as given. Similarly, the value of a filled job is

$$J(w, \ell_F, y, \ell) = \tilde{J}(w, \ell_F, y, \ell_e) \quad (2)$$

The match surplus is defined as

$$S(\ell_F, y, \ell) = \max_{\ell' \in \mathcal{L}} \{\tilde{M}(\ell_F, y, \ell') - k_M \mathbb{1}\{\ell' \neq \ell\}\} - U(\ell) \quad (3)$$

where $\tilde{M}(\ell_F, y, \ell) = \tilde{W}(w, \ell_F, y, \ell) + \tilde{J}(w, \ell_F, y, \ell)$, with \tilde{W} and \tilde{J} defined below. The location in the worker's contract is given by

$$\ell_e(\ell_F, y, \ell) = \arg \max_{\ell' \in \mathcal{L}} \{\tilde{M}(\ell_F, y, \ell') - k_M \mathbb{1}\{\ell' \neq \ell\}\}.$$

I assume that the surplus-maximizing location is unique for each (ℓ_F, y, ℓ) .²⁵ In the case of moving shocks, the worker cannot immediately return to her surplus-maximizing location. Define the match surplus after drawing ℓ' following a moving shock as $\tilde{S}(\ell_F, y, \ell') = \tilde{M}(\ell_F, y, \ell') - U(\ell')$. Following

²⁴The lack of tractability when workers are able to choose their location independently comes from the fact that the worker's location choice affects the probability of renegotiation, whereas the location choice maximizing the match value does not.

²⁵In the quantitative model I allow for indifference by splitting workers evenly across the locations to which they are indifferent.

a moving shock, the worker's location may change only after making a job-to-job transition or receiving another moving shock. Because the worker cannot immediately move following a moving shock, and the match productivity and firm location are fixed, the worker will only move for job-related reasons when she accepts a new job, thus, if a worker is continuing in a match I denote the surplus as $\tilde{S}(\ell_F, y, \ell)$, and the workers' value as $\tilde{W}(w, \ell_F, y, \ell)$.

When a firm meets an unemployed worker, her wage $\phi_0(y, \ell_F, \ell)$ is set to satisfy

$$W(\phi_0, \ell_F, y, \ell) - U(\ell) = \beta S(\ell_F, y, \ell) \quad (4)$$

Henceforth, I will drop the arguments of the wage functions where possible. I use a prime to denote the values of a job offer (e.g. (y', ℓ'_F)). When a worker is employed, she may renegotiate her wage upon the arrival of an outside offer. Suppose a worker's current surplus is given by $S(\ell_F, y, \ell)$ and associated worker value is $W(w, \ell_F, y, \ell)$. If she is contacted by a firm with which her surplus would be $S(\ell'_F, y', \ell)$, there are three possibilities:

- (1) $\tilde{S}(\ell_F, y, \ell) < S(\ell'_F, y', \ell)$
- (2) $\tilde{W}(w, \ell_F, y, \ell) - U(\ell) < S(\ell'_F, y', \ell) < \tilde{S}(\ell_F, y, \ell)$
- (3) $S(\ell'_F, y', \ell) < \tilde{W}(w, \ell_F, y, \ell) - U(\ell) < \tilde{S}(\ell_F, y, \ell)$

In case (1), the worker will be poached by the new firm, with wage $w = \phi_1(y', \ell'_F, y, \ell_F, \ell)$ satisfying:

$$W(\phi_1, \ell'_F, y', \ell) - U(\ell) = \tilde{S}(\ell_F, y, \ell) + \beta(S(\ell'_F, y', \ell) - \tilde{S}(\ell_F, y, \ell)) \quad (5)$$

In this case, the firms enter into Bertrand competition, and the worker extracts the full surplus of her previous match and a share β of the gains in surplus between the poaching firm and her previous employer. Note that the new job may require the worker to move and therefore has no tilde. Following the terminology of [Postel-Vinay and Turon \(2010\)](#), the surplus $\tilde{S}(\ell_F, y, \ell)$ becomes the worker's new "negotiation baseline." In case (2), the worker remains at her current firm, but renegotiates her wage to $w = \phi_2(y, \ell_F, y', \ell'_F, \ell)$ with the outside offer becoming her negotiation baseline:

$$\tilde{W}(\phi_2, \ell_F, y, \ell) - U(\ell) = S(\ell'_F, y', \ell) \quad (6)$$

Finally, in case (3), the outside offer is too low to warrant renegotiation between the worker and her current firm, therefore she remains at the same wage in her current match.

Similarly to [Postel-Vinay and Turon \(2010\)](#), the arrival of a moving shock may trigger a renegotiation due to a change in the worker or firm's values. Consider an employed worker in a match (ℓ_F, y) , who was previously living at ℓ and draws ℓ' upon the arrival of the shock. The worker cannot immediately return to her previous location following the shock, thus, the worker and firm will remain matched if $\tilde{S}(\ell_F, y, \ell') > 0$. She can renegotiate using her new location, thus, her value of employment is given by $\tilde{W}(w, \ell_F, y, \ell')$.

There are four possibilities:

- (a) $\tilde{S}(\ell_F, y, \ell') < 0$
- (b) $\tilde{S}(\ell_F, y, \ell') > 0$, and $\tilde{W}(w, \ell_F, y, \ell') - U(\ell') < 0$
- (c) $\tilde{S}(\ell_F, y, \ell') > 0$, and $\tilde{W}(w, \ell_F, y, \ell') - U(\ell') > \tilde{S}(\ell_F, y, \ell')$
- (d) $\tilde{S}(\ell_F, y, \ell') > 0$, $\tilde{W}(w, \ell_F, y, \ell') - U(\ell') > 0$ and $\tilde{W}(w, \ell_F, y, \ell') - U(\ell') \leq \tilde{S}(\ell_F, y, \ell')$

In case (a), the match is endogenously destroyed due to a negative surplus at the worker's new location. In case (b), the worker's surplus is negative under the old wage and is reset to make the worker indifferent between remaining in the match or quitting into unemployment, $w = \psi_1(\ell_F, y, \ell')$ such that

$$\tilde{W}(\psi_1, \ell_F, y, \ell') - U(\ell') = 0 \quad (7)$$

In this case, the firm gets the full surplus. Conversely, in case (c), the wage is reset to $w = \psi_2(\ell_F, y, \ell')$ to make the firm indifferent between continuing in the match or exiting. Equivalently, the worker gets the full surplus

$$\tilde{W}(\psi_2, \ell_F, y, \ell') - U(\ell') = \tilde{S}(\ell_F, y, \ell') \quad (8)$$

Finally, in case (d), both the worker and firm have positive surplus under the new realization of the worker's location, and therefore the match will continue with no change in the wage.

3.3 Value Functions

The flow value for an unemployed worker who consumes home production b and receives job offers at rate λ_0 is

$$(\rho + \chi)U(\ell) = b - r(\ell) + \lambda_0 \sum_{y', \ell'_F} \max\{0, \beta S(\ell'_F, y', \ell)\} g(\ell'_F, y') \quad (9)$$

At rate λ_0 the worker meets a vacancy drawn from distribution G . If the job is acceptable, the worker receives a share β of the surplus.

Next, consider an employed worker living in ℓ in current firm (y, ℓ_F) earning wage w . Define the sets for which a worker makes a job-to-job transition and renegotiates, respectively, as $B_1(\ell_F, y, \ell) = \{(\ell'_F, y') \in \mathcal{L} \times Y : S(\ell'_F, y', \ell) > \tilde{S}(\ell_F, y, \ell)\}$, and $B_2(w, \ell_F, y, \ell) = \{(\ell'_F, y') \in \mathcal{L} \times Y : \tilde{W}(w, \ell_F, y, \ell) - U(\ell) < S(\ell'_F, y', \ell) \leq \tilde{S}(\ell_F, y, \ell)\}$. The flow value for a worker living in a location ℓ , in current firm (ℓ_F, y) earning wage w , is given by:

$$\begin{aligned} & (\rho + \chi)\tilde{W}(w, \ell_F, y, \ell) = w - r(\ell) - T(\ell, \ell_F, \Omega) + (\delta + \varphi)(U(\ell) - \tilde{W}(w, \ell_F, y, \ell)) \\ & + \varphi \sum_{\ell' \in \mathcal{L}} [\max\{\min\{\tilde{W}(w, \ell_F, y, \ell') - U(\ell'), \tilde{S}(\ell_F, y, \ell')\}, 0\} + U(\ell') - U(\ell)] \pi(\ell') \\ & + \lambda_1 \sum_{(y', \ell'_F) \in B_1(y, \ell_F, \ell)} (\beta S(\ell'_F, y', \ell) + (1 - \beta)\tilde{S}(\ell_F, y, \ell) - \tilde{W}(w, \ell_F, y, \ell) + U(\ell)) g(\ell'_F, y') \\ & + \lambda_1 \sum_{(y', \ell'_F) \in B_2(w, y, \ell_F, \ell)} (S(\ell'_F, y', \ell) - \tilde{W}(w, \ell_F, y, \ell) + U(\ell)) g(\ell'_F, y') \end{aligned} \quad (10)$$

Where the value function W , taking into account the location for this worker is given by (1). I verify below that this location is independent of the worker's current wage.

The first three terms on the right hand side are the wage, rent, and commuting cost. The worker exogenously separates from her match at rate δ . At rate φ the worker experiences a moving shock and may separate into unemployment, renegotiate her wage, or remain at her old wage. The last two lines report the payoffs to the worker when an outside offer arrives. The worker separates if the surplus of the new offer is strictly larger than her current surplus, that is, $(\ell'_F, y') \in B_1(\ell_F, y, \ell)$. The worker and firm renegotiate if the surplus of the outside offer exceeds the worker's current negotiation baseline but does not exceed her current surplus, that is, $(\ell'_F, y') \in B_2(w, \ell_F, y, \ell)$.

The value of a continuing filled job is given by

$$\begin{aligned}
& (\rho + \chi)\tilde{J}(w, \ell_F, y, \ell) = y - w - r(\ell_F) - (\delta + \varphi)\tilde{J}(w, \ell_F, y, \ell) \\
+ & \varphi \sum_{\ell' \in \mathcal{L}} \max\{\min\{\tilde{J}(w, \ell_F, y, \ell'), \tilde{S}(\ell_F, y, \ell')\}, 0\}\pi(\ell') - \lambda_1 \tilde{J}(w, \ell_F, y, \ell) \sum_{(y', \ell'_F) \in B_1(y, \ell_F, \ell)} g(\ell'_F, y') \\
+ & \lambda_1 \sum_{(y', \ell'_F) \in B_2(w, y, \ell_F, \ell)} (\tilde{S}(\ell_F, y, \ell) - S(\ell'_F, y', \ell) - \tilde{J}(w, \ell_F, y, \ell))g(\ell'_F, y') \tag{11}
\end{aligned}$$

where the first three terms are the match output is y , the wage that the firm pays its worker, and the firm's rent ℓ_F . At rate δ the match is destroyed exogenously, and the value of the job if the worker separates is zero, since the job is destroyed when the match ends. At rate φ , the worker receives a moving shock and may separate into unemployment, renegotiate her wage, or remain at her old wage. The last term on the second line is the loss to the firm if the match is destroyed when the worker makes a job-to-job transition, and the third line shows the payoff if the worker and firm renegotiate.

Combining these expressions gives the match value:

$$M(\ell_F, y, \ell) = \max_{\ell' \in \mathcal{L}} \{\tilde{M}(\ell_F, y, \ell') - k_M \mathbb{1}\{\ell \neq \ell'\}\} \tag{12}$$

where $\tilde{M}(\ell_F, y, \ell) = \tilde{J}(w, \ell_F, y, \ell) + \tilde{W}(w, \ell_F, y, \ell)$, with:

$$\begin{aligned}
(\rho + \chi)\tilde{M}(\ell_F, y, \ell) & = y - r(\ell) - r(\ell_F) - T(\ell, \ell_F, \Omega) - (\delta + \varphi)\tilde{S}(\ell_F, y, \ell) \\
& + \varphi \sum_{\ell' \in \mathcal{L}} (\max\{0, \tilde{S}(\ell_F, y, \ell')\} + U(\ell') - U(\ell))\pi(\ell') \\
& + \lambda_1 \beta \sum \max\{0, S(\ell'_F, y', \ell) - \tilde{S}(\ell_F, y, \ell)\}g(\ell'_F, y') \tag{13}
\end{aligned}$$

where the associated policy function for the worker's location is denoted $\ell_e(\ell_F, y, \ell)$. When an outside offer arrives and the worker is able to change location, the match surplus is given by $S(\ell_F, y, \ell) = M(\ell_F, y, \ell) - U(\ell)$. After a moving shock, when the worker cannot move, the surplus that is used to determine whether to renegotiate or continue in the match is given by $\tilde{S}(\ell_F, y, \ell) = \tilde{M}(\ell_F, y, \ell) - \tilde{U}(\ell)$.

Discussion on Contractability of Location

Wages in this model are determined by the current and next-best match surplus. Thus, otherwise identical workers are compensated for their commutes through wages, a seemingly strong assumption. The main reason for using this wage-setting mechanism is to facilitate the analysis with externalities and endogenous rent prices below. Although one may argue that wages offered to new hires should not vary by commuting cost, in this model with renegotiation firms will compensate their worker in order to avoid her being poached by an outside offer. Thus, observed wages after at least one renegotiation will vary for otherwise identical workers due to differences in threat points reflecting heterogeneous commuting costs.

In addition, many contracts include a “mobility clause” defining the maximum distance the worker is expected to live from the workplace. The reason for this assumption here is technical, since the worker’s location affects the match value through commuting and rent costs, but the worker’s choice of location will generally not coincide with the match value-maximizing choice. This is because the worker’s location affects the set of offers resulting in wage renegotiation. It is beyond the scope of this paper to consider the incentive problems related to the interaction between wage contracts and workers’ location choices.

3.4 Worker Flows

This section defines the flows into and out of the worker distributions across employment states and space. Denote the mass of employed workers currently in a match (ℓ_F, y) living at ℓ as $e(\ell_F, y, \ell)$ and the mass of unemployed workers living at ℓ as $u(\ell)$. The distribution of workers is summarized by Ω .

