Economic Shocks and Internal Migration

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Abstract

Internal migration can respond to local shocks through either changes in in- or out-migration rates. This paper documents that most of the response of internal migration is accounted for by variation in in-migration. I develop and estimate a parsimonious general equilibrium dynamic spatial model around this stylized fact. I then use the model to evaluate the speed of convergence and long run change in welfare across metropolitan areas given the heterogeneous incidence of the Great Recession at the local level. The paper shows that while there are some lasting effects of the Great Recession across locations, most of the initial differences potentially dissipate across space within 10 years. This is true even when locals from the most affected metropolitan areas do not out-migrate in higher proportions in response to local shocks.

Key words: Internal migration and local labor market dynamics.
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1 Introduction

A common perception is that "Americans have historically been an unusually mobile people, constantly seeking better economic conditions" (Moretti, 2012). We would thus expect geographic relocation to be an important mechanism for American families to deal with periods of economic crisis. Accordingly, the main goal of this paper is to accurately quantify the importance of internal migration in providing insurance against local shocks.

To do so, I first document a novel stylized fact: in-migration rates respond more than out-migration rates to economic shocks. In other words, if a location is hit by a negative shock, the number of workers who move to that location strongly diminishes. In contrast, the number of people who leave the affected location does not increase significantly.

I document this stylized fact using two alternative and complementary strategies. Using insights from Mian et al. (2013) and Mian and Sufi (2014), I identify local labor demand shocks during the Great Recession that vary in intensity across metropolitan areas. Indeed, metropolitan areas where households were more indebted prior to the Great Recession had to cut back significantly on their consumption and this in turn affected local non-tradable employment. Metropolitan areas where households were indebted *and* where the share of employment in non-tradable sectors was high prior to the crisis thus experienced larger falls in local labor demand. I use this variation to document the internal migration response during the Great Recession. Clear patterns emerge: a 1 percent decrease in wages led to a decrease in the net in-migration rate of around .2 percentage points. This decrease was entirely driven by a decline in the in-migration rate, with little response of the out-migration rate.

The fact that in-migration explains most of the variation in internal migration is a very general feature of internal migration in the United States. To show this, I decompose population growth rates across locations into in- and out-migration rates.[1] Using various publicly available datasets and a number of geographic aggregations, I show that most of the variation in population growth rates is accounted for by variation in in- rather than out-migration. This suggests that the response of internal migration during the Great Recession followed a pattern similar to other unobservable local labor demand shocks and helps to establish the stylized fact.[2]

The second and main contribution of this paper is to develop a quantitative general equilibrium dynamic model with multiple locations around this stylized fact that I then bring to the data. Workers in the model are forward looking and take into account current and future local labor

[1]More specifically, for each sample of the Current Population Survey, the Census, and the American Community Survey, each surveyed individual reports her current and past location of residence. Thus for a given point in time it is possible to reconstruct entire migration patterns for the surveyed individuals. We can then use this to decompose population growth rates across location of the cohort surveyed into in- and out-migration rates.

[2]Coen-Pirani (2010) documents that variation in in-migration is larger than in out-migration. This empirical regularity is entirely consistent with what I document below. This paper builds on this work by precisely identifying the mechanisms leading to this higher variation in in-migration.

market conditions in all of the economy's locations where to reside in each period. When workers move they affect the value of living at their destination. This is the key element of standard spatial equilibrium models (Rosen (1974) and Roback (1982)) and is preserved in this dynamic setting. In other words, the model combines two important strands of literature. One the one hand, it builds on forward looking dynamic discrete choice residential location models (Kennan and Walker (2011), Dix-Carneiro (2014), Bayer et al. (Forthcoming), Bishop (2012), Murphy (2016) or Oswald (2016)) that have been estimated using micro-level data. Given the large number of potential choices for current and future locations, these models are in nature partial equilibrium and miss important insights from standard static spatial equilibrium models. On the other hand, there is a recent and growing literature on quantitative spatial equilibrium models (Redding and Sturm (2008), Ahlfedlt et al. (2014), Redding (2014), Albouy (2009), Notowidigdo (2013), Diamond (2015), and Monte et al. (2015) among others) that has been used to explore long-run consequences of taxation, local shocks, endogenous amenities, or commuting patterns. All these models are static, and thus unequipped to study the transitional dynamics and the speed of adjustment to the new spatial equilibrium.

I manage to bring these two literatures together by modifying the location choice model to match the documented stylized fact. To do so, I assume that for each period, each individual worker decides where to live given current and future labor market conditions and an idiosyncratic taste shock. This idiosyncratic taste shock is drawn from a nested logit distribution that gives a higher weight to the home location. I am therefore able to decompose the flows of workers between any two locations; between the (endogenous) share of workers who move away from their original location and the share who choose each particular destination. This fully characterizes the entire matrix of flows between locations in an economy. It also makes the home location special in a sense, something that is crucial in order to match the empirical regularity of internal migration that in equilibrium is relatively low – around 5 percent when considering metropolitan areas. This modeling choice plays a similar role to the fixed costs of mobility introduced and estimated in Kennan and Walker (2011) and makes the model very tractable.[3]

As far as I am aware, only one contemporaneous paper manages to bring together a dynamic forward looking residential choice model and spatial equilibrium. Caliendo et al. (2015) study how trade with China impacted the US labor market using a dynamic spatial equilibrium model. They manage to solve the model in first differences by conditioning on the observable past flows of workers across locations. This comes at the cost of not solving the model in levels. Their model allows them to quantify the long-run costs of trade with China and perform counterfactuals, but it is not suited to matching the documented internal migration responses to local shocks that I detail in this paper.

[3] In Appendix D, I compare the model presented in this paper with a model where the idiosyncratic taste shocks are drawn from a logit distribution and there are fixed costs of moving, showing that differences are small. I also show how moving costs need to be high to match the findings in this paper.

Furthermore, there are a number of features of the model that I present in this paper that make it particularly attractive. First, the population dynamics can be summarized in a very simple and intuitive equation despite the complexity of having many potential current and future destinations:

$$N_{t+1,m'} = \widetilde{\eta}_t \frac{V_{t,m'}^{1/\lambda}}{V_t^{1/\lambda}} N_t + (1-\eta_{m,t}) N_{t,m'} \tag{1.1}$$

This equation expresses that in each location m the population in the following period $(N_{t+1,m})$ is a weighted average between the value of that location V_m relative to the value of the economy V – scaled by $1/\lambda$ and multiplied by the total number of workers in the economy (N_t) – and the current size of the location $N_{t,m}$, where the weights ($\eta_{t,m}$ and $\widetilde{\eta}_t$) are endogenously determined by the conditions of the economy. The value of each location depends mostly on wages, that are in turn affected by internal migration, depending on the elasticity of the local labor demand. Thus, this equation fully characterizes dynamics within the economy and allows for an examination of the determinants of the speed of convergence to the new steady state. In this paper, I show that the speed of convergence depends crucially both on the sensitivity of internal migration and on the local labor demand elasticity. They jointly determine the size of population spillovers across regions and to what extent these are felt in wages, and thus the value of each location. This makes very explicit the idea that reduced migration to one location is a labor supply shock in another location, as introduced in the seminal work of Topel (1986).[4]

Second, the model is particularly suited to studying welfare. Long run change in welfare across locations can be expressed in a simple and intuitive equation:

$$\Delta \ln V_m \approx \lambda \Delta \ln N_m + \Delta \ln V \tag{1.2}$$

This equation says that the change in long run welfare in a location $(\Delta \ln V_m)$ equals the change in welfare in the economy $(\Delta \ln V)$ plus the long run change in population in that location $(\Delta \ln N_m)$ scaled by λ. It thus allows for study of the degree of importance of internal relocation in insuring locations against local shocks.