The flow into employment for workers living at ℓ employed in matches located at ℓ_F with firm productivity y is made up of three groups. The first is the unemployed who match with a firm (ℓ_F, y) . The second is the employed making job-to-job transitions, who were previously in a match with $y' \neq y$ and/or $\ell'_F \neq \ell_F$. The final group are those employed workers who arrive in ℓ after receiving a moving shock, but remain employed with their firm (y, ℓ_F) . In sum, the flow into such matches is given by:

$$\begin{aligned}
 e^+(\ell_F, y, \ell) &= g(\ell_F, y) \sum_{\ell' \in \mathcal{L}} [\lambda_0 u(\ell') \mathbb{1}\{S(\ell_F, y, \ell') > 0\} \\
 &+ \lambda_1 \sum_{\ell'_F \in \mathcal{L}} \sum_{y' \in Y} \mathbb{1}\{\tilde{S}(\ell'_F, y', \ell') < S(\ell_F, y, \ell')\} e(\ell'_F, y', \ell')] \mathbb{1}\{\ell_e(\ell_F, y, \ell') = \ell\} \\
 &+ \varphi\pi(\ell) \mathbb{1}\{\tilde{S}(\ell_F, y, \ell) > 0\} \sum_{\ell' \neq \ell} e(\ell_F, y, \ell')
 \end{aligned} \tag{14}$$

Similarly, the flow out of such matches is given by the employed previously in matches located at ℓ_F with firm productivity y , who separate either exogenously or endogenously by making a

job-to-job transition or after receiving a moving shock:

$$e^-(\ell_F, y, \ell) = e(\ell_F, y, \ell) [\chi + \delta + \varphi(1 - \pi(\ell)) + \lambda_1 \sum_{\tilde{\ell}_F \in \mathcal{L}} \sum_{\tilde{y} \in Y} \mathbb{1}\{S(\ell'_F, y', \ell) > \tilde{S}(\ell_F, y, \ell)\} g(\ell'_F, y')] \quad (15)$$

The flow into of unemployment of workers living at ℓ consists of those employed workers who separate exogenously following a separation shock δ or endogenously following a moving shock φ , and newborn workers who draw location ℓ with probability $\mu(\ell)$:

$$u^+(\ell) = \chi\mu(\ell) + \delta \sum_{\ell_F \in \mathcal{L}} \sum_{y \in Y} e(\ell_F, y, \ell) + \varphi\pi(\ell) \sum_{\ell'} \sum_{\ell_F \in \mathcal{L}} \sum_{y \in Y} e(\ell_F, y, \ell') \mathbb{1}\{\tilde{S}(\ell_F, y, \ell) \leq 0\} \quad (16)$$

The flow out of unemployment for workers living at ℓ is simply those unemployed workers who successfully match or exit the economy:

$$u^-(\ell) = u(\ell) \left(\chi + \lambda_0 \sum_{\ell_F \in \mathcal{L}} \sum_{y \in Y} \mathbb{1}\{S(\ell_F, y, \ell) > 0\} g(\ell_F, y) \right) \quad (17)$$

Turning to the flows across space, the flow of workers and active firms into a given location $\tilde{\ell}$ is comprised of the flow of newly filled jobs located at $\tilde{\ell}$, those newly hired workers not previously living at $\tilde{\ell}$ whose contract specifies that they live at $\tilde{\ell}$, employed workers who draw $\tilde{\ell}$ upon arrival of moving shock, and the newly unemployed who are located at $\tilde{\ell}$. This inflow is given by:

$$\begin{aligned} \sum_{y \in Y} & \left(\sum_{\ell \in \mathcal{L}} e^+(\tilde{\ell}, y, \ell) + \sum_{\ell_F \in \mathcal{L}} e^+(\ell_F, y, \tilde{\ell}) - g(\ell_F, y) \left[\lambda_0 u(\tilde{\ell}) \mathbb{1}\{S(\ell_F, y, \tilde{\ell}) > 0\} \right. \right. \\ & + \left. \left. \lambda_1 \sum_{\tilde{\ell}_F \in \mathcal{L}} \sum_{\tilde{y} \in Y} \mathbb{1}\{\tilde{S}(\tilde{\ell}_F, \tilde{y}, \tilde{\ell}) < S(\ell_F, y, \tilde{\ell})\} e(\tilde{\ell}_F, \tilde{y}, \tilde{\ell}) \right] \mathbb{1}\{\ell_e(\ell_F, y, \tilde{\ell}) = \tilde{\ell}\} \right) \\ & + u^+(\tilde{\ell}) - \delta \sum_{\ell_F \in \mathcal{L}} \sum_{y \in Y} e(\ell_F, y, \tilde{\ell}) \end{aligned} \quad (18)$$

Similarly, the flow of workers and firms out of location $\tilde{\ell}$ is made up of the firms whose matches were located at $\tilde{\ell}$ and are destroyed, plus the employed and unemployed who lived at $\tilde{\ell}$ and moved following a change in their employment state. This flow is given by:

$$\begin{aligned} \sum_{y \in Y} & \left(\sum_{\ell \in \mathcal{L}} e^-(\tilde{\ell}, y, \ell) + \sum_{\ell_F \in \mathcal{L}} \left(e^-(\ell_F, y, \tilde{\ell}) \right. \right. \\ & - \left. \left. e(\ell_F, y, \tilde{\ell}) [\delta + \lambda_1 \sum_{\ell'_F \in \mathcal{L}} \sum_{y' \in Y} \mathbb{1}\{S(\ell'_F, y', \tilde{\ell}) > \tilde{S}(\ell_F, y, \tilde{\ell})\} \mathbb{1}\{\ell_e(\ell'_F, y', \tilde{\ell}) = \tilde{\ell}\} g(\ell'_F, y')] \right] \right) \\ & + u^-(\tilde{\ell}) - \lambda_0 u(\tilde{\ell}) \sum_{\ell_F \in \mathcal{L}} \sum_{y \in Y} \mathbb{1}\{S(\ell_F, y, \tilde{\ell}) > 0\} \mathbb{1}\{\ell_e(\ell_F, y, \tilde{\ell}) = \tilde{\ell}\} g(\ell_F, y) \end{aligned} \quad (19)$$

3.5 Congestion

Recall that $d(\ell, \ell_F)$ is the distance in miles between a worker located in ℓ and a firm located in ℓ_F . Since locations are discrete, I assume that all workers experience a positive commute even if their firm is in the same location, that is, $d(\ell, \ell) > 0$.

Similar to Brinkman (2016), I define congestion as the share of commuters passing through a location less the number of employed workers living in that location. I consider all of the pairs of locations (ℓ, ℓ_F) and compute the “commuting path,” defined as the locations through which a worker living at ℓ must travel in order to get to ℓ_F . For instance, to travel from location 2 to location N , a worker must travel through $N - 1$ locations. Define the commuting path as $cp(\ell_F, \ell)$ where I impose symmetry: $cp(\ell_F, \ell) = cp(\ell, \ell_F)$, where $cp(\ell, \ell_F) = \{\ell' \in \mathcal{L} : \ell \leq \ell' \leq \ell_F \text{ if } \ell \leq \ell_F \text{ and } \ell_F \leq \ell \leq \ell' \text{ otherwise}\}$. Congestion in a given location $\tilde{\ell}$ is given by the difference between commuters and residents:

$$c(\tilde{\ell}) = \sum_y \left(\sum_{(\ell_F, \ell): \tilde{\ell} \in cp(\ell, \ell_F)} [e(\ell_F, y, \ell) + e(\ell, y, \ell_F)] - \sum_{\ell_F} e(\ell_F, y, \ell) \right) \quad (20)$$

Note that a worker who lives and works in the same location does not add to congestion; similarly, the unemployed have no effect on congestion.

The total cost of commuting between ℓ and ℓ_F is given by

$$T(\ell, \ell_F, \Omega) = \left(\tau d(\ell, \ell_F) + \kappa \sum_{i \in cp(\ell, \ell_F)} c(i) \right) b$$

where τ is the “no traffic” cost of commuting an extra unit of distance and κ measures the congestion cost. The summation computes all of the congestion that a worker encounters by commuting between ℓ and ℓ_F ; in this way commuting costs depend on the distribution Ω . In the case where there is no externality, $\kappa = 0$. The cost of time to the worker is proportional to the opportunity cost of time, given by the value of home production b . Before defining the equilibrium, in the next section I extend the model to be used for the quantitative results.

3.6 Efficiency

I use the quantitative model below to evaluate the welfare implications of congestion taxes, while taking into account the dynamic nature of job search, workers’ location decisions, and congestion. To develop intuition for cases when the congestion externality is inefficient, in Appendix C I show in a simple static framework that the decentralized equilibrium need not align with that of a social planner when moving is costly. I consider workers who receive job offers from two locations, and upon receiving an offer from a location different from their own, must decide whether to commute or pay a moving cost. The social value of some workers moving to the location of their jobs includes the net benefits for all remaining commuters from less congestion plus the output gain from any additional match creation. Because moving is costly, individual matches may find it

privately optimal to commute, failing to take into account their effect on congestion. I show that for any sufficiently large moving cost, there exists an interval of values for the marginal cost of congestion such that it is socially beneficial but privately suboptimal to have workers move to the location of their jobs rather than commute. When rent is exogenous, I derive the optimal tax rate to align the incentives of the planner and workers in the decentralized economy. The optimal tax is proportional to the marginal congestion cost, κ , and equal to the share of workers who benefit from the reduction in congestion, which workers in the decentralized economy do not take into account when making their moving decisions. The tax forces workers to internalize the positive externality they create from reducing congestion. Using this intuition, I consider taxes proportional to congestion in Section 5.

4 Quantitative Model

I incorporate a land market with endogenous supply to take into account how rent prices reflect congestion and labor market frictions. Each location $\ell \in \mathcal{L}$ contains total land L .²⁶ Both workers and firms with filled jobs pay rent, $r(\ell)$, which is determined endogenously. Land is endowed to a continuum of homogeneous landlords in each location. Since workers can move at any time but the locations of all filled jobs are fixed, it is useful to consider the stock of available land, which I denote $\hat{L}(\ell)$, equal to the total land less that occupied by the existing filled jobs:

$$\hat{L}(\ell) = \underbrace{L(\ell)}_{\text{total land}} - \sum_y \sum_{\tilde{\ell}} \underbrace{(e(\ell, y, \tilde{\ell}) - e^-(\ell, y, \tilde{\ell}))}_{\text{existing filled jobs}}$$

The representative landlord maximizes her utility by choosing how much of the available land to consume, denoted $\zeta(\ell)$. Her maximization problem is written

$$\max_{\zeta(\ell) \in [0, \hat{L}(\ell)]} \{ \nu(\zeta(\ell), r(\ell)[L - \zeta(\ell)]) \} \quad (21)$$

where the first argument is the amount of land the landlord consumes, and the second argument is the amount of resources she gets from renting the remaining land $L - \zeta(\ell)$ at price $r(\ell)$. I assume that ν is twice continuously differentiable and strictly increasing in both of its arguments. The strictly positive derivative with respect to the first argument insures that the landlord will not rent any of her land at a price of zero.

Given the land occupied by existing jobs, land demand is determined by the total mass of employed and unemployed workers residing in ℓ and newly filled jobs located in ℓ . Equilibrium in

²⁶In the counterfactuals below, I assume that $L(2N + 1)$ is large. If it were small, some workers would be forced to leave the economy in order for the market to clear. The model allows for this possibility by assuming that all workers have the outside option of leaving the labor market, but in the calibrated model this does not occur.

the land market requires the supply of land be equal to the demand of for land:

$$L - \zeta(\ell) = u(\ell) + \sum_{y \in Y} \sum_{\tilde{\ell} \in \mathcal{L}} e(\tilde{\ell}, y, \ell) + e(\ell, y, \tilde{\ell}) \quad (22)$$

I now define a steady state equilibrium.

Definition 1. A steady state equilibrium consists of value functions $M : \mathcal{L} \times Y \times \mathcal{L} \rightarrow \mathbb{R}$ for each $\ell_F \in \mathcal{L}$ and $U : \mathcal{L} \rightarrow \mathbb{R}$, a policy function $\ell_e(\ell_F, y, \ell) \in \mathcal{L}$, wage functions when employed $\phi_1 : \mathcal{L} \times Y \times \mathcal{L} \times Y \times \mathcal{L} \rightarrow \mathbb{R}_+$, $\phi_2 : \mathcal{L} \times Y \times \mathcal{L} \times Y \times \mathcal{L} \rightarrow \mathbb{R}_+$, $\psi_1 : \mathcal{L} \times Y \times \mathcal{L} \rightarrow \mathbb{R}_+$ and $\psi_2 : \mathcal{L} \times Y \times \mathcal{L} \rightarrow \mathbb{R}_+$, a wage function when unemployed, $\phi_0 : \mathcal{L} \times Y \times \mathcal{L} \rightarrow \mathbb{R}_+$, a rent function $r : \mathcal{L} \rightarrow \mathbb{R}_+^{2N+1}$, landlords' consumption $\zeta : \mathcal{L} \rightarrow \mathbb{R}_+^{2N+1}$, and distributions of workers across employment states, and of workers and firms across space such that given the commuting externality $c : \mathcal{L} \rightarrow \mathbb{R}_+^{2N+1}$,

- (i) For each $(\ell_F, y, \ell) \in Y \times \mathcal{L} \times \mathcal{L}$, $M(\ell_F, y, \ell)$ satisfies (13) and $\ell_e(y, \ell_F, \ell)$ is the associated policy function. For each $\ell \in \mathcal{L}$, $U(\ell)$ satisfies (9).
- (ii) When an outside offer arrives, wages $\phi_1(y', \ell'_F, y, \ell_F, \ell)$ and $\phi_2(y, \ell_F, y', \ell'_F, \ell)$ are determined by the surplus splitting equations (5) and (6). When an offer arrives to the unemployed worker, the wage $\phi_0(y, \ell_F, \ell)$ is determined by (4). When a moving shock is realized, wages $\psi_1(\ell_F, y, \ell')$ and $\psi_2(\ell_F, y, \ell')$ are determined by (7) and (8).
- (iii) For each $(\ell_F, y, \ell) \in Y \times \mathcal{L} \times \mathcal{L}$, the distributions across employment states satisfy $e^+(\ell_F, y, \ell) = e^-(\ell_F, y, \ell)$ and $u^+(\ell) = u^-(\ell)$, given by (14)-(17). The distributions across space equate (18) and (19).
- (iv) The congestion externality c is consistent with the distributions and given by (20).
- (v) For each $\ell \in \mathcal{L}$, $\zeta(\ell)$ satisfies (21) and rent $r(\ell)$ adjusts such that (22) holds.

I restrict attention to the steady state for tractability. In the steady state, equating the flows of employed and unemployed workers determines $e(\ell_F, y, \ell)$ and $u(\ell)$. Under the assumption that vacant firms do not occupy space and thus do not enter into the flows across space, imposing steady state in the labor market implies the spatial steady state, that is, the equality of (18) and (19).

Existence

The steady state distributions $\Omega = (e, u)$ are pinned down by the surplus value function S and policy functions determining workers' locations. Proposition 1 states that there exists a bounded price vector r satisfying the conditions of a steady state equilibrium.

Proposition 1. A steady state price vector r exists.

The proof is shown in Appendix B. Proving existence of the equilibrium for the model with endogenous rent is nontrivial due to the dependence of the distributions of workers and firms on the rent price. The complication arises here because the rent price function r affects steady state distributions of workers across firms and locations, and these distributions must also be consistent with the land market clearing condition. The demand correspondence that takes prices and returns a vector of demands corresponding to the right hand side of (22) is clearly nonempty. However, it is not clear that the correspondence is upper hemicontinuous nor convex-valued, since the distributions of vacancies and workers may not respond continuously to changes in price and agents can choose only one discrete location in which to reside.

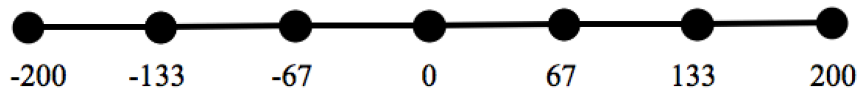
The proof follows and extends the arguments presented in Kaneko and Yamamoto (1986). It differs from the previous literature because not only do the demands for land change by worker type, but also the mass of each type of worker and of filled jobs, that is, the worker’s employment status and current match, responds to changes in rent prices. Intuitively, when types are fixed, workers and firms are permanently matched. An increase in rent near the most productive jobs will make the surplus of these matches fall, and workers will respond by trading off their commuting and rent costs. When workers and firms can choose who to match with, an increase in rent will not only cause changes in residential patterns of workers in existing firms, but also change the set of acceptable matches and the level of employment. This causes the distributions of workers and firms, match surplus, and wages all to change in response to rent prices. The proof thus hinges on showing that the steady state distributions respond continuously to the price. This mechanism by which spillovers exist between labor and rental markets is a fundamental feature of the model as it is tightly linked to the level of congestion.