In these two expressions, λ – essentially the sensitivity of in-migration to local wage changes – plays a crucial role. Lower estimates of λ mean that different locations are more substitutable and thus shocks spread more quickly and dissipate better. I propose simple strategies to estimate this parameter using the local incidence of the Great Recession.

Finally, the third contribution of the paper is the use of a quantitative model calibrated to the US economy to study the potential role of internal migration in dissipating the incidence of the

[4]In this paper I focus on local labor markets. A crucial aspect for the model is that there are congestion forces, i.e. holding everything fixed, more people in a location should diminish the value of that location. There are many alternative congestion forces. While I focus here on the labor market, similar results can be obtained by, for example, considering congestion in the housing market.

Great Recession across metropolitan areas and the speed of convergence to a new steady-state. The results suggest that internal migration plays an important role in the US. With only internal migration as a mechanism dissipating local shocks, I show that the model predicts that within 10 years the economy is back to a steady state and as much as 60 percent of the initial wage drop has dissipated across space.

This paper intersects with a large body of prior work. Many of the results reported in the seminal contribution of Blanchard and Katz (1992) can be interpreted within the model proposed. For instance, Blanchard and Katz (1992) report that wages recover across space within about 8 years, a magnitude similar to that implied by the model from the structural parameters and consistent with the work of Kennan and Walker (2011) and Bound and Holzer (2000). The model in this paper can also be amended to match other features of the labor market studied in Blanchard and Katz (1992), something I explain in the Appendix B.1. This paper also builds upon a number of articles that have directly or indirectly studied internal migration during the Great Recession, including Mian et al. (2013), Cadena and Kovak (2016), and Yagan (2014). I provide model based estimates of the welfare consequences of the Great Recession that go beyond employment or population changes estimated in this body of work. In addition, I provide explanations in A.3 for the findings in these papers that are in conflict with my own findings.

2 Stylized Fact

2.1 Data

I employ five main data sources in this paper. I use American Community Survey (ACS) data from Ruggles et al. (2016) to compute migration rates across US metropolitan areas and labor market outcome variables during the Great Recession. These data are available for the period 2005 - 2010. To compute migration rates, I use information on residents' current and past locations. I also use ACS data to compute unemployment rates and average wages across metropolitan areas. Average wages and unemployment rates are computed using males aged 25-59, while migration is computed for both males and females aged 18 to 59.[5] The two samples differ in that the first is meant to compute the price of labor, while the second focuses on the decision of agents potentially moving for work-related reasons.[6]

My second source is the Bureau of Economic Analysis, whose data allow for a measure of real gross domestic product per capita, which I use in some of the calibrations. The third and fourth data sources include Census and Current Population Survey data, again from Ruggles et al. (2016). These are used in the same way as the ACS data. The last data set I employ is taken from Mian et

[5]ACS data reports wages in the past year, something that I take into account throughout.

[6]Sample selection does not drive any of the results.

al. (2013) andused to compute metropolitan level debt to income ratios, by aggregating the county level information to metropolitan areas using population as weights.

More specifically, I define the in-migration rate to metropolitan area m at time t as follows:

$$\text{In-migration rate}_{m,t} = \frac{I_{m,t}}{N_{m,t}}$$

where $I_{m,t}$ denotes the number of individuals that live in m at time t and were living somewhere else at time $t-1$.[7]

Similarly, I define the out-migration rate from a metropolitan area m as:

$$\text{Out-migration rate}_{m,t} = \frac{O_{m,t}}{N_{m,t}}$$

where, $O_{m,t}$ denotes the number of individuals that lived in m at time $t-1$ and were living somewhere else at time t. In both equations, $N_{m,t}$ is the population in m at time t.

The net migration rate is simply the in-migration rate minus the out-migration rate.

One limitation of the ACS data set is that it only contains information on metropolitan areas of residence from 2005 to 2011. Prior to 2005, the ACS reports only the current state of residence and the state of residence in the previous year. While this information can be used to define local labor markets, metropolitan areas are a much better approximation of a local labor market. One alternative is to use CPS data, where both state and metropolitan areas are reported. The use of CPS data, however, is limited by its small sample size. Furthermore, concerns have been raised about how the US Census Bureau deals with missing data, further limiting the number of available observations.[8] Sample size is particularly important when studying yearly migration rates since the latter are usually below 6 percent of the population. After 2011, the definition of metropolitan area changes. As a result, I limit the period of study to ACS data from 2011 where the 2010 wages are reported. For a detailed discussion of data sources available for the study of internal migration, see Molloy et al. (2011), who argue that recent internal migration is best estimated using ACS data.

2.2 Demographic response during the Great Recession

2.2.1 Summary statistics

Although life-long migration rates are relatively high in the US, year-to-year migration rates are more modest (Molloy et al. (2011)). In a typical metropolitan area, around 5 percent of residents

[7]I use the 3 digit METAREA and MIGMET1 variables from Ruggles et al. (2016). I do not use observations where metropolitan area is not identified. In addition, there are some metropolitan areas for which the MIGMET1 variable was not constructed. I do not, accordingly, use these metropolitan areas. Equivalently, I use analogous variables at the state or regional level when utilizing an alternative geographic disaggregation.

[8]Molloy et al. (2011) reports lower migration rates in the CPS than in the ACS, something explained in Kaplan and Schulhofer-Wohl (2012) as an undocumented error in the Census Bureau's imputation procedure for dealing with missing data in the Current Population Survey.

lived in a different location the previous year. In fact, migration rates have declined over the last 20 years or so, as documented in Molloy et al. (2011).

[Tables 1 go here]

Table 1 shows that around 5.4 percent of the population were internal migrants before the Great Recession, and this number drops to 4.8 percent in the post-2007 period. This result is in line with both the secular decline in internal migration and with the counter-cyclicality of internal migration Molloy et al. (2011) and Saks and Wozniak (2011).

Table 1 also shows how labor market conditions worsened on aggregate between 2005-06 and the post-2007 period. Average weekly wages dropped by 20 dollars and unemployment rates rose from around 5 percent to over 7 percent.

Finally, table 1 also reports a number of cross-sectional characteristics that accurately predict where the crisis was felt most strongly. For instance, there is much dispersion in the debt to income ratio – directly taken from Mian et al. (2013) paper – as well as the share of non-tradable employment across different metropolitan areas, ranging from 16 to 43 percent of total employment.

2.2.2 In- and out-migration rates during the Great Recession

2.2.3 Empirical strategy

One of the main objectives of this paper is to estimate the (short-term) migration response to local economic shocks. This can be done using the following specification:

$$\text{Migration rate}_{m,t} = \beta X_{m,t} + \delta_m + \delta_t + \varepsilon_{m,t} \tag{2.1}$$

where Migration rate$_{m,t}$ is either the number of people that move into metropolitan area m (divided by the population in that area), the number of people that move out of metropolitan area m, or the net in-migration to metropolitan m. δ_m are metropolitan area (MSA) fixed effects, while δ_t are year fixed effects. $X_{m,t}$ is a measure of local economic activity. While I show results using three different measures: average (log) wage, unemployment rate, and employment rate, I focus much of the discussion on the wage results.

2.2.4 First stage: local economic variables and the crisis

There is, most likely, a two-way relationship between local wages and internal migration. If wages increase in a location, it is quite likely that internal migrants will be attracted to this location. At the same time, holding everything fixed, a greater number of workers in one place is likely to put downward pressure on wages.

In order to obtain an estimate of the effect of changes in wages on internal migration patterns, we need a reason for changing wages within the metropolitan area that is independent of how internal migration reacts. The Great Recession offers just such an opportunity to measure local labor demand shocks.