4.1 Calibration

The model is calibrated at a monthly frequency. The number of match-specific productivities is set to 5. The local labor market is divided into 7 locations defined by the round trip commuting distance from the center, shown in Figure 3. As discussed in Section 2, I calibrate the model to match the metropolitan area defined by those LADs within 100 miles (one-way) of the City of London. An alternative definition of the local labor market defined by the “commuting zone” around the City, which consists of those locations for which a large share of workers commute within the zone’s boundaries, is discussed in Appendix D. The reason for using the 100 mile radius is quantitative: in the alternative definition, many observations from the BHPS data are lost, and the empirical moments used in the calibration are much more noisy. Given two locations ℓ and ℓ_F , the distance in miles is $d(\ell, \ell_F) = |\ell - \ell_F| + 10\mathbb{1}\{\ell = \ell_F\}$. In words, this functional form for distance implies that the round trip distance between the worker and firm in the same location ℓ is 10 miles.

Regarding the other distributional assumptions, the location and productivity of vacancies is drawn from the joint distribution G . The location distribution is assumed to be symmetric around the center, where the probability of drawing a location, from left to right, is given by

Figure 3: Locations



$[g(1), g(2), g(3), g(4), g(3), g(2), g(1)]$, with $g(4) + 2 \sum_{i=1}^3 g(i) = 1$. The distribution for y is conditional on the draw of the firm location ℓ_F and drawn from a Normal distribution with mean $1 + A(\ell_F)$ and standard deviation σ_y , discretized using the Tauchen method to span two standard deviations from the mean in each location. Finally, the location distribution for newborn workers (μ) is equal to the distribution after moving shocks (π) and is chosen to match the spatial distribution in the BHPS for workers 24 years old with less than 2 years of labor market experience.

Appendix E describes the numerical solution algorithm. I first discuss the standard parameters of the model and then turn to those particular to the spatial dimension and commuting.

4.1.1 Standard Parameters

Two parameters are calibrated exogenously. The discount rate ρ is set to match an annual interest rate of 5% and the death rate χ is chosen to match an average working lifetime²⁷ of 31 years. The remaining parameters, including those in the next section, are calibrated jointly using the Simulated Method of Moments. Given a set of parameter values, I solve for the steady state of the model and simulate 3,000 worker histories over 3,000 months, discarding the first 300 months. Because solving the model is computationally intensive, I do not compute standard errors. The standard labor market parameter values and their targets are shown in Tables 3 and 4, respectively. I next discuss the relationship between the targeted moments and structural parameters.

The parameters related to transitions are δ , φ , λ_0 , λ_1 , and β . The separation rate into unemployment (EU rate) is driven by exogenous separations, occurring at rate δ , and endogenous separations which may occur after the arrival of a moving shock φ . The unemployment to employment (UE) rate is mainly driven by the arrival rate of offers for the unemployed, λ_0 . The job-to-job transition (EE) rate is primarily driven by λ_1 . Bargaining power β is chosen to match the ratio of the average wage for new entrants relative to the average wage for all employed workers. Because φ is a spatial parameter, I leave its discussion to the next section.

The standard deviation of productivity, σ_y , is chosen to match the variance of the observed log wage distribution.²⁸ Since the mean of y is location-specific, it is discussed in the next section. The home production value b is chosen to match a replacement rate of 0.71 following Hall and Milgrom (2008), defined as the flow benefits of unemployment relative to the average wage.²⁹

²⁷The working lifetime corresponds to ages 24-55, the same range considered in the empirical results of Section 2.

²⁸Wages used to compute the calibration moments are in real terms and in logs, after subtracting the year, month, education level, and commuting method effects, see Appendix E.

²⁹The benefits of unemployment include the commuting costs saved from not working, for a discussion of a similar

Table 3: Standard Parameter Values

Parameter		Value
Discount Rate	ρ	.0041
Exit rate	χ	.0027
Bargaining Power	β	.33
Home Production	b	.83
Separation Rate	δ	.0033
Arrival Rate, Unemployed	λ_0	.117
Arrival Rate, Employed	λ_1	.095
Standard Deviation, Productivity	σ_y	.023

Table 4: Targets: Standard Parameters

Moment	Data	Model
Annual interest rate	.05	.05
Years in LF	31	31
Relative wage, new hires from U	.87	.85
Replacement rate (Hall and Milgrom 2008)	.71	.70
EU rate (Q, Gomes 2012)	.014	.013
UE rate (Q, Gomes 2012)	.26	.26
EE rate (Q, Gomes 2012)	.027	.029
Variance, $\ln(w)$.186	.181

4.1.2 Spatial Parameters

The probabilities $g(1)$, $g(2)$, and $g(3)$ are chosen to match the average jobs density for LADs 5-33, 33-66, and 66-100 miles (one way) from the City of London as defined by Google Maps and discussed in Section 2. Jobs density is defined as the ratio of the number of jobs to resident working age population. The probability of drawing a vacancy in the city center, $g(4)$ is given by $1 - 2 \sum_{i=1}^3 g(i)$.

Returning to the conditional mean for match-specific productivity y , the value of A in the center is normalized to one, and is symmetric around the center. The remaining values for A are chosen to match the average wage for workers residing in LADs 5-33, 33-66, and 66-100 miles from the City of London relative to the average wage for workers residing within 10 miles of the City. The parameter values imply that output is much higher on average in the center: the level of A in the center is over 40% higher than in the periphery. Lower rent in the periphery offsets the effect of lower production, increasing wages and creating the need for large productivity differences across locations to match relative wages as a function of distance. Brinkman (2016) estimates agglomeration effects implying a 40% productivity loss at a radius 100 miles from the city center, here the estimate for $A(1)$ implies an average productivity loss of 15%. In my model, workers have an option value of remaining

point see [Bils et al. \(2012\)](#).

unemployed, there is a trade-off between low A and high unemployment.

The choice of φ targets the share of job-related moves: in the data, workers state that the main reason for moving was for employment reasons just 12.9% of the time. The remaining share of moves is attributed to moving shocks in the model. The calibrated value for φ implies a non-job related move once every 29 years, or about one time between the ages of 24 and 55. Given the rate of exogenous moves, the annual average moving rate pins down the moving cost k_M . This moving cost is equivalent to roughly 8 years of average wages, in line with the literature: Kennan and Walker (2011) estimate that the cost of moving house in the US is as high as \$300,000.

Landlords' preferences are assumed to be CES:

$$\nu(\zeta(\tilde{\ell}), r(\tilde{\ell})(L - \zeta(\tilde{\ell}))) = \left[\omega_L \zeta(\tilde{\ell})^{\frac{\sigma_L - 1}{\sigma_L}} + (1 - \omega_L)(r(\tilde{\ell})(L - \zeta(\tilde{\ell})))^{\frac{\sigma_L - 1}{\sigma_L}} \right]^{\frac{\sigma_L}{\sigma_L - 1}}$$

where $\omega_L \in (0, 1)$ is the weight on the landlord's consumption and σ_L is the elasticity of substitution between consumption and rental income. The parameter ω_L is chosen to match an average monthly rent to wage income ratio and σ_L is chosen to match the price elasticity of housing supply in the UK (Barker 2003). The endowment of land L is constant and chosen such that there is enough land in the economy for the maximum mass of workers and filled jobs.³⁰

Table 5: Spatial Parameter Values

	Parameter	Value
	Moving cost	k_M 128
	No-traffic commuting cost	τ .003
	Congestion Cost	κ .68
	Moving rate	φ .003
	Landlords' preferences	ω_L .16
	Landlords' preferences	σ_L .95
	Location-specific productivity, 5-33 mi	$A(3)$.91
	Location-specific productivity, 34-66 mi	$A(2)$.79
	Location-specific productivity, 67-100 mi	$A(1)$.71
	Vacancy location probability, 5-33 mi	$g(3)$.033
	Vacancy location probability, 34-66 mi	$g(2)$.173
	Vacancy location probability, 67-100 mi	$g(1)$.245

Recall that the commuting cost function is

$$T(\ell, \ell_F, \Omega) = \left(\tau + \kappa \left(\sum_{i \in cp(\ell, \ell_F)} c(i) \right) \right) d(\ell, \ell_F) b$$

³⁰As long as L is constant, a change in L would be equivalent to a rescaling of the parameter ω_L .

Table 6: Targets: Spatial Parameter Values

Moment	Data	Model
Moving probability (A)	.045	.041
Share of offers rejected for commute	.15	.16
Relative increase in commuting cost with congestion	.65	.65
Share of job-related moves	.129	.150
Avg rent/income	.365	.289
Elasticity of supply (Barker, 2003)	.3	.3
Relative wage, residence 5-33 mi	.82	.88
Relative wage, residence 33-66 mi	.79	.75
Relative wage, residence 66-100 mi	.70	.73
Jobs density, 5-33 mi from center	.83	.83
Jobs density, 33-66 mi from center	.80	.88
Jobs density, 66-100 mi from center	.78	.96

The parameter τ determines the marginal disutility from commuting in the absence of the externality (the “no traffic” cost) and κ is the congestion cost. Together, these two parameters determine the share of job offers rejected because of the commute and the average increase in commuting costs with congestion. The share of job offers rejected because of the commute is the share of offers with higher productivity that a worker rejects; in the data this corresponds to the question in the New York Federal Reserve’s Survey of Consumer Expectations regarding the main reason for rejecting a job offer. To pin down κ , I use the average commuting time with and without congestion from Google Maps shown in Figure 2. For all LADs considered, the average increase in time to commute to the City of London on a weekday morning is 65% higher than on a weekend. Assuming that commuting costs are proportional to time, this moment identifies the congestion cost, κ . The value of κ can be interpreted as follows: when 10% of workers in the economy congest a location, commuting costs increase by $\kappa b/10 = 0.06$ units of output, or roughly 4% of the average wage.³¹

4.2 Properties of the Calibrated Economy

In this section I evaluate the model’s performance against a set of untargeted moments in the data. Table 7 compares several untargeted moments in the model to the data. The share of wage cuts is equal to the proportion of job to job transitions resulting in a wage at least 5% lower than the worker’s previous wage. The model predicts this share to be far higher than in the data, because there are two mechanisms giving rise to wage cuts. First, workers are willing to take lower wages today when the continuation value of the match is much higher than their previous job, similarly

³¹The average wage in the calibrated model is 1.34.

to Cahuc et al. (2006). Second, workers face a trade-off between productivity and commuting, and will take wage cuts when job offers are located at a shorter commuting distance. In the model, the share of movers who remain in the same job is purely due to the moving shock φ . This moment is lower in the model than in the data, possibly because respondents to the survey mis-report the share of job-related moves. The next two lines show wage growth between and within jobs in the data and in the model. The model captures the magnitudes of within- and between-job wage growth well.

Table 7: Untargeted Moments

Moment	Data	Model
Share of wage cuts	.16	.30
Share of movers who stay in the same job	.018	.009
Average wage growth, J2J	.065	.082
Average wage growth, within job	.016	.019
Annual J2J transition rate, residence in center	.147	.074
Annual J2J transition rate, residence in periphery	.105	.139
Relative Moving Distance, J2J to All Movers	1.39	1.42

In the data, the share of workers residing in the periphery (locations more than 66 miles one-way from the City of London) making job-to-job transitions is less than for workers living in the center (within 10 miles from the City). In the model, job-to-job transitions in the center are lower than in the periphery because workers who live in the periphery receive relatively many job offers close to home where congestion is low, leading the to more frequently make transitions. The last line in Table 7 shows the moving distance for workers making job-to-job transitions relative to all movers in the model and data. Movers in the data are workers moving within the local labor market (those who appear in the sample the year prior to the move). Although the model predicts much larger distances due to the discrete number of locations, it reproduces the longer moving distance for job related reasons because workers will move for a job when the net gain in surplus is larger than the moving cost. Since this cost is fixed, workers will tend to move farther for job related reasons.

Figure 4: Commuting Distance by Place of Residence

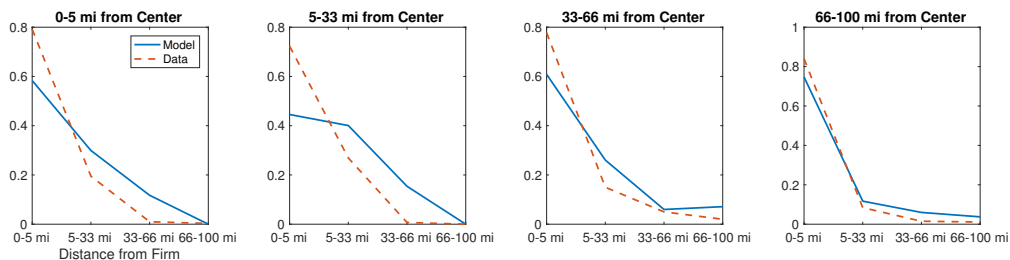
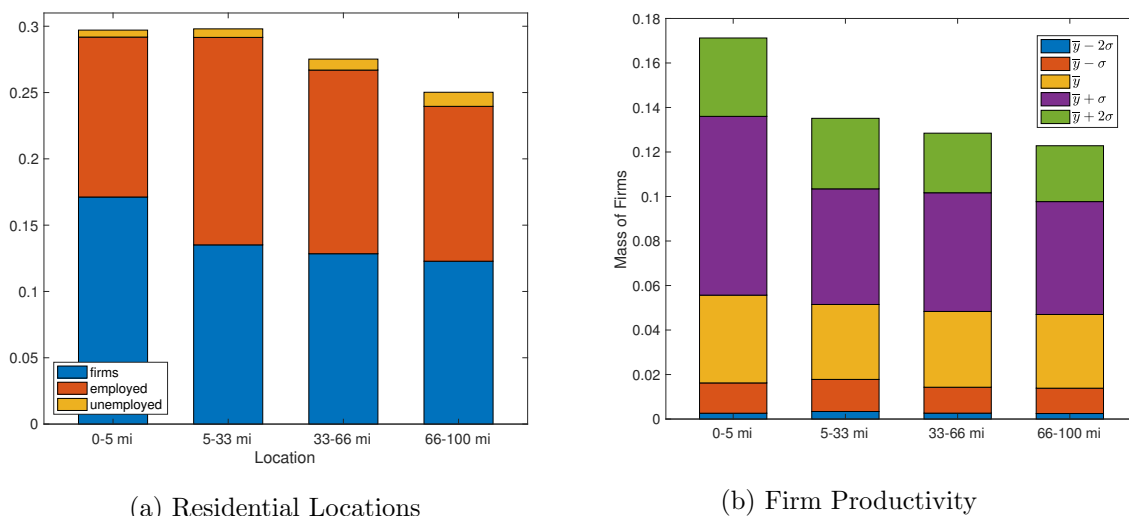


Figure 4 shows the commuting patterns by place of residence in the model and data. The

horizontal axis corresponds to the distance from the place of residence, and the vertical axis shows the share of commuters living in each location and commuting a given distance. In all four locations, the model matches the data well, both in terms of the share of workers living and working in the same location as well as the farther the commuting distance, the lower is the share of commuters.

Figure 5 shows the spatial distribution of workers and firms and of firm productivity. The model successfully captures the declining density of jobs in distance from the center, and the larger share of the highest productivity jobs in the center. The exogenous distribution of vacancies has just 10% of offers in the center; more filled jobs are located in the center because of the higher average output through the location-specific productivity distribution. The increase in productivity more than offsets the higher congestion that workers must face if they need to commute to these jobs. The rent price by location is shown in Figure 13 in Appendix F. In the calibration, I target the average rent to income, and the average wage by location, but these do not determine the slope of the rent price as a function of distance (the “rent gradient”). As seen in the figure, the model successfully captures the gradient.