Mian et al. (2013) argue that the level of debt that households held prior to the Great Recession is a good predictor of where the Great Recession hit hardest. The idea is that indebted households had to cut back on consumption of both tradable and non-tradable goods. The reduction of consumption of tradable goods is a shock that affects all metropolitan areas similarly, while the diminution of consumption of non-tradable goods directly affects the local market. Mian et al. (2013) show how counties with high levels of household debt lost significantly more employment, especially in non-tradable sectors. They thus identify a mechanism that reduces the demand for labor at the local level that affects different metropolitan areas with different intensity.

An even more refined way to capture local labor demand shocks is to consider that the mechanism identified by Mian et al. (2013) is more likely to affect local employment if the metropolitan area relies heavily on employment in non-tradable sectors. In other words, metropolitan areas where households were heavily indebted and at the same time had high levels of employment in non-tradable goods were precisely the areas where thedecrease in labor demand was largest.

In order to adopt this strategy, I first document that wages, employment, and unemployment rates effectively worsened in metropolitan areas that were hit by a higher local labor demand shock.[9] To do so I use the following specification:

$$X_{m,t} = \beta * \text{shock}_t * Z_{m,T} + \delta_m + \delta_t + \eta_{m,t}$$

where $X_{m,t}$ is either average (log) wage, employment rate, or unemployment rate in metropolitan area m at time t, shock_t is a dummy variable that takes value 1 after 2007, and where $Z_{m,T}$ is either the average household debt to income ratio in 2006, or the interaction of the average household debt to income ratio in 2006 with the share of workers in non-tradable sectors in 2000[10]. I call these two alternative strategies IV1 and IV2. δ_m are metropolitan area fixed effects, while δ_t are year fixed effects.

Table 3 shows the results of running these regressions. As documented in Mian et al. (2013), at the county level, metropolitan areas with higher debt to income ratios before the crisis experienced larger drops in employment. Wage decreases take a bit longer, as shown in Appendix A.1, but the estimate of comparing 2005-06 to 2007-10 is clear. A 100 percentage point higher debt to income ratio translates into 1.7 percent lower wages.

[9]In Mian et al. (2013), little effect on wages is reported. This is due to the time period they utilize for their sample. I further discuss this in Appendix A.1. The wage dynamics shown in appendix A.1 are in fact consistent with the idea that wages are downward nominal rigid Daly et al. (2012), and thus it takes time for the aggregate wage in a location to react. To keep the discussion simple, I abstract from downward wage rigidities in this paper.

[10]I follow Mian et al. (2013) to define non tradable sectors.

[Table 3 goes here]

We can thus use these results as a first stage for assessing the degree to which internal migration rates change relative to variation in local employment conditions, as measured by wage, employment, and unemployment.

2.2.5 Second stage: internal migration rates and the crisis

In Table 4 I show the relation between net in-migration rates and the local labor market economic variables. The results are clear. Net in-migration rates decrease when wages decrease. A 1 percent decrease in wages leads to a .2 percentage points decrease in the net in-migration rate. Similarly, a 1 pp increase in the unemployment rate leads to a .3 pp decrease in net in-migration, while a 1 pp decrease in the employment rate leads to a .35 pp decrease in net in-migration.

[Table 4 goes here]

These responses of net migration rates are entirely due to the response of the in-migration rates, as shown in Table 5. A metropolitan area with a typical in-migration rate of around 5 percent would see in-migration drop by around .2 percentage points as a result of a 1 percent decrease in average wages. In levels, a 1 percent decrease in wages leads to around a 4 percent decrease in in-migration. Table 5 shows that allthe adjustment to the crisis took place through reductions in in-migration rates, as opposed to increases in out-migration rates.

[Table 5 goes here]

In the following section I show that this is a prevalent feature of internal migration in the United States. I later investigate the relevance of this fact for the economy.

2.3 Population growth and internal migration

2.3.1 Summary statistics

Results in the previous section show that the short run response to the negative economic shocks of the Great Recession was a decrease in in-migration rates and little change in out-migration rates. In this section, I investigate how general this result is by decomposing population growth rates in different locations between the in- and the out-migration rates in a number of standard data sets.

More precisely, I can decompose the population growth rate of a particular cohort of workers – i.e. workers that I observe at a given year in the data set and for whom I know their previous location – as follows:

$$\frac{N_{m,t} - N_{m,t-1}}{N_{m,t-1}} = \frac{I_{m,t}}{N_{m,t-1}} - \frac{O_{m,t}}{N_{m-1,t}} \tag{2.2}$$

where $N_{m,t}$ refers to the cohort of workers that at time t are between 18 and 59 years of age in each metropolitan area m, and $N_{m,t-1}$ refers to the exact same cohort but at their $t-1$ residence (either 5 or 1 year, depending on whether I use Census or CPS data). Equation 2.2 exactly decomposes population growth rates in various metropolitan areas for particular cohorts of workers. Note that, on aggregate, the population growth rate is exactly 0, such that this decomposition measures differential growth across locations.

Table 2 shows internal migration rates for the various data sets and geographic aggregations that I later use. The results reflect findings that have been highlighted in previous work. More specifically, it shows how internal migration decreased between the 1980s and the 2000s. In the 1970s and 1980s, on average around 18 percent of the workforce had changed metropolitan area in the preceding 5 years, a number that dropped to around 17 percent in the 1990s. The same pattern is observed in cross-state migration.

[Table 2 goes here]

Table 2 similarly shows that emphasized in Coen-Pirani (2010): in-migration is significantly more volatile than out-migration. The standard deviation in in-migration rates is almost twice as large as the variation in out-migration rates. In this paper, I explain this as a consequence of the sensitivity of internal migration to shocks at destination, making flows towards a particular place very reactive to shocks in that place.

2.3.2 Empirical evidence

Given that equation 2.2 is an exact decomposition, we can measure how much of the variance in population growth rates is explained by in-migration rates and how much by out-migration rates. In equations, we can run the following two regressions:

$$\frac{I_{m,t}}{N_{m-1,t}} = \alpha_1 + \beta_1 \frac{N_{m,t} - N_{m,t-1}}{N_{m-1,t}} + \delta_m + \delta_t + \varepsilon_{m,t} \tag{2.3}$$

$$\frac{O_{m,t}}{N_{m-1,t}} = \alpha_2 - \beta_2 \frac{N_{m,t} - N_{m,t-1}}{N_{m-1,t}} + \delta_m + \delta_t + \epsilon_{m,t} \tag{2.4}$$

In this situation, it is necessarily the case that $\beta_1 + \beta_2 = 1$. β_1 is then the share of the variation explained by variation in in-migration rates while β_2 is the share explained by variation in out-migration rates.

Table 6 shows the results from using these decompositions. Across a number of specifications and datasets, the message is clear: most variation in population growth rates, generally above 70 percent (and many times even above 90 percent), is explained by variation in in-migration rates rather than variation in out-migration rates.

In panel A, I show these decompositions at the metropolitan level. We observe that cities grow (or decline) mainly because they have disproportionately high (or low) in-migration rates. This is true for each of the decades considered independently, i.e. 1980 to 2000, as well as when pooling all of the data together as in Table 6.[11] My preferred specification is the one shown in columns (5) and (6) where I include metropolitan area fixed effects that account for systematic differences in levels of in- and out-migration rates across metropolitan areas, and time fixed effects that account for possible shocks to internal migration at the national level in the given year (such as different moments of the business cycle). This specification suggests that in-migration accounts for more than 80 percent of the variation of population growth rates across metropolitan areas.

The fact that definitions of metropolitan area vary slightly across decades, drives the computation of the exact same decomposition but at the state level using data from the 1970 to the 2000 US Census. The advantage here is that state borders do not change across decades, so state in- and out-migration rates can be computed more reliably and more consistently across decades. This is shown in Panel B of the same Table 6. The picture is virtually the same. Again, in my preferred specification, over 70 percent of the variation in population growth rates across states is accounted for by variation in in-migration rates.