Figure 5: Workers and Firms



4.3 Effect of Congestion

This section examines the effect of commuting and congestion on labor market outcomes. Figure 6 shows the possible outside offers for a worker living in a location 33 miles from the center working for a firm with average productivity in the center. The vertical axis shows the change in surplus from an offer in each location with low, medium, and high productivity. The worker accepts all offers above the horizontal line, which have a higher surplus than her current job. When productivity is the only match-specific factor driving job mobility, workers accept all offers with higher productivity. The figure shows the trade-off between the commute and productivity: when the firm location is closer

to her own, the worker accepts offers with productivity that is lower than that in her current match. Conversely, when the firm is sufficiently far away, offers with higher productivity give little gain in terms of surplus. The worker uses some offers that have a lower commuting cost to renegotiate her wage, shown by the shaded region in the figure. Moving decisions are shown for workers living in various locations in Appendix F.

Figure 6: On-the-Job Search Outcomes

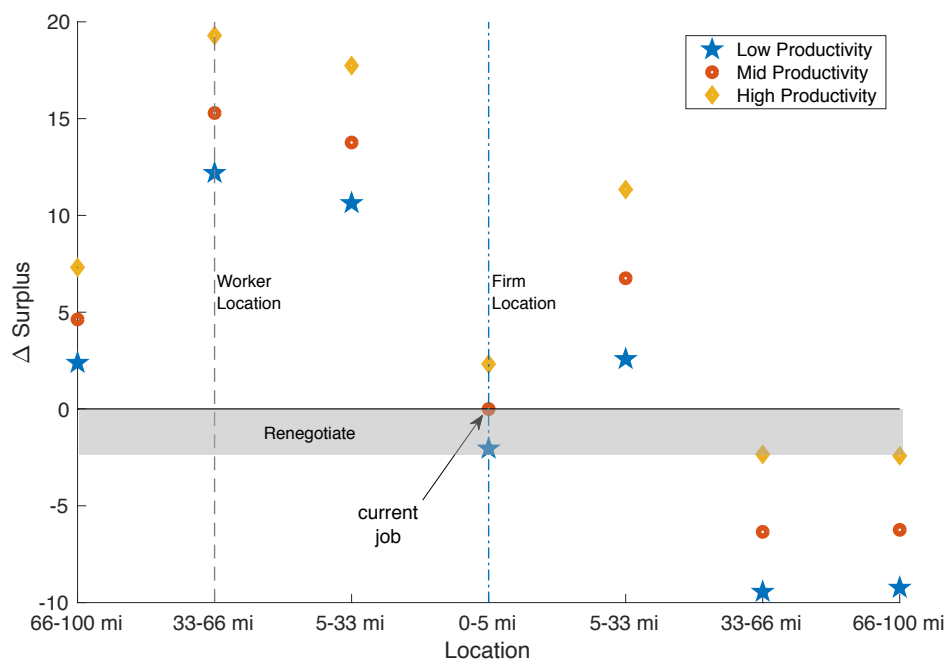
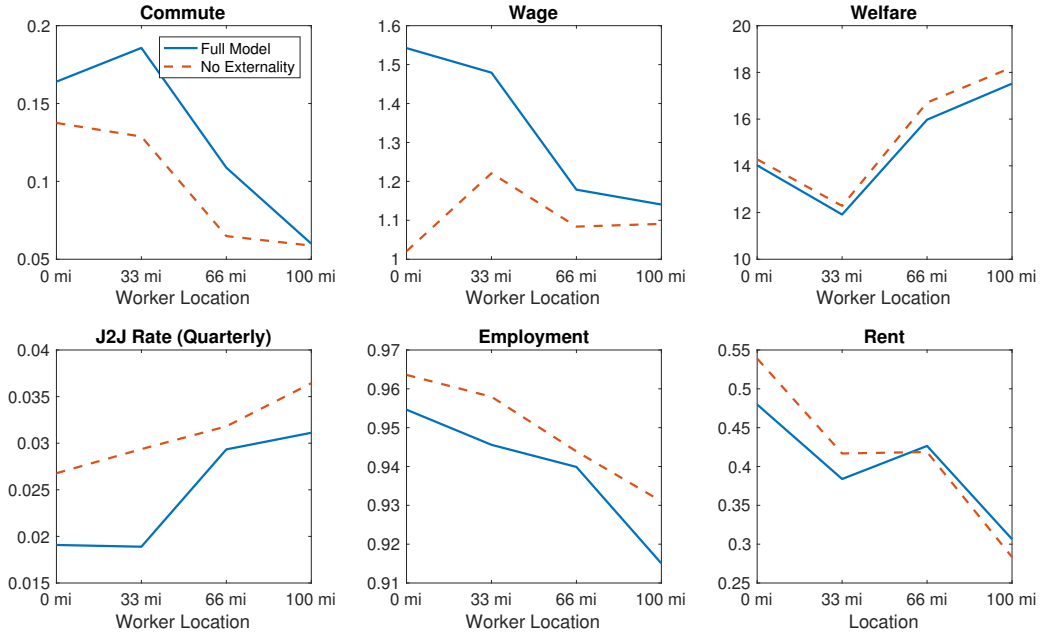


Figure 7 compares aggregate outcomes in the model with and without the externality, setting $\kappa = 0$. The top row of the figure shows the changes in average commuting costs, average wages, and welfare by worker location. The top left panel shows that commuting costs are lower without the externality. The difference between the two lines is the effect of congestion on commuting costs. Workers who travel through more than one location experience the sum of all congestion in the path between their residence and the location of their firm. On average, commuting costs are about 35% higher without congestion, but this varies widely depending on the worker's location. Because congestion is highest near the city center, wages significantly increase to compensate workers for their more costly commutes. Since congestion is negligible in the periphery, the difference in wages between the two models gets smaller with distance from the center. Across all locations, welfare measured as the expected value at entry into the labor market is 3.7% higher in the no externality model. Because rent is lower in the city center with congestion, discussed below, welfare for workers living in the center is slightly higher with congestion than without.

Figure 7: Aggregate Patterns Across Space

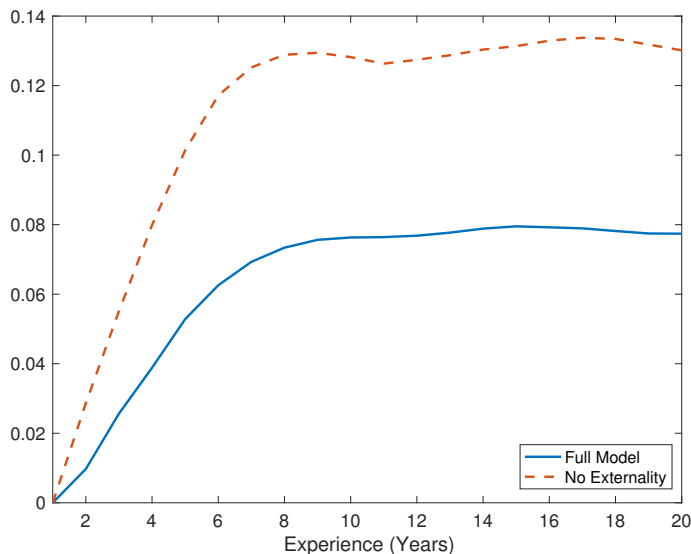


In the second row of Figure 7, I present the job-to-job transition rate, employment, and rent. The externality causes the job-to-job transition rate to decrease because workers are less likely to accept distant offers. Workers employed by firms located 33 miles from the center have the most experience, longest tenure, and shortest commutes in the model with no congestion: because these job offers are rare (just 6.6% of all vacancies), the rent is almost as low as more distant locations, but productivity is significantly higher. Thus, job-to-job transitions are low because there are few dominating job offers. With congestion, many workers are commuting through this location, decreasing its attractiveness relative to locations farther from the center. Employment increases in all locations in the absence of congestion, as the flow value of all matches increases relative to the value of unemployment. Finally, rent increases in locations within 33 miles of the center due to less congestion and more demand for land from both workers and firms. Indeed, in the full model congestion and rent both make the city center less attractive: without congestion, equilibrium rent would increase far more in the center in order to clear the land market. With congestion, the center is less attractive as a workplace from the perspective of commuting workers and thus fewer jobs are created in the center, decreasing firms' demand for land and therefore rent.

Figure 8 plots average wage growth with experience in the models with and without the externality. Without congestion, wage growth is twice as large as in the full model. By increasing the share of acceptable job offers, as shown in Figure 7, wage growth increases as workers make more job-to-job transitions for which they receive significant wage gains on average. In addition, the wage level falls significantly, especially for workers living in the city center, leading wage growth to be higher. After roughly 8 years of labor market experience, wages become flat in both models, as

the model has no skill accumulation or returns to experience and the job ladder has finitely many steps.

Figure 8: Wage Growth with Labor Market Experience



4.4 Wage and Utility Dispersion

As highlighted by [Hornstein et al. \(2011\)](#), there is a large amount of wage dispersion across otherwise identical workers in the data. My model highlights the role of commuting costs and congestion for job search, giving rise to a non-wage amenity that depends on a negative externality. This externality is largest in the most productive areas, potentially giving rise to large frictional wage dispersion.

I compute wage dispersion, defined as the standard deviation of the log of the monthly wage, and utility dispersion, defined as log wages net of commuting costs, or as log wages net of commuting and rent costs. [Table 8](#) contains the results, comparing the model with and without the externality and the model with zero commuting costs. As in the previous section, the model without the externality corresponds to setting $\kappa = 0$.

Comparing the first two rows, wage dispersion is 14% higher in the model with the externality. Wages reflect the level of congestion through two channels: first, workers who have long commutes have higher costs due to congestion and therefore have low flow utility today. This decreases the worker’s surplus as well as that for the match, but increases the worker’s wage because of the out-of-pocket cost she must pay to commute. Second, congestion affects workers’ future job outcomes through the set of offers they are willing to accept through on-the-job search.

Before taking into account differences in housing rent, utility dispersion is more than twice wage dispersion, and is higher in the no congestion model. The model fails to capture the positive

correlation between wages and commuting times.³² The reason for this is that the dynamic sorting from the job ladder is strong enough to reverse the static trade-off between wages and commutes: for newly hired workers out of unemployment, the correlation between wages and commutes is positive, but as workers climb the job ladder, they move toward jobs with short commutes and high productivity, causing the cross-sectional correlation to turn negative.

Without the externality, the correlation between wages and commuting times becomes more negative, leading to a larger dispersion in wages net of commuting costs relative to the full model. After taking rent into account utility dispersion is 5% higher in the full model relative to the no congestion model. It is important to take into account differences in rent for workers' utility. A standard prediction of models in urban economics is that workers will trade-off rent and commuting costs and therefore will be indifferent across locations in the absence of frictions (e.g. Fujita 1989), I therefore focus on the results in the last column. Because workers with lower rent live in the periphery and tend to commute farther, rent and commuting costs have offsetting effects. With the congestion externality, the strength of this relationship differs depending on the worker's location: workers in the center have high rents, but face more congestion to commute a short distance, raising their marginal cost of commuting. Since dispersion in both wages and commuting costs is higher because of heterogeneity in the commuting cost per mile, utility dispersion may be larger in the presence of congestion. However, the model predicts that the increase in dispersion as measured by utility relative to wages is lower in the full model (20%) than in the model without congestion (30%), since congestion discourages workers from taking the longest commutes, compressing differences in utility.

Table 8: Standard Deviation: Wage and Utility

Model	$\ln w$	$\ln w - \ln T(\ell, \ell_F)$	$\ln w - \ln(T(\ell, \ell_F) + r(\ell))$
Full	.434	.891	.520
No Congestion	.381	1.09	.495
No Commuting Cost	.081	-	.171

5 Counterfactual Exercise: Congestion Taxes

This section examines the effects of a linear congestion tax on welfare. This model could be used for many policy experiments, for instance infrastructure investment, remote working arrangements, or flexible working time.³³ I consider a congestion tax to understand the labor market implications of the simplest policy directly targeting the externality, as well as to follow the intuition of the

³²This correlation is .14 in the data, and -.17 in the calibrated model

³³Regarding infrastructure, Duranton and Turner (2011) show that improvements in roads have little effect on congestion, because better infrastructure makes it easier to commute, causing an increase in commuting distance and in congestion. Bloom et al. (2014) empirically evaluate the benefits of remote working for call center employees. Arnott et al. (1993) consider workers' choice of the time of departure to avoid peak-period congestion.

simple planner’s problem of Section 3.6. The welfare measure corresponds to the expected value of unemployment at entry, defined as the weighted average of the value of unemployment, with weights corresponding to the location distribution for newborn workers. I document the results for the cases when rent is fixed to its level in the baseline economy and when rent endogenously adjusts to the policy. The congestion tax, t increases commuting costs through congestion:

$$T(\ell, \ell_F, \Omega) = \left(\tau d(\ell, \ell_F) + (1 + t)\kappa \sum_{i \in cp(\ell, \ell_F)} c(i) \right) b$$

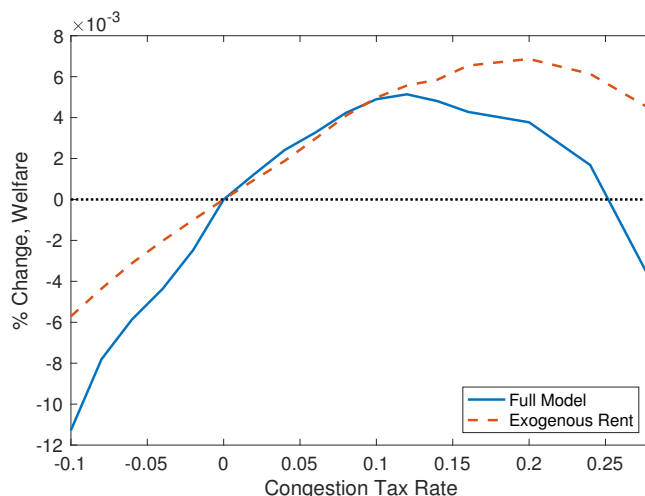
Revenues from the tax are rebated lump sum to workers, and are computed as a fixed point consistent with the distributions of workers over commuting costs in response to the tax.

The introduction of a tax on congestion and lump sum transfer redistributes resources from workers in matches with more congested commutes to unemployed workers and those with less congested commutes. The tax leads workers to accept less productive jobs with shorter commutes on average, since productivity is highest in the most congested location, the city center. Because moving is costly, most workers find jobs closer to home rather than moving closer to their workplace, resulting in the steady state distribution of firms becoming flatter as the tax increases. Fewer workers are employed by the most productive jobs in the center, but those who accept these jobs are more likely to move to minimize their commute, increasing their utility. By decreasing the probability that a worker accepts a job that requires a commute, the congestion tax changes the shape of the job ladder: in the limit, workers accept only jobs in their own location and evaluate offers based only on their productivity, decreasing the job-to-job transition rate. The effect of the congestion tax on unemployment is more subtle: on the one hand, by making the most productive offers less attractive, an increase in commuting costs decreases the option value of waiting for such offers while unemployed. On the other, jobs closer to home become relatively more attractive, increasing the option value of waiting for a nearby job. Because there are more workers and vacancies in the periphery, the latter effect dominates, thus, the the unemployment rate is increasing in the tax.