Panel C in Table 6 investigates whether these results are sensitive to the frequency of the data used. Although regressions using the Great Recession suggest that in-migration rates tend to respond more, this result should also be found using CPS data, and in a much larger time series (1981-2012). In this case, I present internal migration at the regional level. This is due to the fact that there are some small states in the US for which the computation of migration rates is less reliable, due to a lack of individual level movers in some years. The results are, again, very similar. In my preferred specification, we observe how almost 70 percent of the variation in population growth rates is accounted for by variation in in-migration rates.

[Table 6 goes here]

[11] In fact, when considering each decade on a separate regression, the coefficients on in-migration are always above .9. It is also worth noting that there are some metropolitan areas for which out-migration rates cannot be computed and some that did not exist in the 1980 Census. I consequently dropped these metropolitan areas, leaving a total of 148 metropolitan areas.

In sum, most of the internal migration adjustments take place through change in in-migration rate patterns. In what follows I build a model around this stylized fact.

3 Model

In this section, I introduce the model that builds on the above stylized fact and guides the analysis of the potential long run effects of the Great Recession across metropolitan areas when only internal migration helps to dissipate local shocks. I show the quantitative predictions of this model calibrated to the US economy in the final section of the paper.

Two features of the model are crucial. First, congestion forces need to be stronger than agglomeration forces. This is attained in the model by having congestion in the local labor market (i.e. local labor demands in the various locations are downward sloping), guaranteeing the existence of an equilibrium. This simply means that if more workers move to a particular location, wages and thus the value of that location, decrease on impact. Second, workers are continually deciding where to live in the following period by considering current and future conditions in each location. This creates a constant flow of workers across locations who react to unexpected local shocks in particular places. In other words, this generates population dynamics.

The model has M regions – which can be thought of as metropolitan areas. There is a single final consumption good that is freely traded across regions, at no cost.[12] There is a fixed factor of production, called land, that makes the local labor demand downward sloping. Workers live for an infinite number of periods. At each given point in time, they reside in a particular location m. Unexpected permanent shocks that affect the local labor market conditions in each location can occur. Workers can then decide whether to stay or move elsewhere in the following period, taking into account the current and future state of the economy in each local labor market.[13]

In what follows, I start by describing the general model. I then present further results derived from imposing some structure on the location choice part of the model.

3.1 Basic setup

3.1.1 Timing

The timing of the model is as follows. At the beginning of each period, an unexpected permanent shock can happen in a location. Next, given the current distribution of workers across locations,

[12] This assumption can be relaxed by introducing a static model of trade.

[13] Caliendo et al. (2015) introduce a model similar to the one presented in this paper. They cannot, however, capture the divergence in the response of in- and out-migration rates to local shocks. Moreover, while they provide a very nice method for solving the model in first differences, their model is too complicated to be solved in levels. The model presented here makes some simplifications in terms of migration patterns but is much richer in capturing migration responses to shocks. It also results in simpler population dynamics that are easier to analyze.

firms maximize profits and wages are determined. Lastly, given current and future wages in the economy and an i.i.d. idiosyncratic taste shock, workers decide where to live.

3.1.2 Production function

The production function is the same in all regions. Each region has a perfectly competitive representative firm producing according to:

$$Q_m = B_m^{\rho}[\theta_m K_m^{\rho} + (1-\theta_m)N_m^{\rho}]^{1/\rho} \tag{3.1}$$

where N_m is labor or population and K_m is land. θ_m represents the different weights or factor specific productivities of the two factors in the production function, while ρ governs the elasticity of substitution between these factors. B_m^{ρ} is the Total Factor Productivity (TFP) of each location. Only ρ is assumed to be the same across local labor markets.

3.1.3 Labor market

For simplicity, I assume that the labor market is perfectly competitive and workers inelastically supply all their labor in the location where they reside.[14] Thus the labor market is determined by firms' behavior:

$$w_m = p_m(1-\theta_m)B_m Q_m^{\frac{1}{\sigma}} N_m^{\frac{-1}{\sigma}}$$

where $\sigma = 1/(1-\rho)$ is the elasticity of substitution between labor and land. This defines the labor demand curve. We can normalize $p_m = 1$.[15] Free trade will guarantee that prices are the same across regions. We can re-express the labor demand curve as:

$$\ln w_m = \ln(1-\theta_m) + \ln B_m + \frac{1}{\sigma}\ln Q_m - \frac{1}{\sigma}\ln N_m \tag{3.2}$$

More generally, we can define the inverse of the labor demand elasticity as:

$$\frac{\partial \ln w_m}{\partial \ln N_m} = -\frac{1}{\sigma}(1 - \frac{1}{Q_m^{\frac{\sigma-1}{\sigma}} N_m^{\frac{1}{\sigma}}}) = -\varepsilon_m^D$$

This is the source of congestion forces in this model. There are other ways to model congestion forces such as including a housing market, competition for land, or a non-tradable sector that defines a local price index.[16] However, only the strength of all the combined congestion forces (if there were more than one) matters for (most of) the results presented in this paper.

[14] It is easy to introduce search and matching frictions, which I do in the appendix.

[15] It is also possible to introduce more realistic models of internal trade. I discuss this point in Appendix B.2.

[16] If the local price index of the non-tradable sector depends negatively (resp. positively) on the size of the local market then this is an additional congestion (resp. agglomeration) force.

3.1.4 Location choice

The indirect utility of workers who live in m and are considering moving to m' is given by the local wage $w_{m'}$, the amenities $A_{m'}$, the continuation value of living in m' in the following period, and the idiosyncratic draw they get for location m' given that they live in m:

$$v^i_{t,m,m'} = \ln V_{t,m'} + \epsilon^i_{t,m,m'} = \ln A_{m'} + \ln w_{t,m'} + \beta \mathrm{E}_t\{\ln V_{t+1,m'}\} + \epsilon^i_{t,m,m'}$$

Note that the indirect utility has a component common to all workers ($\ln V_{t,m'}$) that depends on variables at destination – in the current and future periods – and an idiosyncratic component $\epsilon^i_{t,m,m'}$ specific to each worker and her current residence.

Thus, for each period workers maximize:

$$\max_{m' \in M} \{\ln V_{t,m'} + \epsilon^i_{t,m,m'}\}$$

The general solution to this maximization problem gives the probability that an individual i residing in location m moves to m', given current and future wages and valuations of amenities $\mathbf{A}$, $\mathbf{w}_t$ in each location:[17]

$$p^i_{t,m,m'} = p_{m,m'}(\mathbf{A}, \mathbf{w}_t)$$

This shapes the flows of workers across locations. By the law of large numbers we can obtain the flow of people between m and m':

$$P_{t,m,m'} = p_{m,m'}(\mathbf{A}, \mathbf{w}_t) * N_{t,m} \tag{3.3}$$

where $N_{t,m}$ is the population residing in m at time t. Note that this defines a matrix that represents the flows of people between any two locations in the economy. I later make assumptions that help to parametrize this matrix and thus reduce the dimensionality of the characterization of the migration patterns.

It is worth emphasizing that this determines the flows of workers, not the final distribution in each location. This is not typical in static spatial equilibrium models, but it means that the model presented here is dynamic and not static.

Finally, note that as long as the support of ϵ is unbounded, the flows of workers between any two locations are always positive. This is line with migration patterns in the United States and cannot be captured by static spatial equilibrium models.

[17] I use bold to denote the vector of all the locations in the economy. Generally, flows of workers between two locations depend on the entire vector of amenities and wages in all of the locations. I later make simplifying assumptions to obtain tractable functional forms.

3.1.5 Dynamics

By definition, the number of individuals in m at time t is the number of individuals who were living in that location – possibly multiplied by the natural growth rate n_m which I assume here to be 0 – plus those who arrive minus those who leave:

$$N_{t+1,m} = N_{t,m} + I_{t,m} - O_{t,m}$$

Thus, internal relocation can take place through either in-migration or through out-migration. We can use the definition of the flow of people across locations to define in- and out-migration in each location:

$$I_{t,m} = \sum_{j \neq m} P_{t,j,m}$$

$$O_{t,m} = \sum_{j \neq m} P_{t,m,j}$$

$$N_{t+1,m} = \sum_{j} P_{t,j,mz}$$

This notation is useful for the derivation of a number of results.

3.1.6 Equilibrium

The definition of the equilibrium has two parts. I start by defining the equilibrium in the short run. It satisfies two conditions. First, firms take as given productivity B_m andthe productivity of each factor θ_m, and factor prices in each location to maximize profits. Second, labor markets clear in each location. This equates the supply and the demand for labor and determines wages in each local labor market. More formally:

Definition I. *A short-run equilibrium is defined by the following decisions:*

- *Given* $\{\theta_m, B_m, K_m, \sigma, w_{t,m}, r_{t,m}\}_{m \in M}$ *firms maximize profits.*
- *Labor and land markets clear in each* $m \in M$ *so that* $\{w_{t,m}, r_{t,m}\}$ *is determined.*

Note that in the short run, the two factors of production are fixed. Thus, changes in technologies or factor quantities directly affect prices. At the end of each period relocation takes place, determining the distribution of workers across space in the following and subsequent periods. We can define the long-run equilibrium by adding an extra condition to the short run definition. In words, the economy is in long run equilibrium when the distribution of workers across locations is stable. More specifically,

Definition II. *Given* $\{\theta_m, B_m, K_m, \sigma, A_m\}_{m \in M}$*, a long run equilibrium is defined as a short run equilibrium with a stable distribution of workers across space, i.e. with* $N_{t+1,m} = N_{t,m}$ *for all* $m \in M$*.*

3.2 Mobility, propagation of local shocks, and welfare

3.2.1 A structural model of mobility

To bring the model to the data, reduce the dimensionality of the migration matrix previously discussed, and derive further properties, I assume that the distribution of the idiosyncratic taste shocks is a nested logit. At the individual level, this means that the home location will be more likely to have a higher draw than any other destination. At the aggregate level, it will appear that a representative worker decides as follows: first, whether to stay in m or look for new destination away from m; second, conditional on moving away from m, where to go given all the possible destinations. Figure 1 shows this nested structure.

[Figure 1 goes here]

The key feature of the model is that this nesting structure makes the home location special relative to all other locations. This is attained through modeling the location choice decision, and not through the fixed costs of moving, as other papers have done. In Appendix D I compare these two modeling strategies. Not having fixed costs of moving simplifies the derivation of some results and the estimation and calibration of the model to the data. This is particularly important given the difficulty of combining forward looking migration decisions and spatial general equilibrium models (see for instance Kennan and Walker (2011) and subsequent literature).

This decision structure results in a closed form solution for the probability of an individual moving from m to m'. As such, we can write the bilateral flows between any two locations as follows:

$$P_{t,m,m'} = N_{t,m}\eta_{t,m}\frac{V_{t,m'}^{1/\lambda}}{\sum_{j \in M} V_{t,j}^{1/\lambda}} \tag{3.4}$$

where $N_{t,m}$ is the population in m at time t, $\eta_{t,m}$ is the fraction of people in m that (endogenously) consider relocating and λ is the inverse of the elasticity of substitution between different nodes in the second nest (when people decide where to move). Lower values of λ make people more sensitive to the local economic conditions at destination.

The expected value of relocating, conditional on relocating, is given by:

$$\ln V_t = \lambda \ln \sum_{j \in M} V_{t,j}^{1/\lambda}$$

while the share of people that decide to relocate is be given by:[18]

$$\eta_{t,m} = \frac{V_t^{1/\gamma}}{V_{t,m}^{1/\gamma} + V_t^{1/\gamma}}$$

where γ is the inverse of the elasticity of substitution in the upper nest, i.e. between staying or leaving the original location. I assume that $\lambda < \gamma$, i.e. that the elasticity of substitution within the lower nest is larger than that of the upper one. This expression simply says that if current and future economic conditions elsewhere (V_t) are good or current and future economic conditions in m ($V_{t,m}$) are bad, a higher fraction of the population in m will try to look for a new destination.

It is useful to think what happens in the limiting cases when $\frac{1}{\gamma} \to \frac{1}{\lambda}$ and $\frac{1}{\gamma} \to 0$. When $\frac{1}{\gamma} \to \frac{1}{\lambda}$ staying in the original location ceases to play a special role. In turn this implies that, in equilibrium, almost everyone in each location will be switching locations at each point in time. While this is a possibility, it is at odds with the empirical fact that only a small share of the population (around 5 percent) changes local labor market in a given year. This is also why other papers need to assume fixed costs of moving. All the unobserved reasons that limit movement are explained in these models by the fixed costs of moving.

When $\frac{1}{\gamma} \to 0$ then $\eta_{t,m} \to \frac{1}{2}$. This means that in each period half of the population in a given location considers whether they want to relocate, while the other half stays no matter what happens in the current location. This might be unrealistic, since we would expect that if things were quite bad, a higher share of the population would leave their location in a given period. It remains, however, an empirical question. It may similarly be unrealistic because if half of the population does decide on a future location (and locations are more or less equal in terms of expected utility) and there are M locations, then, in equilibrium, only a fraction $\frac{1}{2}(1 + \frac{1}{M})$ would stay in the same location in each period. This would certainly be much higher than the empirical fact of around 95 percent of the population staying where they are from one year to the next.

A simple intuitive assumption can address this issue. Assuming that the positive draw in the location of origin is $(1 - \eta)/\eta$ times more likely than any other location implies that:

$$\eta_{t,m} = \frac{\eta V_t^{1/\gamma}}{(1 - \eta) V_{t,m}^{1/\gamma} + \eta V_t^{1/\gamma}} \tag{3.5}$$

In terms of the decision tree described in Figure 1, this extra assumption simply means that the upper nest takes place with probability η and the lower one with probability $1 - \eta$, with $0 < \eta < 1$. In this case, when $\frac{1}{\gamma} \to 0$ we have $\eta_{t,m} \to \eta$, so only a fraction η looks for a new destination. Or

[18] In the next equation, I make the share that decide to relocate more realistic.

conversely, a fraction $1-\eta$ always decides to stay in the location of origin, no matter what the economic conditions in the various other places are. The fact that in equilibrium only 5 percent relocate each year would imply that η is around 0.05, something that I discuss further when I calibrate the model.

3.2.2 Solving the model

Under these assumptions, obtaining the expected continuation value in each location is straightforward:

$$E_t(\ln V_{t+1,m'}) = \gamma \ln[(1-\eta)V_{t+1,m'}^{1/\gamma} + \eta V_{t+1}^{1/\gamma}]$$

Using this, we can express the value of each location as:

$$\ln V_{t,m'} = \ln A_{m'} + \ln w_{t,m'} + \beta\gamma(\ln[(1-\eta)V_{t+1,m'}^{1/\gamma} + \eta V_{t+1}^{1/\gamma}]) \tag{3.6}$$

This expression says that the value of location m' is the value of its amenities and wages plus a CES aggregate of the value of remaining in m' and the value of moving away from m' discounted by β.