Although solving a dynamic planner’s problem is beyond the scope of this paper, I determine the optimal tax by varying the tax rate and computing welfare. Figure 9 shows that the welfare-maximizing tax rate on congestion is $t = 12\%$, leading to welfare gains of 0.51%. Without endogenous rent, the welfare-maximizing tax is 20%, with welfare gains of .69%. To understand these welfare effects, I begin by discussing the case when rent is exogenous, and then move on to the case with endogenous rent. As discussed above, the congestion tax flattens the firm distribution across space. When rent is exogenous, the periphery is more attractive because rent is lower, and many jobs will be created far from the center, significantly reducing congestion. The trade-off that workers face is between lower rent and lower productivity of jobs that are far from the center. The steady state effect is for workers and firms to locate in intermediate locations, between 5 and 66 miles from the city center, where this trade-off is maximized. By creating more matches farther from the city center, jobs are less productive, decreasing the average match surplus. However, the

productivity loss is dominated by two effects that increase match surplus: average commuting costs endogenously fall in response to the tax, and jobs are created in locations with lower rent.

Figure 9: Change in Welfare, Congestion Tax



When rent can adjust, fewer workers and firms will locate far from the center since rent increases with the demand for land. The adjustment of rent offsets the higher cost of congestion, resulting in a larger share of filled jobs in the city center relative to the case when rent is fixed, and a negligible decline in average match productivity. Figure 9 suggests that the higher average productivity of jobs increases welfare by less than the effect of higher rent in the periphery. As the tax rate increases, the loss in output from commuting costs and the productivity loss from jobs locating far from the center increase, leading to welfare losses for large tax rates. Welfare is less sensitive to the tax rate in the model with exogenous rent because the higher is the tax, the more workers benefit from living in areas with lower rent. With endogenous rent, when the tax rate increases, rent increases in the intermediate locations faster than congestion falls, causing a steeper decline in welfare.

Figure 10 shows the responses of congestion and rent when the congestion tax is equal to its welfare-maximizing rate in the full model, 0.12. The tax has the direct effect of decreasing congestion, shown in the right panel, for all locations except the periphery. Relative to workers, more firms locate in the periphery in response to the tax, leading to a small increase in congestion. In all other locations, workers and firms are less likely to locate because of higher commuting costs. When rent is fixed, the decline in congestion is largest in the center as workers move to less expensive locations. As discussed above, the trade-off between location-specific productivity and rent leads workers to locate more in intermediate locations. When rent is endogenous, these are the locations for which rent increases the most, shown in the left panel of the figure. For this reason, congestion falls by more in the full model as fewer workers choose to live in these locations due to higher rent.

Table 9 shows the effects of the congestion tax on steady state labor market outcomes, for the

Figure 10: Effect on Congestion and Rent, Optimal Congestion Tax

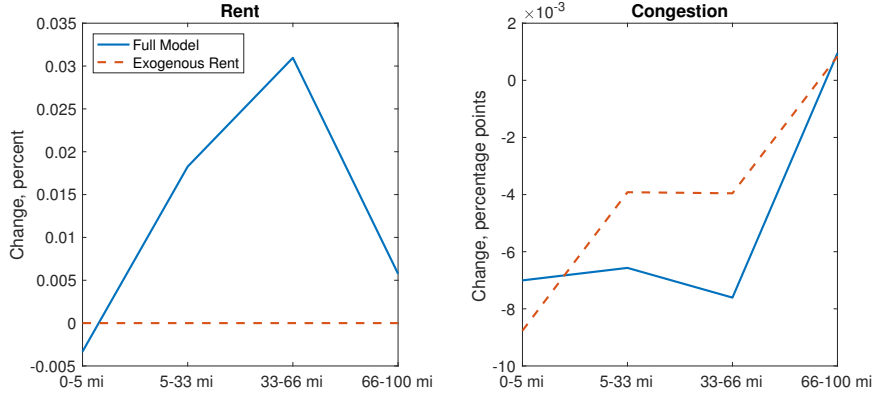


Table 9: Steady State Effects of the Congestion Tax

	Baseline	12% Congestion Tax	12% Congestion Tax (Exog. Rent)
Average Congestion	.080	.076	.075
Average y	1.75	1.74	1.75
Share of Jobs, Center	.181	.169	.180
Share of job-related moves	.14	.14	.14
EE Rate	.029	.029	.029
UE Rate	.256	.257	.258
EU Rate	.0125	.0128	.0129
Unemployment Rate	.056	.058	.059
Average Wage	1.37	1.37	1.34
Wage Growth, J2J	.082	.076	.063
$\sigma \ln w$.432	.436	.425
$\sigma \ln w - \ln(T(\ell, \ell_F) + r(\ell))$.520	.519	.511
% Change Welfare	0	0.52%	0.51%
Tax Revenues/Total Output	0	0.48%	0.47%
Average Tax/Wage	0	0.62%	0.62%

Welfare is measured as the expected value of unemployment at entry. Columns correspond to the model calibrated in Section 4.1, the model with rent fixed at the equilibrium rent in the baseline model with a congestion tax, and the model with exogenous rent with a congestion tax. The tax is equal to the welfare-maximizing tax rate in the model with endogenous rent, shown in Figure 9.

models with exogenous and endogenous rent. The first row of the table shows the direct effect of the tax: congestion falls by 5% and 6.25% in the models with exogenous and endogenous rent, respectively. This results from lower congestion in the intermediate locations in the endogenous rent model, shown in Figure 10. Average output is not significantly affected, which is driven by changes in the composition of firms: when the tax is introduced, workers prefer to work in a location close to

home, and therefore more jobs with the highest location-specific productivity are created, causing output to increase even if the share of jobs in the center slightly falls. Although the tax has the effect of decreasing match surplus for jobs that would require a commute, in the baseline model, workers always move to the farthest job offers rather than commute, thus, job-to-job transition rates and unemployment to employment transition rates are not much affected by the tax since workers have a way to decrease their commutes when accepting a distant offer. Differently, the employment to unemployment rate increases, since when workers receive moving shocks, they are more likely to separate rather than pay the tax when commuting, increasing the unemployment rate.

The effect of the tax is to make the distribution of commuting costs more compressed, and decrease average commuting costs through the endogenous response of workers' job search to the tax. Lower average commutes cause wages to fall, as workers' out of pocket costs decrease. Wage growth following job-to-job transitions also falls sharply due to lower average productivity gains when changing jobs: because workers are more likely to live and work in the same location, the gain that they get in match surplus when switching jobs is small because of the small variance of the productivity distribution. Finally, dispersion in wages and utility also fall. It is straightforward that compression in the distribution of commuting costs implies compression in wages, but the intuition for dispersion of utility is more subtle. The standard deviation of wages less spatial costs depends on the correlation between the two. An increase in the tax increases this correlation, so there is an offsetting effect between both the dispersion in wages and commuting costs falling, and an increase in their variance. Because the change in covariance is small, dispersion in utility also falls because dispersion in both commuting costs and wages fall.

By using a frictional model of the labor market, the model is able to quantify the monetary gains from commuting without imposing that the value of time is equal to the wage at the margin. Instead, workers who commute to full-time jobs without flexible working hours must commute during the time they would otherwise be enjoying leisure, valued at the flow value of home production, b . Because the value of time is less than the average wage, commuting costs are smaller than in a model without labor market frictions, and therefore so are the gains from decreasing congestion. In the model with endogenous rent, the tax bill is almost 0.5% of total output, and the average tax paid by workers is 0.6% of wages.

Comparing this result to the literature, [Brinkman \(2016\)](#) estimates that with exogenous, location-specific productivity, welfare are in the order of 5% with the optimal congestion tax, but can turn negative if agglomeration externalities are strong enough.³⁴ The estimated gains here are about one order of magnitude lower, because this model has two additional sources of frictions that prevent larger welfare gains: moving costs and labor market frictions. Both of these decrease the welfare gains because many workers still find it optimal to commute and not to change their residence even after the tax is implemented. Importantly, with a frictionless labor market, employment increases in response to the tax for nearly all of his specifications. Here employment falls slightly due to the

³⁴Welfare gains correspond to changes in aggregate production reported in Table 4 of [Brinkman \(2016\)](#).

increased separations. Workers also do not move house much in response to the tax due to the moving cost, resulting in changes in congestion about 20% of those in the previous literature. The novel channel in this model through which labor market frictions contribute to congestion has the largest effect on wage growth and inequality, both of which would be absent without the frictions introduced here.

6 Conclusion

In this paper I argue that commuting congestion and labor market outcomes are inherently linked in urban areas. I develop a model that can address this link and that allows for endogenous wages and housing prices, both of which are key in the determination of the spatial configuration of workers and firms. Workers' commuting paths across space contribute to congestion, which has important effects on individual workers' search strategies, and on the dispersion in wages and utility across workers. Adopting a frequently used bargaining protocol, the model remains tractable but rich in its ability to replicate features of urban labor markets. I show several empirical patterns linking the commute to current and future labor market outcomes for individuals. Without congestion, welfare in a model with the same average commuting costs is almost 4% higher, due to the lost output due to the costs of congestion. The model can directly speak to crucial questions faced by policymakers and urban planners, and introduces important frictions necessary to properly price the value of time and therefore of congestion taxes. I find that the optimal congestion tax increases welfare by 0.5%, increasing the cost of commuting through congested areas by 12% at a cost to workers 0.6% of average wages. More interestingly, congestion taxes raise the unemployment rate due to more workers separating from their jobs when forced to move for reasons outside of the model. In addition, they have significant effects on wages: congestion taxes cause average wages and wage growth following job-to-job transitions to fall. Regarding inequality, the model predicts that the welfare-maximizing tax on congestion leads to a 1.7% decline in wage dispersion and a 1.8% decline in utility dispersion.

An important feature absent from this model is the labor-demand response to spatial frictions, which I rule out by assuming an exogenous location-productivity distribution for vacancies. Allowing firms to choose their locations is an important avenue for future research. Relatedly, I do not explore how entry is affected by the presence of the amenity or the externality associated with it. Another important topic that I leave to future work is to understand how the conclusions of this model are affected by alternative mechanisms for job search and bargaining. Spatially-directed job search has been explored for the unemployed by [Marinescu and Rathelot \(2018\)](#) and [Manning and Petrongolo \(2017\)](#) among others. It is important to understand how spatial mismatch affects workers' progress up the job ladder when search is directed or when wages are posted rather than the result of bargaining. Relatedly, incorporating search effort (e.g. [Bagger and Lentz](#)) into the model would allow for workers to respond to congestion taxes in between job offers, with potentially ambiguous effects on the efficacy of the policy. Regarding policy, in current work in progress

I am using the framework developed here consider the welfare benefits of remote working arrangements. The model could also be used to study alternative urban policies such as infrastructure investment or spatially-targeted employment subsidies. Finally, I do not consider rationing of land; an interesting exercise would be to examine the effects of policies such as rent control in the present model.

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A Data Description and Micro-Level Regressions

In this section I first describe the data and main variables used in the quantitative analysis. I then document the robustness of the results in Section 2, and then run a series of regressions to show the importance of commuting for job-to-job transitions.

A.1 Data

The data used in Section 2 and the remainder of this section come from three sources (1) the British Household Panel Survey (BHPS), (2) the Census flow data, and (3) Google Maps. This section discusses details and use of each source.

A.1.1 BHPS

For each wave of the survey, I merge data from the household questionnaire (*hhresp*), the full and proxy questionnaires (*indresp*), employment history (*jobhist*), relationship between household members (*egoalt*), residential locations at the local authority district level (*oslaua_protect*), and House price statistics for small areas in England (HPSSA) from the ONS. The records are linked using the household and person ID (*hid* and *pid*), and then years are linked using the person ID, keeping individuals appearing in at least 2 years of the survey. All nominal variables are deflated using annual CPI in the UK from the ONS.

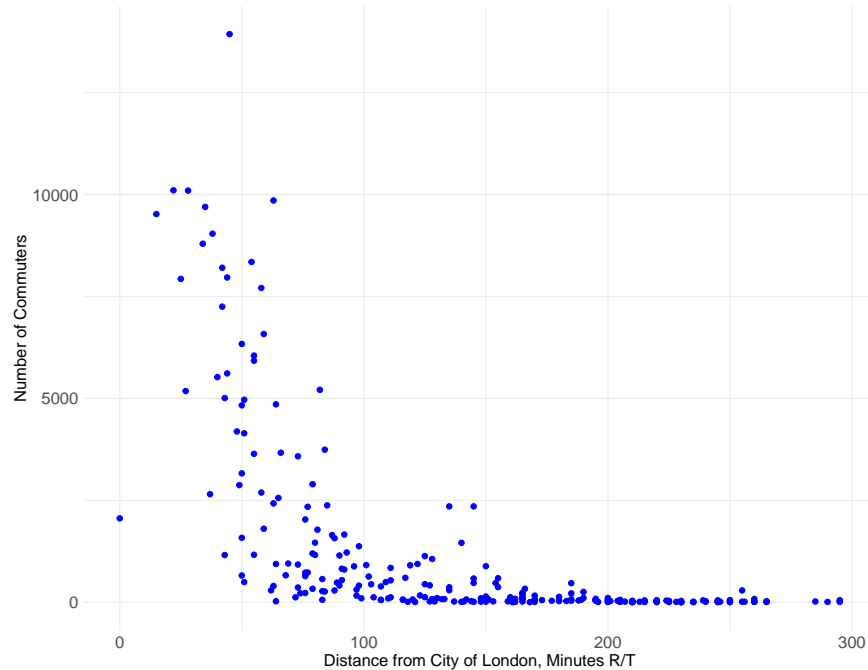
Transitions across labor market states are identified from the employment history. The employment history contains information from September 1 of the previous year through the date of the interview. A job-to-job transition in year t is defined as a worker who was employed at the date of the interviews in year t and $t - 1$, who reports a different job in the job history between the two interviews with no more than 30 days of nonemployment between the previous and current job. Unemployment-to-employment transitions are identified by workers who are employed in year t in the first job following an unemployment spell reported at the date of the interview in $t - 1$.

Wages are given by the CPI-deflated usual net pay per month (*payn*). Commuting time (*jbttwt*) is defined as the answer to “About how much time does it usually take for you to get to work each day, door to door (in minutes)?” Commuting method is the answer to “And what usually is your main means of travel to work?”, with possible responses: British rail, train ; Underground, tube, metro; Bus, minibus or coach (public or private); Motor cycle, scooter, moped; Driving a car or van; Passenger in car or van; Pedal cycle; On foot (walks all the way); Other.

A.1.2 Census Flow Data

Responses from the decennial Census on usual place of residence and usual place of work are aggregated to compute the flow tables. For each pair of locations (A,B), the Flow tables contain the number of individuals originating in A and finishing in B, either for residential moves or daily commutes. The data used are the Special Workplace Statistics (Level 1), which contain commuting flows for each LAD. For consistency with the time span of the BHPS sample, the 2001 Census is

Figure 11: Number of Commuters to City of London by Time



Data: UK Census Flow Data 2001, Special Workplace Statistics (Level 1). Number of workers commuting to the City of London as a function of commuting time in minutes, round trip, computed by Google Maps.

used to construct Figure 1. I consider all LADs of residence for which a positive number of workers commute to the City of London LAD (“the City”), plotted on the vertical axis.