We can solve the model forward and obtain the value of each location in terms of its current and future wages and amenities.[19]

$$\ln V_{t,m'} = \frac{\beta}{1-\beta}\gamma \ln(1-\eta) + \frac{1}{1-\beta}\ln A_{m'} + \sum_{k=0}^{\infty}\beta^k \ln w_{t+k,m'} + \sum_{k=0}^{\infty}\beta^k \ln \nu_{t+k,m'}$$

When $1/\gamma = 0$ we obtain much simpler expressions. In this case, the value of each location can be expressed as:

$$\ln V_{t,m'} = \ln A_{m'} + \ln w_{t,m'} + \beta\eta \ln V_{t+1} + \beta(1-\eta)\ln V_{t+1,m'}$$

which iterating forward can be written as:

$$\ln V_{t,m'} = \frac{1}{1-(1-\eta)\beta}\ln A_{m'} + \sum_{k=0}^{\infty}((1-\eta)\beta)^k \ln w_{t+k,m'} + \beta\eta \sum_{k=0}^{\infty}((1-\eta)\beta)^k \ln V_{t+1}$$

These expressions mean that for $1/\gamma = 0$ the value of a location is the exact discounted sum of the value of its amenities, the current and future value of wages, and the current and future state

[19] See appendix for the derivation. Note that $\ln \nu_{t+k,m'} = \frac{\gamma}{(\eta-1)}(\frac{V_{t+k}}{V_{t+k,m'}})^{1/\gamma}$, which, given that $1-\eta$ is large, is a small residual.

of the economy, all entering separately. The discount factor is $\beta(1-\eta)$, i.e. the individual time discount factor multiplied by the share of people that stay in a location each period.

3.2.3 Mobility and labor relocation

Given this, in what follows I analyze how the population adapts to local shocks. It is convenient to first analyze how the various bilateral flows react when there is an unexpected shock in one of the local labor markets and then aggregate to the relevant locations. When not needed, I omit the time subscript to simplify the notation.

Lemma 1. *If $\epsilon^i_{m,m'}$ are i.i.d. and drawn from a nested logit distribution with shape parameters λ and γ then, in the environment defined by the model, we have that:*

$$\frac{\partial \ln P_{j,m}}{\partial \ln w_m} \approx \frac{1}{1-\beta_m}\frac{1}{\lambda}$$

$$\frac{\partial \ln P_{m,m}}{\partial \ln w_m} \approx \frac{1}{1-\beta_m}(\frac{1}{\lambda} - \frac{1}{\gamma}(1-\eta_m))$$

$$\frac{\partial \ln P_{j,m}}{\partial \ln w_j} \approx \frac{1}{1-\beta_j}(-\frac{1}{\gamma}(1-\eta_j))$$

$$\frac{\partial \ln P_{j,m}}{\partial \ln w_{m'}} \approx 0$$

where $\frac{1}{1-\beta_m} = \frac{\partial \ln V_{t,m}}{\partial \ln w_m} \approx 1 + \beta \frac{\partial \ln V_{t+1,m}}{\partial \ln w_m}(1 - \frac{\eta}{1-\eta}(\frac{V_{t+1}}{V_{t+1,m}})^{1/\gamma})$

Proof. See Appendix.

□

Lemma 1 shows that there will be a first order effect of shocks at a destination that is governed by $1/\lambda$. If a potential destination m increases wages then a larger number of in-migrants from all the other locations will be attracted. Similarly, if wages improve in m, more workers who were living in m will decide to stay in m. To what extent this happens is governed by both $1/\lambda$ and $1/\gamma$. Finally, given the structure of the idiosyncratic taste shocks, economic shocks to a third location will have a negligible impact on the bilateral flows between two locations.

The following proposition discusses to what extent the response of bilateral flows translate into population change. To do so, we begin by discussing the responses of in- and out-migration rates.

Proposition 2. *If $\epsilon^i_{m,m'}$ are i.i.d. and drawn from a nested logit distribution with shape parameters λ and γ then, in the environment defined by the model, we have that:*

1. $\frac{\partial \ln I_m}{\partial \ln w_m} \approx \frac{1}{1-\beta_m}\frac{1}{\lambda}$

2. $\frac{\partial \ln O_m}{\partial \ln w_m} \approx -\frac{1}{1-\beta_m}\frac{1}{\gamma}(1-\eta_m)$

Proof. See Appendix

□

This last proposition can be re-expressed in terms of migration rates, which may be useful for empirical applications.[20]

Corollary 3. *If $\epsilon^i_{m,m'}$ are i.i.d. and drawn from a nested logit distribution with shape parameters λ and γ then, in the environment defined by the model, we have that:*

1. $\frac{\partial (I_m/N_m)}{\partial \ln w_m} \approx \frac{1}{1-\beta_m}\frac{1}{\lambda}\frac{I_m}{N_m}$
2. $\frac{\partial (O_m/N_m)}{\partial \ln w_m} \approx -\frac{1}{1-\beta_m}\frac{1}{\gamma}(1-\eta_m)\frac{O_m}{N_m}$

Proof. See Appendix.

□

Proposition 2 and Corollary 3 show that the responses of in-migration and out-migration rates are respectively governed by two different parameters: $1/\lambda$ and $1/\gamma$. We can use these to obtain population responses.

Proposition 4. *If $\epsilon^i_{m,m'}$ are i.i.d. and drawn from a nested logit distribution with shape parameters λ and γ then, in the environment defined by the model, we have that:*

$$\frac{\partial \ln N'_m}{\partial \ln w_m} \approx \frac{1}{1-\beta_m}\frac{1}{\lambda}\frac{I_m}{N'_m} - \frac{1}{1-\beta_m}\frac{1}{\gamma}(1-\eta_m)\frac{O_m}{N'_m} = \frac{1}{1-\beta_m}\varepsilon^S_m$$

Proof. It is straightforward from the definition of N'_m (i.e. population in the following period) and Proposition 2.[21] □

[20] In- and out-migration rates are usually stationary series that are easier to analyze empirically.

[21] Again, we obtain particularly simple expressions when $1/\gamma = 0$. In this case, we have that:

$$\frac{1}{1-\beta_j} = \frac{\partial \ln V_{t,m}}{\partial \ln w_m} \approx 1 + \beta(1-\eta)\frac{\partial \ln V_{t+1,m}}{\partial \ln w_m}$$

Which we can iterate forward and obtain:

$$\frac{\partial \ln V_{t,m}}{\partial \ln w_m} \approx \sum_{k=0}^{\infty}(\beta(1-\eta))^k + \lim_{k\to\infty}(\beta(1-\eta))^k\frac{\partial \ln V_{t+k,m}}{\partial \ln w_m} = \frac{1}{1-\beta(1-\eta)} \tag{3.7}$$

Thus again obtaining a discount factor reached by combining the time discount factor times the share of people who remain in a location.

3.2.4 The propagation of a local shock

We have seen that if a shock affects labor market conditions in one location, there will consequently be some adjustment. We have also seen that this adjustment can come disproportionately from change in in-migration rates or out-migration rates. This, combined with congestion forces, is the source of spillovers across locations in this model. If the local labor demand is downward sloping, changes in the distribution of people across space will have consequences on wages in non-affected locations. Fewer people will move to the shocked location or more will leave. In either case, the labor supply in that location decreases. Reduced in-migration or increased out-migration translates into an increase in labor supply in the non-affected locations, which tends to equalize wages across locations. For all this to happen, we need downward sloping labor demands in the short run. In this model, this is a consequence of the fixed factor of production.[22]

In fact, one of the main strengths of this model is that, despite the forward looking behavior of the agents and the elements of standard spatial general equilibrium models, this model delivers very simple population dynamics. Using the flows of workers across locations we obtain the following expression:

$$N_{t+1,m'} = (\sum_j P_{t,j,m'}) = \widetilde{\eta}_t \frac{V_{t,m'}^{1/\lambda}}{V_t^{1/\lambda}} N_t + (1 - \eta_{m,t}) N_{t,m'} \tag{3.8}$$

where $\widetilde{\eta}_t = \sum_j \eta_{j,t}\omega_{t,j}$ and $\omega_{t,j} = \frac{N_{t,j}}{N_t}$.