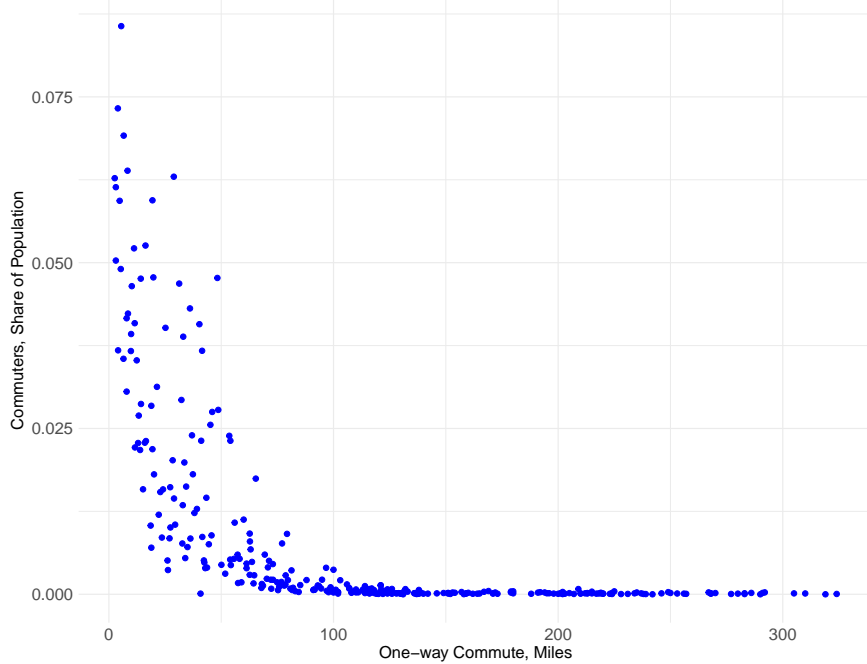
A.1.3 Google Maps

Using Google Maps, I collect data on the shortest driving distance from each LAD to the City, as well as the recommended travel mode to arrive at the destination by 9am on an arbitrary weekday (July 19, 2018).³⁵ I select those LADs for which the Census Flow Data reports a positive number of individuals whose usual place of work is the City (see above). The recommended travel mode is the fastest way to get from the origin to destination according to Google’s algorithm, taking into account traffic and other delays. The location of the LAD corresponds to the latitude and longitude automatically selected by Google for each district.³⁶ Figures 11 and 12 show plots identical to Figure 1 using distance as the fastest commuting time rather than shortest driving distance and commuters as a share of the LAD population going to the City, respectively.

³⁵To ensure to be firmly within Google’s terms of service, I hand-collected the data by searching for each LAD.

³⁶For instance, a Google Maps search for directions from Kensington to the City of London returns directions leaving from 112 Kensington High St, Kensington, London and arriving at 21 Bloomberg Arcade, London.

Figure 12: Share of Commuters to City of London by Distance



Data: UK Census Flow Data 2001, Special Workplace Statistics (Level 1). Share of workers commuting to the City of London relative to population of LAD of residence, as a function of commuting distance in miles computed by Google Maps. Map data: Google, DigitalGlobe.

A.2 EE and UE Transitions: Robustness

Table 10 contains estimates from a linear probability model similar to the marginal effects in the probit regression of Table 1. To test whether unobservable worker fixed effects are driving the results, I include individual fixed effects in both columns of the table. The regressions therefore rely on individuals that I observe employed for at least 3 years of the sample.

Tables 11 to 20 show the wage cut tables similar to Table 2 for the subsamples of men, women, occupation switchers and stayers, residential movers and stayers, married and single, and with and without children. Tables 21 and 22 respectively define commuting increases and decreases as $+/-$ 5 or 10 minutes of commuting time, rather than by percent changes in the commute. Table 23 shows the table after allowing for job-to-job transitions with zero days of nonemployment between the two employment spells.

Reservation Wages

Following the arguments of Hall and Mueller (2018), I consider workers who made an UE transition between years $t - 1$ and t , for whom both the wage and commute in year t are available and who reported their reservation wage in year $t - 1$. I compute the log difference between the realized wage and reservation wage, and subtract the average realized to reservation wage for all workers making

Table 10: Effect of Lagged Commute and Wage on Job-to-Job Transition Probability, Linear Probability Model

	J2J _t	J2J _t
Commute _{t-1} × 30	0.018*** (0.005)	0.022*** (0.005)
Real log Wage _{t-1}	-0.071*** (0.013)	-0.069*** (0.014)
Individual Characteristics		✓
Individual FE	✓	✓
Region, Time, Commute Method Industry & Occ FE	✓	✓
R ²	.051	.059
N ind	1,259	1,122
N obs	7,023	6,338

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time in year t . Estimated coefficients from a linear probability model of J2J_t, which is a dummy equal to one if a worker made a job-to-job transition in the past year and 0 if she remained in the same job, on commute time and wages in the previous year. Individual characteristics include the annual regional house price index, a quadratic term in labor market experience, age, education, marital status, and number of children, 1-year lagged tenure, 1-year lagged dummies for outright homeownership, mortgage holding, whether the individual moved in the past year, real housing expenditures, whether the worker was unemployed in the past year, the number of employment spells, whether the spouse or partner was employed last year, a government job dummy, and union status. All regressions include individual fixed effects, and region, month, year, 1-digit industry and occupation fixed effects. Robust standard errors are reported in parentheses. * denotes $p < .1$, ** $p < .05$, and *** $p < .01$.

Table 11: After Job-to-Job Transition, Men

		Wage		
		Down	Same	Up
Commute	Down	0.43	0.50	0.36
	Same	0.24	0.17	0.26
	Up	0.32	0.33	0.38
	N	78	54	234

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

UE transitions. Table 24 shows this difference for workers who accepted jobs with commutes below (center column) and above (right column) the mean commute of 53 minutes round trip. The first row of the table can be interpreted in the following way: for workers commuting less than average,

Table 12: After Job-to-Job Transition, Women

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.56	0.37	0.31
	Same	0.14	0.20	0.25
	Up	0.30	0.43	0.44
	N	79	49	203

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 13: After Job-to-Job Transition, Occupation Switchers

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.53	0.48	0.29
	Same	0.17	0.14	0.24
	Up	0.30	0.38	0.46
	N	96	56	234

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs and 2-digit occupation since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 14: After Job-to-Job Transition, Occupation Stayers

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.44	0.38	0.39
	Same	0.23	0.23	0.27
	Up	0.33	0.38	0.34
	N	61	47	203

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs but not 2-digit occupation since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

their realized to reservation wage is 10% below average, while the realized to reservation wage ratio for workers commuting more than average is 14% above average. Further splitting the sample shows that this difference in means, though not statistically significant, is qualitatively robust across

Table 15: After Job-to-Job Transition, Residential Movers

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.33	0.42	0.35
	Same	0.19	.05	0.19
	Up	0.48	0.53	0.46
	N	21	19	74

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs and residence since year $t - 1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 16: After Job-to-Job Transition, Residential Stayers

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.52	0.44	0.34
	Same	0.19	0.21	0.27
	Up	0.29	0.35	0.40
	N	136	84	363

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs but not residence since year $t - 1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 17: After Job-to-Job Transition, Married

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.48	0.44	0.31
	Same	0.17	0.22	0.28
	Up	0.35	0.34	0.41
	N	75	50	209

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t - 1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 18: After Job-to-Job Transition, Single

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.51	0.43	0.37
	Same	0.20	0.15	0.23
	Up	0.28	0.42	0.40
	N	82	53	228

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 19: After Job-to-Job Transition, Children

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.46	0.38	0.24
	Same	0.17	0.24	0.28
	Up	0.37	0.38	0.48
	N	59	21	138

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 20: After Job-to-Job Transition, No Children

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.52	0.45	0.38
	Same	0.20	0.17	0.24
	Up	0.28	0.38	0.37
	N	98	82	299

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t-1$. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 21: After Job-to-Job Transition, Commute \pm 5 min

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.50	0.44	0.33
	Same	0.20	0.21	0.28
	Up	0.30	0.35	0.39
N		157	103	437

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t - 1$. Wage "Up" and "Down" indicate differences from the last reported wage of more than 5%, and "Same" indicates differences less than 5%. Commute "Up" and "Down" indicate differences from the last reported commute of more than 5 minutes.

Table 22: After Job-to-Job Transition, Wage \pm 10 min

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.44	0.31	0.25
	Same	0.35	0.42	0.46
	Up	0.21	0.27	0.29
N		157	103	437

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t - 1$. Wage "Up" and "Down" indicate differences from the last reported wage of more than 5%, and "Same" indicates differences less than 5%. Commute "Up" and "Down" indicate differences from the last reported commute of more than 10 minutes.

Table 23: After Job-to-Job Transition, 0 Days Nonemployment

		<u>Wage</u>		
		Down	Same	Up
<u>Commute</u>	Down	0.50	0.42	0.34
	Same	0.19	0.20	0.25
	Up	0.30	0.38	0.41
N		149	97	417

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t - 1$ with 0 days nonemployment between employment spells. "Up" and "Down" indicate differences from the last reported wage or commute of more than 5%, and "Same" indicates differences less than 5%.

Table 24: Log Realized to Reservation Wage Relative to Average

Group	Commute Below Median	Commute Above Median
All	-0.10	0.15
Some College or Less	-0.02	0.03
College Graduates	-0.21	0.23
Men	-0.20	0.25
Women	-0.01	0.01

Notes: BHPS Sample 1993-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 employed in year t and reporting a minimum weekly wage (“Reservation wage”) while unemployed in year $t - 1$. Columns report the log difference between the realized and reservation wage relative to the average across all commutes, conditional on the new job requiring an above or below-mean commuting time. In the sample, the mean round trip commute is 53 minutes. All: N=103, Men: N=57, Women: N=46, College Graduates: N=47, Some College or Less: N=56.

Table 25: After Job-to-Job Transition, Weighted Sample

		Wage		
		Down	Same	Up
<u>Commute</u>	Down	0.51	0.45	0.31
	Same	0.19	0.17	0.26
	Up	0.20	0.38	0.43
N		101.44	61.50	277.1

Notes: BHPS Sample 1992-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 working full-time, who changed jobs since year $t - 1$. “Up” and “Down” indicate differences from the last reported wage or commute of more than 5%, and “Same” indicates differences less than 5%. Observations are weighted by the Longitudinal individual respondent weights.

almost all groups.

Results Using Longitudinal Weights

In this section I weight the observations by their longitudinal sample weights ($lrught$) and reproduce the empirical analysis above. Longitudinal weights are nonzero only for individuals in year t who gave full interview starting with the first wave up to and including year t (or children who were under 16 in families present in the first wave, who at the age of 16 are allocated the minimum of the longitudinal weights of their parents). Because using these weights further reduces the already small sample size for workers making UE transitions, I do not report results for the subsamples by education or gender.

Table 26: Log Realized to Reservation Wage Relative to Average, Weighted Sample

Group	Commute Below Median	Commute Above Median
All	-0.07	0.13

Notes: BHPS Sample 1993-2008, annual. Universe: respondents living in LADs within 100 miles of the City of London aged 24-55 employed in year t and reporting a minimum weekly wage (“Reservation wage”) while unemployed in year $t - 1$. Columns report the log difference between the realized and reservation wage relative to the average across all commutes, conditional on the new job requiring an above or below-median commuting time. In the sample, the median round trip commute is 40 minutes (standard deviation = 36.7 minutes). Observations are weighted by the Longitudinal individual respondent weights. All: N=73.

B Proof of Proposition 1

For the purposes of the proof, I define value functions, policy functions, and distributions as functions of the price vector r , e.g. $U(\ell; r)$, omitting the distributional dependence on Ω . I assume that the distributions contained in Ω , $u(\ell; r)$ and $e(\ell_F, y, \ell; r)$ are continuous in r .

Part 1a - Demand Correspondence

Define the demand correspondence for newly matched vacancies for each $\ell \in \mathcal{L}$ and $y \in Y$ as

$$\begin{aligned} D_V(\ell, y; r) &= e^{\ell+1} \sum_{\tilde{\ell}} [\lambda_0 u(\tilde{\ell}; r) \mathbb{1}\{S(\ell, y, \tilde{\ell}; r) > 0\} \\ &+ \lambda_1 \sum_{\hat{\ell}} \sum_{\hat{y}} \mathbb{1}\{S(\ell, y, \tilde{\ell}; r) > S(\hat{\ell}, \hat{y}, \tilde{\ell}; r)\} e(\hat{\ell}, \hat{y}, \tilde{\ell}; r)] \end{aligned}$$

where e^ℓ is the ℓ -th unit vector of dimension $2N + 2$, and the second term is the probability a meeting occurs and the match is accepted. The unit vector's dimension is the sum of the outside option of leaving the city and the number of locations $2N + 1$, where e^1 is the demand for leaving the city, and $e^{\ell+1}$ is the demand for land in location $\ell = 1, \dots, 2N + 1$.

Similarly, define the demand correspondence for the employed and unemployed, respectively, as

$$\begin{aligned} D_E(\ell_F, y, \hat{\ell}; r) &= \{x \in \{e^1, e^2, \dots, e^{2N+2}\} : \beta S(\ell_F, y, \hat{\ell}; r) > \bar{u} \text{ and} \\ &x(\ell) \in \arg \max M(\ell_F, y, \hat{\ell}; r)\} \end{aligned}$$

for each $(\ell_F, y) \in \mathcal{L} \times Y$ and $\hat{\ell} \in \mathcal{L}$ and

$$D_U(\hat{\ell}; r) = \{x \in \{e^1, e^2, \dots, e^{2N+2}\} : U(\hat{\ell}; r) \geq \bar{u} \text{ and } x(\ell) \in \arg \max U(\hat{\ell}; r)\}$$

for each $\hat{\ell} \in \mathcal{L}$. I denote the location choice implied by x as $x(\ell) \in 0 \cup \mathcal{L}$. Clearly, since all of the sets include 0, all three sets are nonempty. Define the aggregate demand correspondence $D(r)$ as

$$D(r) = \sum_{\hat{\ell}} \sum_{\hat{y}} D_V(\hat{\ell}, \hat{y}; r) g(\hat{\ell}, \hat{y}) + D_U(\hat{\ell}; r) u(\hat{\ell}; r) + \sum_{\ell_F} \sum_y D_E(\ell_F, y, \hat{\ell}; r) e(\ell_F, y, \hat{\ell}; r)$$

The first term is the demand correspondence for land for each vacancy which is created, multiplied by the mass of vacancies of each type $(\hat{\ell}, \hat{y})$. The second and third terms are the demand correspondences, respectively, of the unemployed and employed workers living in $\hat{\ell}$ times their mass. Importantly, the mass of workers and firms in each location and of workers in each employment state depends on the price vector r .

It is clear that $M(\ell_F, y, \hat{\ell}; r)$ and $U(\hat{\ell}; r)$ are continuous functions of r . By assumption, $u(\hat{\ell}; r)$ and $e(\ell_F, y, \hat{\ell}; r)$ are continuous in r . Thus, U , W , and J are all continuous in r . Given these results, I now prove each element of $D(r)$ is upper hemicontinuous (UHC). Below I assume that the unemployed can move at fixed cost k_M . The case in which the unemployed cannot move, assumed

in the model, is a special case.

(i) Unemployed $D_U(\hat{\ell}; r)u(\hat{\ell}; r)$

Take an arbitrary $\hat{\ell} \in \mathcal{L}$. Take a sequence $r^n \rightarrow r^0$, $x^n \rightarrow x^0$ with $x^n \in D_U(\hat{\ell}; r^n)$ for all n .