This expression shows that population evolves according to a weighted average between the share of value of location m (relative to the overall value of the economy) and the population already in m. It clearly shows that an increase in the value of a location attracts more people and that movement to a new equilibrium is not instantaneous, as part of the current population is determined by the past number of workers in that location. When $1/\gamma = 0$, η and $\widetilde{\eta}$ are independent of m and t.

The propagation of the shock through wages and population is entirely determined by equation 3.8. To obtain the evolution of wages we simply need to combine equation 3.8 and the labor demand equation 3.2 such that:

$$Q_{t+1,m} w_{t+1,m}^{-\sigma} = \widetilde{\eta}_t \frac{V_{t,m}^{1/\lambda}}{V_t^{1/\lambda}} N_t + (1 - \eta_{t,m}) Q_{t,m} w_{t,m}^{-\sigma} \tag{3.9}$$

This equation shows that a greater value of the current location will tend to depress wages in the following period, as more people will move to that location and thus put downward pressure on future wages. On the contrary, low wages in the current period will tend to recover in subsequent

[22] Note that in spatial equilibrium, it is not possible that the average utility of a city is (always) increasing in population. If that was the case, more people would move until everyone in the country lived in the same city.

periods.

3.2.5 Steady state

In steady state or long run equilibrium, the value of each location remains unchanged, thus for all m, $V_{t,m} = V_{t+1,m}$. With this we can obtain the steady state value of each location:

$$\ln V_m \approx \frac{\beta}{1-\beta}\gamma \ln(1-\eta) + \frac{1}{1-\beta}\ln A_m + \frac{1}{1-\beta}\ln w_m + \gamma\frac{\beta}{1-\beta}\frac{\eta}{1-\eta}(\frac{V}{V_m})^{1/\gamma} \tag{3.10}$$

This expression says that in the long run equilibrium, the value of each location can be expressed in terms of its current wages and amenities.[23]

Furthermore, we can also obtain a very simple expression for the allocation of people across locations. Using 3.8 we obtain :

$$N_m = \frac{V_m^{1/\lambda}}{V^{1/\lambda}}N \tag{3.11}$$

Thus, population is distributed across locations according to the location's share in the total value of the economy.[24]

3.2.6 Long run welfare and population

In this section, I analyze the properties of the model in the long run, i.e. when bilateral flows between regions are equalized. The model shares many of the properties of standard spatial equilibrium models that are typically meant to capture the long run distribution of people across space, but within a dynamic location choice framework (Rosen (1974), Roback (1982), Glaeser (2008)).

It is simple to show that the equilibrium exists and is unique. This is based on the fact that congestion forces dominate, as there are no endogenous agglomeration forces in the model.

Proposition 5. *Given an initial distribution of people across space there is a unique equilibrium.*

Proof. See Appendix. □

[23]For $1/\gamma = 0$ we again obtain a very simple expression for the steady state value of living in each location:

$$\ln V_m = \frac{1}{1-\beta(1-\eta)}\ln A_m + \frac{1}{1-\beta(1-\eta)}\ln w_m + \beta\frac{\eta}{1-\beta(1-\eta)}\ln V$$

[24]Another implication of this result is that in the long run equilibrium, bilateral flow across any two locations are equalized. That is, we have that:

$$P_{t,m,m'} = P_{t,m',m}, \forall m, m' \in M$$

This expression also means that internal migration decreases city size. I show that this is indeed the case in the United States in Table 9 discussed in Appendix A.4.

In this model, workers in large cities need to have, on average, higher equilibrium indirect utilities for the city to sustain its size. To see this we need only to look at equation 3.11.

We can also use equation 3.11 to evaluate long run welfare:

$$\Delta \ln V_{m'} = \lambda \Delta \ln N_{m'} + \Delta \ln V \tag{3.12}$$

This expression shows that the change in welfare between any two long run equilibria is determined by both changes in population,(which are specific to each location) and the overall change in the welfare of the economy (which affects everyone equally, independent of location).

We can use a base location to obtain a very simple expression for the dispersion of changes in welfare across locations:

$$\frac{\Delta \ln V_m - \Delta \ln V_{m'}}{\Delta \ln N_m - \Delta \ln N_{m'}} = \lambda \tag{3.13}$$

This equation is very important. It implies that to evaluate the unobservable long run change in welfare between two time periods in one location (relative to a base location), we need only to compute the change in population and multiply it by λ. Moreover, λ can be easily estimated using variation in the instantaneous response of the in-migration rate to local changes.

We can summarize these results in the following proposition:

Proposition 6. *With the assumptions made, a negative shock to one location induces internal migration that helps to attenuate the labor market consequences of the shock in that location. In the short run, wages in the affected location decrease relative to the rest of the economy and workers in that location loose in terms of welfare and wages relative to other locations. In the long run, wages in said location recover thanks to internal migration but to a lower level, while wages in other non-affected locations are higher than in the affected location in the short run, but then decrease. In the long run, the lost welfare in each location (relative to a baseline location) is proportional to the lost population, where λ is the factor of proportionality.*

4 The economic importance of internal migration

In the sections above, I have shown that the determinant of gains or loses in population in a given location is due more to in-migration than to out-migration. I have also shown that the reaction of in-migration rates to local shocks is much greater than that of out-migration rates. This explains how internal migration helps to dissipate local shocks.

In this section, I investigate quantitatively how these local shocks propagate through local labor markets using a calibrated version of the model introduced above with the parameters estimated in the empirical section. In particular, I study the potential role of internal migration in mitigating negative consequences in the metropolitan areas most affected by the implied local labor demand shocks during the Great Recession in the US, assuming that those become permanent. This quantifies the importance of in-migration rate responses as a mechanism providing insurance against local shocks. The model abstracts from other mechanisms that could also provide insurance against shocks, or from the fact that some of the local labor demand shocks during the Great Recession may have been temporary.

4.1 Model calibration

4.1.1 Internal migration and local labor demand elasticity

There are four key parameters in the model that govern how local shocks spread. The first two have been estimated in the empirical section: the reaction of the in-migration rate (governed by λ) and the out-migration rate (governed by γ) to local shocks. The third key parameter is the local labor demand elasticity (or more generally, the congestion forces). As this parameter is not estimated in this paper, I make several assumptions, showing in Appendix E just how sensitive the results are to this assumption. The fourth parameter is η, which determines the equilibrium internal migration rate in the economy and is computed in the summary statistics Table 1.

Based on my previous research (Monras (2015), Borjas and Monras (2016)), a short run (relative) local labor demand elasticity of -1 is a reasonable parameter. In these papers, we estimate the local labor demand elasticity using (exogenous) migration shocks. Under the assumption that natives and immigrants are perfect substitutes, this is exactly the parameter needed in this paper.

Assuming a (relative) local labor demand elasticity of -1 implies that the production function at the local level is Cobb-Douglas. Other elasticities only change the speed at which local shocks are transmitted. Again, I investigate alternative estimates in Appendix E.