Since S is continuous and $x^n \in \arg \max U(\hat{\ell}; r^n) \forall n$, it follows that x^0 must be feasible. Suppose $x^0 \notin \arg \max U(\hat{\ell}; r^0)$. Then since $D_U(\hat{\ell}; r^0)$ is nonempty, there exists $x' \in \{e^1, e^2, \dots, e^{2N+2}\}$ with $x' \in \arg \max U(\hat{\ell}; r^0)$. Thus,

$$\tilde{U}(x'(\ell); r^0) - k_M \mathbb{1}\{x'(\ell) \neq \hat{\ell}\} > \tilde{U}(x^0(\ell); r^0) - k_M \mathbb{1}\{x^0(\ell) \neq \hat{\ell}\}$$

Since $x' \neq x^0$, it must be the case that $x'(\ell) \neq \hat{\ell}$ or $x^0(\ell) \neq \hat{\ell}$ or both. Then

$$\begin{aligned} & \tilde{U}(x'(\ell); r^0) - k_M \mathbb{1}\{x'(\ell) \neq \hat{\ell}\} - \tilde{U}(x^n(\ell); r^n) + k_M \mathbb{1}\{x^n(\ell) \neq \hat{\ell}\} \\ & > \tilde{U}(x^0(\ell); r^0) - k_M \mathbb{1}\{x^0(\ell) \neq \hat{\ell}\} - \tilde{U}(x^n(\ell); r^n) + k_M \mathbb{1}\{x^n(\ell) \neq \hat{\ell}\} \end{aligned}$$

For n large enough, the right hand side can be made arbitrarily close to zero, thus

$$\tilde{U}(x'(\ell); r^0) - k_M \mathbb{1}\{x'(\ell) \neq \hat{\ell}\} > \tilde{U}(x^n(\ell); r^n) - k_M \mathbb{1}\{x^n(\ell) \neq \hat{\ell}\}$$

But U is continuous in r , so

$$\tilde{U}(x'(\ell); r^n) - k_M \mathbb{1}\{x'(\ell) \neq \hat{\ell}\} > \tilde{U}(x^n(\ell); r^n) - k_M \mathbb{1}\{x^n(\ell) \neq \hat{\ell}\}$$

which is a contradiction since $x^n \in D_U(\hat{\ell}; r^n)$. Since $\hat{\ell} \in \mathcal{L}$ was arbitrary, it follows that $D_U(\ell; r)$ is UHC for all $\ell \in \mathcal{L}$, and given the guess that $u(\ell; r)$ is continuous, $D_U(\hat{\ell}; r)u(\hat{\ell}; r)$ is UHC.

(ii) Employed: $\sum_{\ell_F} \sum_y D_E(\ell_F, y, \hat{\ell}; r)e(\ell_F, y, \hat{\ell}; r)$

Similarly to the argument in part (i), consider an arbitrary $(\ell_F, y) \in \mathcal{L} \times Y$ and $\hat{\ell} \in \mathcal{L}$, and let $r^n \rightarrow r^0$, $x^n \rightarrow x^0$ with $x^n \in D_E(\ell_F, y, \hat{\ell}; r^n)$ for all n . Clearly x^0 is feasible, but suppose that $x^0 \notin D_E(\ell_F, y, \hat{\ell}; r^0)$. Then there exists $x' \in D_E(\ell_F, y, \hat{\ell}; r^0)$. Then $x'(\ell) \in \arg \max M(\ell_F, y, \hat{\ell}; r^0)$. Since M is continuous $\exists N$ such that for $n > N$, $x^n(\ell) \notin \arg \max M(\ell_F, y, \hat{\ell}; r^n)$, a contradiction.

Since (ℓ_F, y) and $\hat{\ell}$ were arbitrary, and using our guess $e(\ell_F, y, \hat{\ell}; r)$ is continuous in r , the above argument holds for all $(\ell_F, y) \in \mathcal{L} \times Y$ and $\hat{\ell} \in \mathcal{L}$, and thus $\sum_{\ell_F} \sum_y D_E(\ell_F, y, \hat{\ell}; r)e(\ell_F, y, \hat{\ell}; r)$ is upper hemicontinuous.

(iii) Vacancies: $\sum_{\hat{y}} D_V(\hat{\ell}, \hat{y}; r)g(\hat{\ell}, \hat{y})$

Consider an arbitrary $(\hat{\ell}, \hat{y}) \in \mathcal{L} \times Y$. Each

$$\begin{aligned} & \sum_{\ell} [\lambda_0 u(\ell; r) \mathbb{1}\{S(\ell_i, y, \ell; r) > 0\} \\ & + \lambda_1 \sum_{\hat{\ell}} \sum_{\hat{y}} \mathbb{1}\{S(\ell_i, y, \ell; r) > S(\hat{\ell}, \hat{y}, \ell; r)\} e(\hat{\ell}, \hat{y}, \ell; r)] \end{aligned}$$

is continuous since S is continuous under the assumption that u and e are continuous. Thus, D_V is UHC for all $(\hat{\ell}, \hat{y}) \in \mathcal{L} \times Y$, and $\sum_{\hat{y}} D_V(\hat{\ell}, \hat{y}; r) g(\hat{\ell}, \hat{y})$ is UHC.

Given the continuity of S , it follows from the steady state conditions equating the flows into and out of employment and unemployment that $u(\hat{\ell}; r)$ and $e(\ell_F, y, \hat{\ell}; r)$ are continuous in r for each $\hat{\ell} \in \mathcal{L}$, verifying the guess. Thus, the aggregate demand correspondence $D(r)$ is nonempty and UHC.

Part 1b - Supply Correspondence

The supply of land at each location ℓ available to allocate to each group making up the demand correspondence above is given by the land choice of the landlord, $\zeta(\ell)$, less the land occupied by continuing jobs, for whom the location is a state. In steady state, the amount of land occupied by continuing jobs is constant and equal to the mass of jobs located in ℓ less the mass of endogenously or exogenously destroyed matches. In each location $\ell \in \mathcal{L}$, the supply is given by

$$\Sigma(\ell, r) = \zeta(\ell, r) - \sum_y \sum_{\hat{\ell}} (e(\ell, y, \hat{\ell}; r) - e^-(\ell, y, \hat{\ell}; r))$$

where $\Sigma(\ell, r) \geq 0$ if $r \geq 0$ and 0 otherwise since landlords will not rent at a negative price by assumption. The term $e^-(\ell, y, \hat{\ell}; r)$ corresponds to (15). The supply function in each location is clearly continuous in r given landlords' preferences and given that e is continuous in r . Thus, the aggregate supply correspondence is the vector

$$E(r) = [\Sigma(0, r), \dots, \Sigma(2N + 1, r)]$$

which is nonempty and upper hemicontinuous.

Part 2 - Excess Demand

Define the excess demand correspondence as

$$E(r) = D(r) - \Sigma(r)$$

It follows from Part 1 that the excess demand correspondence maintains the nonemptiness and upper hemicontinuity of the supply and demand correspondences. Define the set of prices as

$P = [0, P_{max}]^{2N+2}$, where

$$P_{max} = \max_{\ell_F, y, \ell} \left\{ \left(y + \delta U(\ell) + \lambda_1 \beta \sum_{\hat{\ell}_F, \hat{y}} \max \{0, M(\hat{\ell}_F, \hat{y}, \ell; r) - M(\ell_F, y, \ell; r)\} g(\hat{\ell}_F, \hat{y}) \right) / (\rho + \chi + \delta) \right\}$$

Letting the minimum and maximum values of $E(r)$ given the set P as $[\underline{E}, \overline{E}]$, the excess demand correspondence maps the convex set P into the convex set $C = [\underline{E}, \overline{E}]^{2N+2}$ where $-\infty < \underline{E} < \overline{E} < \infty$.

Part 3 - Existence of a Fixed Point

This part of the proof uses results presented in Kaneko and Yamamoto (1986) (henceforth KY). By Lemma 4 in KY, the convex hull of $E(r)$, denoted $covE(r)$ inherits the nonemptiness and upper hemicontinuity of $E(r)$. By Lemma 5 in KY, $covE(r)$ is convex-valued. Further, denoting x as an element of $E(r)$, the following two results hold:

1. If $r(\ell) = 0$ for some $\ell \in \mathcal{L}$ and $x \in covE(r)$, then $x(\ell) \geq 0$
2. If $r(\ell) = S_{max}$ for some $\ell \in \mathcal{L}$ and $x \in covE(r)$, then $x(\ell) \leq 0$

To prove 1, notice that if $r(\ell) = 0$, $\Sigma(r, \ell) = 0$. Since $D(r)$ is nonempty, aggregate demand at ℓ must be weakly positive. To prove 2, since for $r(\ell) \geq 0$, supply is weakly positive and the surplus of all matches is weakly negative. Thus, no vacancies that draw ℓ will match, and no employed or unemployed workers will demand to locate in ℓ since the employed can at most extract their total match surplus and the unemployed have a lower value than the maximum match surplus. By Kakutani's fixed point theorem, there exists a price vector $r \in P$ such that $0 \in covE(r)$.

Denote this solution by x_{ch} and σ_{ch} , where x_{ch}^i , $i = 0, \dots, 2N + 1$ is given by the sum of each type of worker's demand for land in location i . Including the outside option of leaving the city, there are $2N + 2$ "types" of unemployed workers, and $(2N + 2)^2 Y$ "types" of employed workers, thus, the maximum number of types in each location is $M \equiv 2N + 2 + (2N + 2)^2 Y$. I therefore denote $x_{ch}^{j,i}$ as the demand for land in location i by type $j = 1, \dots, M$. Similarly, σ_{ch}^i is the supply of land in each location i , after taking into account the demand for new vacancies. The market clearing condition for land can be written

$$\sum_{j=1}^M x_{ch}^{j,i} + \sigma_{ch}^i = L \quad \text{for all } i = 0, \dots, 2N + 1$$

Since each worker can consume at most 1 unit of land:

$$\sum_{i=0}^{2N+1} x_{ch}^{i,j} \leq 1 \quad \text{for all } j = 1, \dots, M$$

Since x_{ch} and σ_{ch} may not be integers, consider the system

location by paying a moving cost, k_M .

Workers are born at the beginning of the period and draw a vacancy with probability λ . A vacancy is a draw of the location of the match, ℓ_F from distribution G , with the probability of drawing a vacancy in location ℓ denoted $g(\ell)$, with $g(1) = 1 - g(2)$.

The Decentralized Economy

Upon arrival of an offer, a worker has three options. She may (i) accept the job and remain in her current location, (ii) accept the job and move, or (iii) reject the job and stay unemployed. If a worker accepts a job, she receives a wage conditional on her match and location: $w(\ell_F, \ell)$ which is a share β of the match surplus, where ℓ is her chosen location. To highlight the role of the inefficiency in location decisions, I assume that $\beta = 1$. If the worker commutes, that is $\ell \neq \ell_F$, she pays commuting cost $T(\Omega)$, where Ω is the mass of commuters.

Employed workers consume their wages net of commuting and rent costs, and unemployed workers consume the value of home production b net of rent. Workers take expectations over the equilibrium value of Ω , and their beliefs are assumed to be consistent with the realized value of Ω in equilibrium.

Suppose that in the decentralized equilibrium all workers receiving offers from another location prefer to commute rather than move. If it is optimal for both of these groups to commute, the following conditions must hold:

$$1 - r(\ell) - T(e(\ell, \ell') + e(\ell', \ell)) > b, \quad \ell = 1, 2 \quad (23)$$

$$T(e(\ell, \ell') + e(\ell', \ell)) + r(\ell) - r(\ell') < k_M, \quad \ell = 1, 2, \ell' \neq \ell \quad (24)$$

where $e(\ell, \ell') = \lambda f(\ell)g(\ell')$ is the mass of workers born in location $\ell = 1, 2$ receiving an offer from $\ell' \neq \ell$. Conditions (23) and (24) imply that all workers in the decentralized economy located in 1 (2) receiving an offer located in 2 (1) accept and commute. In this case, the commuting cost in the decentralized equilibrium is given by $T(\lambda(f(2)g(1) + f(1)g(2)))$. The parameters are assumed to satisfy (23), (24), and: $1 - r(\ell) > b$ for $\ell = 1, 2$, which states that workers who receive an offer in their own location always accept.

A Constrained Planner

The planner's objective is to maximize output by choosing the mass of workers in each match and employment state, and whether a worker moves or commutes in the case of a job offer in a different location than the worker's residence. The planner is subject to feasibility constraints due to the

labor market frictions and a restriction on the total mass of workers in the economy.

$$\begin{aligned}
& (1 - 2r(1))e(1, 1) + (1 - 2r(1) - k_M)\pi(1)e(1, 2) + (1 - 2r(2) - k_M)\pi(2)e(2, 1) \\
& + \left(1 - r(1) - r(2) - T((1 - \pi(1))e(1, 2) + (1 - \pi(2))e(2, 1))\right)(1 - \pi(1))e(1, 2) + (1 - 2r(2))e(2, 2) \\
& \quad + \left(1 - r(1) - r(2) - T((1 - \pi(1))e(1, 2) + (1 - \pi(2))e(2, 1))\right)(1 - \pi(2))e(2, 1) \\
& \qquad \qquad \qquad + (b - r(1))u(1) + (b - r(2))u(2) \quad (25)
\end{aligned}$$

Subject to the feasibility constraints:

$$\begin{aligned}
e(\ell, \ell_F) &\leq \lambda f(\ell)g(\ell_F), \quad \text{for } \ell, \ell_F = 1, 2 \\
e(\ell, \ell_F) &\geq 0 \quad \forall (\ell, \ell_F) \\
u(\ell) &\geq (1 - \lambda)f(\ell) \quad \forall \ell \\
\sum_{\ell=1}^2 \left(u(\ell) + \sum_{\ell_F=1}^2 e(\ell, \ell_F) \right) &= 1 \\
\pi(\ell) &\in [0, 1] \quad \forall \ell
\end{aligned}$$

The first condition restricts the mass of employed in each match to be at most the mass of workers who received that offer. The second and third conditions restrict the mass of employed workers of each type to be weakly positive and the mass of unemployed to be at least equal to the mass of workers receiving no job offer. The fourth condition requires that the total mass of workers in the economy is 1. The last condition restricts the planner's choice between moving and commuting to be a share between 0 and 1 of the mass of workers with offers in a location different from their own.

Consider an alternative allocation in which the mass $e(1, 2)$ moves to location 2 and $e(2, 1)$ continues to commute to location 1, that is $\pi(1) = 1, \pi(2) = 0$. Recall that in the decentralized allocation, all workers receiving offers different from their own commute. All other workers' contributions to output are unchanged. The planner prefers this allocation to the decentralized allocation if

$$T(e(1, 2) + e(2, 1))(e(1, 2) + e(2, 1)) - T(e(2, 1))e(2, 1) > (r(2) - r(1) + k_M)e(1, 2) \quad (26)$$

where $e(1, 2) + e(2, 1)$ is the mass of commuters in the decentralized allocation and $e(2, 1)$ is the mass of commuters under the alternative allocation. The condition states that the benefit to all workers from lower commuting costs must be greater than the moving cost. Assume that commuting costs are of the form $T(\Omega) = (\tau + \kappa\Omega)b$, then we can write (24) and (26) as

$$r(1) - r(2) + (\tau + \kappa(e(1, 2) + e(2, 1)))b < k_M < r(1) - r(2) + (\tau + \kappa(e(1, 2) + 2e(2, 1)))b$$

If the above condition holds, then the decentralized equilibrium is inefficient and the planner will choose for some workers to move. Rewriting the right hand side as the sum of the private benefit of reducing commuting and the social benefit: $r(1) - r(2) + (\tau + \kappa(e(1, 2) + e(2, 1)))b + \kappa e_2 b$ it is clear that if the social benefit, $\kappa e_2 b$, is large enough, it can be welfare-improving to have some workers move, but privately optimal to commute.

In order for the above allocation to be constrained efficient, the planner must prefer to have $e(1, 2)$ move and $e(2, 1)$ commute rather than $e(2, 1)$ move and $e(1, 2)$ commute, or for both $e(1, 2)$ and $e(2, 1)$ to move. First, note that the planner will never have both $e(1, 2)$ and $e(2, 1)$ move, since it is privately suboptimal for both to move, and there is no social benefit since no workers would commute in this case. Second, the planner will prefer to have $e(1, 2)$ move and $e(2, 1)$ commute rather than $e(2, 1)$ move and $e(1, 2)$ commute if

$$\begin{aligned} (1 - r(1) - r(2) - T(e(1, 2)))e(1, 2) + (1 - 2r(1) - k_M)e(2, 1) \\ < (1 - r(1) - r(2) - T(e(2, 1)))e(2, 1) + (1 - 2r(2) - k_M)e(1, 2) \end{aligned} \quad (27)$$

Noticing that $r(1) - r(2) - T(e(2, 1)) + k_M > 0$ by (24), rearranging this expression gives

$$\frac{r(2) - r(1) - T(e(1, 2)) + k_M}{r(1) - r(2) - T(e(2, 1)) + k_M} < \frac{e(2, 1)}{e(1, 2)}$$

The numerator and denominator on the left hand side are the output losses to workers $e(1, 2)$ and $e(2, 1)$, respectively, if the worker moves rather than commutes. From the decentralized equilibrium, it is clear that if there were no benefits from reducing congestion, no workers will choose to move. The expression above compares the net gain for each worker from moving relative to commuting when the other type of worker moves. First, observe that if the left hand side is equal to the right hand side, the net gain from workers $e(1, 2)$ moving and $e(2, 1)$ commuting and vice versa are equal, and the planner is indifferent. This is the case if $e(1, 2) = e(2, 1)$. If rent in the two locations are equal, since commuting costs are increasing in the mass of workers, the left hand side is greater than one if $e(1, 2) < e(2, 1)$, that is, the mass of workers paying the moving cost must be less than the mass of workers benefiting from lower congestion. As rent in location 2 increases relative to rent in location 1, the loss from moving workers $e(1, 2)$ increases, implying that it is only optimal to move these workers if their mass is small relative to $e(2, 1)$.

The constrained efficient allocation is to have workers $e(1, 2)$ move and $e(2, 1)$ commute, and all other workers to make choices identical to the decentralized equilibrium, if (26) and (27) hold.

Proposition 2 describes the conditions under which the decentralized equilibrium is inefficient.

Proposition 2. *Suppose $T(\Omega) = (\tau + \kappa\Omega)b$. Then the following are true:*

- (i) *For any $k_M > r(1) - r(2) + \tau b$ there exists $\underline{\kappa}$, $\bar{\kappa}$ such that the decentralized equilibrium is inefficient for all $\kappa \in (\underline{\kappa}, \bar{\kappa})$.*
- (ii) *As k_M approaches τb from above, $\underline{\kappa}, \bar{\kappa} \rightarrow 0$. As k_M increases, the distance $\bar{\kappa} - \underline{\kappa}$ increases.*

(iii) The tax that implements the constrained efficient allocation, t , satisfies $t = \frac{e(2,1)}{e(1,2)+e(2,1)}$, where $e(1,2)$ is the mass of movers in the constrained efficient equilibrium and $e(2,1)$ is the mass of commuters benefiting from a reduction in congestion.

Proof. Define $\underline{\kappa}$ as

$$\underline{\kappa} = \frac{k_M - r(1) + r(2) - \tau b}{b(e_1 + 2e_2)}$$

Similarly, define $\bar{\kappa}$ by

$$\bar{\kappa} = \frac{k_M - r(1) + r(2) - \tau b}{b(e_1 + e_2)}$$

For $\kappa \in (\underline{\kappa}, \bar{\kappa})$, both (24) and (26) hold, proving part (i).

For part (ii), notice that as k_M approaches τb , the values of $\underline{\kappa}$, $\bar{\kappa}$ approach zero. Similarly, we can define

$$\Delta\kappa = \bar{\kappa} - \underline{\kappa} = \frac{k_M - r(1) + r(2) - \tau b}{b} \left(\frac{1}{e_1 + e_2} - \frac{1}{e_1 + 2e_2} \right)$$

which is strictly increasing in k_M .

To prove part (iii), recall that the decentralized equilibrium is constrained inefficient if

$$r(1) - r(2) + (\tau + \kappa(e(1,2) + e(2,1)))b < k_M < r(1) - r(2) + (\tau + \kappa(e(1,2) + 2e(2,1)))b$$

Letting t be the tax on congestion, we can write the left hand side as

$$r(1) - r(2) + (\tau + (1+t)\kappa(e(1,2) + e(2,1)))b$$

Setting the above expression equal to $r(1) - r(2) + (\tau + \kappa(e(1,2) + 2e(2,1)))b$ and solving for t gives

$$t = \frac{e(2,1)}{e(1,2) + e(2,1)}$$

□

In this static setting, the congestion externality arises when two conditions are met. First, the moving cost must be sufficiently large, and second, the effect of congestion on commuting costs is bounded by two values. The first condition must hold in order for workers in the decentralized economy to prefer to commute rather than move. The second condition bounds the congestion cost so that the planner prefers that a group of workers moves rather than commutes. The social benefit of moving is the private benefit of lower commuting costs for the movers plus the marginal reduction in commuting costs for the commuters who benefit from less congestion, times their mass. Part (i) of Proposition 2 states that for any sufficiently large moving cost, there exist a range of values for the marginal cost of congestion such that the decentralized equilibrium is inefficient. The lower bound for κ insures that the social value of reducing congestion is high enough to overcome the cost of moving. Symmetrically, the upper bound restricts the congestion cost to be small enough such that workers in the decentralized economy do not always take the constrained efficient action. Part

(*ii*) states that the smaller is the moving cost, the smaller is the range and the lower is the value for congestion costs such that the decentralized equilibrium is constrained inefficient. When moving costs are small, there is only a positive effect of moving and it is privately and socially optimal for all workers who would otherwise commute to move to the location of their firms. The smaller the moving cost, the more likely that the decentralized equilibrium is efficient. Part (*iii*) derives the optimal tax, which is equal to the share of workers who continue to commute after some workers move. These workers benefit from the reduction in congestion, which workers in the decentralized economy do not take into account when making their moving decision. By increasing their own commuting costs by taxing congestion, the optimal tax aligns their incentives with the planner's and achieves the constrained efficient allocation.

D Alternative Definition of the Local Labor Market

I redefine the local labor market used in the empirical analysis and derivation of moments. In Section 4, the local labor market is defined as those LADs within 100 miles of the City of London, seen in Figure 1 as the point below which a significant number of workers commute to the City. An alternative definition is explored here, specifically, by defining the local labor market as a “commuting zone”. The commuting zone is comprised of those locations for which over half of all workers commute within its boundaries.

As in Section 2, I use the 2001 Census Flow Data to identify the set of regions for which a positive number of workers commute to the City of London, and consider all origin-destination pairs for which both LADs are in this set. For each origin, I compute the number of workers commuting to each destination as a share of the total number of commuters. I define the commuting zone as those LADs with a share above 30%. Under this definition, the location farthest from the City of London is Colchester (65 miles). There are 1,655 individuals under this definition, equal to 13% of the sample size when using the 100-mile radius in the main model. Results for the empirical analysis in Section 2 and Appendix A are similar and are available upon request. Table 27 shows how the parameters used in the calibration and the untargeted moments differ in the two definitions. Because more than 80% of individual observations are lost, the estimates in the second column are much more imprecise than using the 100 mile radius, though overall they are quantitatively similar.

Table 27: Targets: Parameters

Moment	≤ 100 miles	“Comm. Zone”
Relative wage, new hires from U	.87	.87
Variance, $\ln(w)$.186	.205
Moving probability (A)	.036	.034
Relative increase in commuting cost with congestion	.65	.73
Share of job-related moves	.129	.132
Avg rent/income	.365	.378
Relative wage, residence 5-33 (5-22) mi	.82	.84
Relative wage, residence 33-66 (22-44) mi	.79	.84
Relative wage, residence 66-100 (44-65) mi	.70	.89
Jobs density, 5-33 (5-22) mi from center	.83	.77
Jobs density, 33-66 (22-44) mi from center	.80	.85
Jobs density, 66-100 (44-65) mi from center	.78	.80
Share of wage cuts	.16	.15
Share of movers who stay in the same job	.033	.035
Average wage growth, J2J	.065	.083
Average wage growth, within job	.016	.018
Annual J2J transition rate, residence in center	.147	.147
Annual J2J transition rate, residence in periphery	.105	.101
Relative Moving Distance, J2J to All Movers	1.40	0.67

E Numerical Solution Algorithm

I solve the model in the following steps:

1. Guess a rent function, initial distributions of workers, and initial value functions for U , W , and S . Set the initial externality to zero.
2. Given the rent function and distributions of workers, solve for the value functions U , W , and S and optimal moving choices using (1), (3), (9), (10), and (13) by iterating on the value functions until convergence.
3. Given the value functions computed in step 2, compute the worker distributions given steady state flow conditions (14)-(17).
4. Given worker distributions, compute the level of congestion using (20).
5. Given worker distributions, compute the difference between the left and right hand sides of

(22) for each ℓ . Denoting the excess demand in (22) as $D_E(\ell)$, update the rent price as

$$r'(\ell) = r(\ell) + f(D_E(\ell))$$

where f is a normalization to avoid large jumps in the price: $f(x) = x/50$.

6. Using solutions for W , U , S , \tilde{W} , and \tilde{S} , compute wages satisfying (4)-(8).
7. Compute the difference between the guessed and updated worker distributions and repeat steps 2 to 6 until convergence.

F Calibration

F.1 Moments for Calibration

All moments used in the calibration relating to wages correspond to the residuals of log real monthly wages on year, month, education level, and commuting method. Wage observations more than 3 standard deviations outside of the mean are omitted. Further, the moments correspond to the subset of workers considered in Section 2: age 24-55, in the labor force, with a commute up to 180 minutes round trip, living within 100 miles from the City of London as defined by Google Maps. Locations in the model correspond to LADs within 10 miles of the center (location 4), and 5-33 miles (locations 3 and 5), 34-66 (2 and 6), and 66-100 (1 and 7) miles from the center.

To calibrate the productivity process, I discretize the y distribution to approximate a Normal $(1 + A(\ell_F), \sigma_y)$ using the Tauchen method, where the parameters $A(\ell_F)$ are calibrated to match relative wages by worker location.

The moving probability is the share of workers who report moving more than three miles (5km) from their residence in the last wave of the survey. The share of job-related moves is the share of movers who state that their main reason for moving was for their own job. Jobs density is available from the Office for National Statistics, defined as the ratio of the number of jobs to resident working age population (16-64), and corresponds to the year 2001, though at the aggregated level used here the figures are stable over time.

The value for the replacement rate is standard in the literature; [Bils et al. \(2012\)](#) point out that this value should include the saved costs due to not working which here include commuting costs. The UE, EU, EE rates come from [Gomes \(2012\)](#) and correspond to the quarterly rates for the UK between 1994 and 2009. The variance of the wage corresponds to the cross-sectional residual log wage variance. Average rent to income is the average net monthly housing cost for individuals who rent their residence relative to the net unresidualized wage. The elasticity of UK housing supply comes from [Barker \(2003\)](#). The newborn distribution across locations is given by [0.1475, 0.1550, 0.1180, 0.1630, 0.1180, 0.1550, 0.1475].

Figure 13: Housing Rent

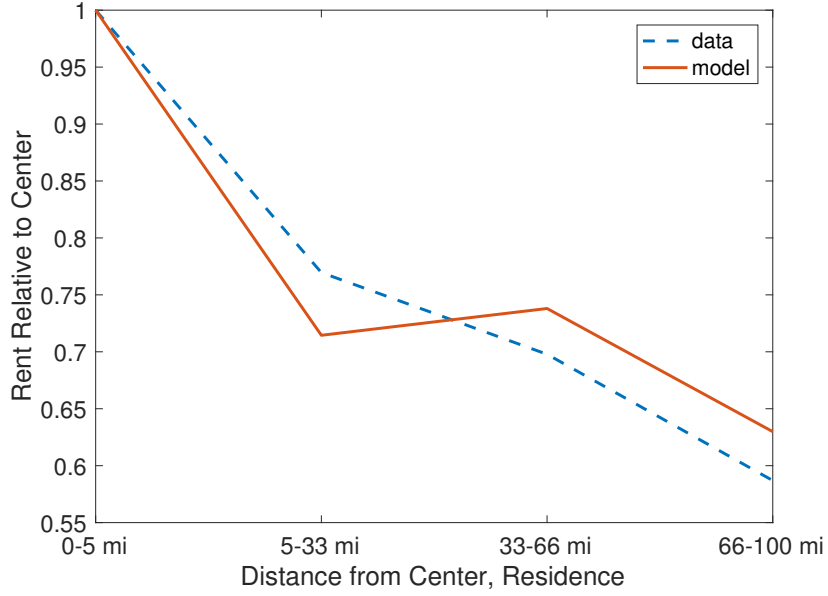
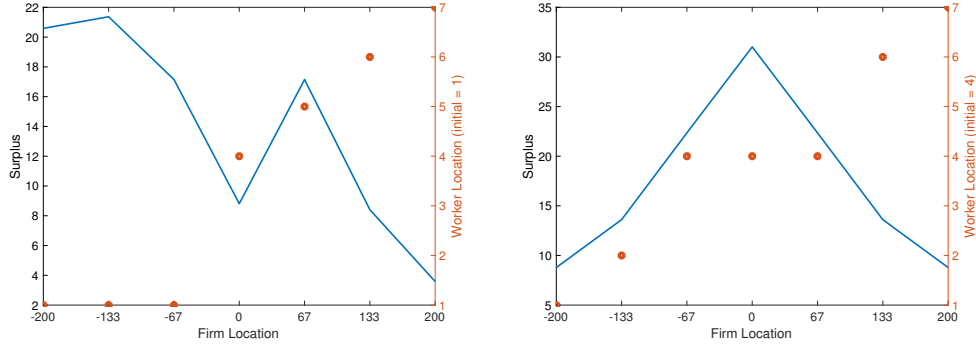


Figure 14: Moving Decisions and Match Surplus



F.2 Figures

Figure 14 shows the policy function for offers with the highest productivity, given the worker’s initial location. The left panel shows the surplus and location decisions of a match $(\ell_F, y_H, 1)$ as a function of ℓ_F . When the firm is in or near the worker’s location, at the left side of the figure, surplus is high and the worker does not move. As the job nears the center, the surplus drops because congestion faced by the worker and rent for the firm rise. When commuting costs are high enough, the worker moves to the firm’s location. The moving decision is different for a worker with initial location in the center (right panel). For this worker, again the surplus is higher when the firm and worker locations are the same, but decreases in both directions as the firm moves toward the periphery. If the firm is two or more locations away, the worker moves in order to decrease her rent and commute. Comparing the two figures, if an unemployed worker living in location 1 gets a

job offer from location 3, she will accept it and commute, whereas if a worker living in 4 gets an offer from 2, he will move to the firm's location. Both are equidistant in terms of miles, but the commuting time is very different due to differences in congestion in the center and periphery.