In section 2.2 I estimated that $\partial(\frac{I_m}{N_m})/\partial \ln w_m$ is around 0.2, and $\partial(\frac{O_m}{N_m})/\partial \ln w_m$ is around 0. Thus, $1/\gamma = 0$ and $\frac{1}{1-\beta_m}\frac{1}{\lambda}\frac{I_m}{N_m} = 0.2$. We have seen that I_m/N_m is around 5 percent. We also need to know the other parameters. With $1/\gamma = 0$ we have that $1/(1-\beta_m) = 1/(1-\beta(1-\eta))$. Thus:

$$\frac{1}{\hat{\lambda}} = \frac{0.2}{0.05}(1-\hat{\beta}(1-\hat{\eta}))$$

Hence, we need to know the discount factor, which has been studied at length in the macroeconomics literature, and $1-\eta$ which can be approximated by the share of the population that, on average, stay in a location, i.e. 95 percent. I assume that the discount factor $\beta = .95$ is consistent with an annual interest rate of around 5 percent. This is the same estimate that Kennan and Walker (2011) use. The results are not very sensitive to the discount factor. Lower discount factors, i.e. β close to 1, accelerate the internal migration response. Thus, assuming $\beta = 0.95$ is a rather conservative estimate.

Putting all these together, I obtain an estimate of λ of around 2.56:

$$\frac{1}{\hat{\lambda}} = \frac{0.2}{0.05}(1 - .95 * .95) = 0.39 \Rightarrow \hat{\lambda} = 2.56$$

These parameters govern the migration decisions and the strength of spillovers across locations. We can use the long run equilibrium conditions to obtain the other parameters – which, however, play a minor role in the dynamics studied in the paper.

4.1.2 Technology, amenities, and initial conditions

The rest of the parameters are calibrated to match the US data. When $\sigma = 1$, I obtain θ_m by looking at the share of output that is devoted to labor. I calibrate B_m (the total factor productivity of the city) and the contribution of land.In what follows, I refer to the combination of these two as TFP, or the difference between what is produced and labor's contribution. More specifically I set:[25]

$$\hat{\theta}_m = 1 - \frac{w_m}{Q_m/N_m}$$

And:

$$\widehat{B_m K_m^{\theta_m}} = \frac{Q_m}{N_m} N_m^{\hat{\theta}_m}$$

The parameters that are a bit more challenging to calibrate are the city-specific amenity levels. For these, I use the long run equilibrium condition. Put otherwise, I assume that in 2005 the US economy was in long run spatial equilibrium, i.e. I assume that the distribution of people across space would have remained stable had it not been for the Great Recession.[26] In this case, I observe the average wages and the population levels in all the locations in the US and I infer the amenity levels as the values that make the bilateral flows of workers across locations stable – a necessary and sufficient condition for the model to be in long run equilibrium.[27]

[25] When σ is different from one, then the production function 3.1 is no longer Cobb-Douglas, so I cannot put together the fixed factor and productivity as I do in the Cobb-Douglass case. For $\sigma \neq 1$ I calibrate $\hat{\theta}_m = 1/(1 + \frac{w_m N_m^{1/\sigma}}{Q_m - w_s N_m})$ and $\hat{B}_m = w_m^{-1}(1-\hat{\theta}_m)^{-1} Q_m^{-1/\sigma} N_m^{1/\sigma}$. I use this last calibration for Table 7.

[26] Alternatively, I can assume that the US is in long run spatial equilibrium in any other year, and analyze the effect of the Great Recession on that distribution of population across locations.

[27] To obtain the amenity levels we need to use the long run equilibrium. This is:

$$\frac{N_{0,m}}{N} = (\frac{V_{0,m}}{V_0})^{1/\lambda} = \frac{(A_m w_{0,m})^{\frac{1}{\lambda(1-(1-\eta)\beta))}}}{\sum_j (A_j w_{0,j})^{\frac{1}{\lambda(1-(1-\eta)\beta)}}}$$

which holds for every m. From that we have:

$$\frac{A_m}{A_0} = (\frac{N_{0,m}}{N_{0,0}})^{\lambda(1-(1-\eta)\beta))} \frac{w_{0,0}}{w_{m,0}}$$

Thus, we obtain the value of the amenities in each location relative to a base location.

Assuming that the US is in long run equilibrium also allows me to compute the initial conditions of the dynamic system governed by equations 3.8 and 3.6. More specifically, I obtain the initial values $N_{0,m}$ and $V_{0,m}$ from the 2005 data. $N_{0,m}$ is directly observable in the data and we can use the conditions of the long run equilibrium to obtain $V_{0,m}$. To solve for that we need to use 3.6, which can be re-written as:

$$V_{0,m} = (A_m w_{0,m} V_0^{\eta\beta})^{\frac{1}{1-(1-\eta)\beta}}$$

where $V_0 = (\sum_j V_{0,j}^{1/\lambda})^{\lambda}$. Putting the two together we can solve for V_0:

$$V_0 = [[\sum_j (A_j w_{0,j})^{\frac{1}{\lambda(1-(1-\eta)\beta)}}]^{\lambda(1-(1-\eta)\beta))}]^{1/1-\beta}$$

This equation says that the long run value of the economy is a CES aggregate of the value of each of the locations.

4.1.3 Dynamics

Given the estimates and the calibration of the model, we obtain a simple dynamic system of two equations and two unknowns:

$$N_{t+1,m} = \eta \frac{V_{t,m}^{1/\lambda}}{V_t^{1/\lambda}} N_t + (1-\eta) N_{t,m} \tag{4.1}$$

$$V_{t+1,m} = (A_m w_{t,m})^{\frac{-1}{\beta(1-\eta)}} V_{t,m}^{\frac{1}{\beta(1-\eta)}} V_{t+1}^{\frac{-\eta}{(1-\eta)}} \tag{4.2}$$

where the last equation comes from inverting $V_{t,m} = A_m w_{t,m} (V_{t+1,m}^{1-\eta} V_{t+1}^{\eta})^{\beta}$. The biggest complication to solving this dynamic system is that we have V_{t+1} on the right hand side. We thus again need to use the fact that $V_{t+1} = (\sum_j V_{t+1,j}^{1/\lambda})^{\lambda}$ to obtain:

$$V_{t+1} = [\sum_j [(\frac{V_{t,j}}{A_j w_{t,j}})^{\frac{1}{\beta}}]^{\frac{1}{\lambda(1-\eta)}}]^{\lambda(1-\eta)}$$

We can now use this in the previous equation, obtaining:

$$V_{t+1,m} = (A_m w_{t,m})^{\frac{-1}{\beta(1-\eta)}} V_{t,m}^{\frac{1}{\beta(1-\eta)}} ([\sum_j [(\frac{V_{t,j}}{A_j w_{t,j}})^{\frac{1}{\beta}}]^{\frac{1}{\lambda(1-\eta)}}]^{\lambda(1-\eta)})^{\frac{-\eta}{(1-\eta)}} \tag{4.3}$$

This equation gives the value of $V_{t+1,m}$ exclusively as a function of $V_{t,m}$ and, together with equation 4.1, Equation 3.7, and the initial conditions previously derived, fully characterizes the dynamics of the system.

4.2 The Great Recession shock and the role of internal migration

With all these parameters in hand, I can simulate the model. One way to think about the Great Recession is to assume that it caused a permanent loss in the TFP of cities of various magnitudes. This might mean for example, the functioning of the financial systems in these different localities, or the importance of particular sectors more affected by the crisis. This change in TFP is, however, unobservable. It can only be predicted from the wage equations used in the first stage of section 2.2. In other words, we can compare the predicted wages in 2005 with those of 2010, assume that population levels are stable throughout this period, and infer the TFP in 2010 so as to justify the predicted wages in 2010. This is how I obtain levels of TFP that in turn cause certain cities to be more affected than others by the Great Recession in 2010. I can then feed these values back into the model and obtain the new long run equilibrium and the full transition dynamics for wage and population levels consistent with the actual internal migration responses observed in the data.

It is worth emphasizing that the model provides the effect of internal migration on wages and population levels across locations if nothing else was changing in the economy. In this respect, it isolates the contribution of internal migration to the mitigation of wage decreases in the most affected locations. Other mechanisms, such as technology adoption or trade could potentially contribute to convergence in welfare across locations.

The top panel of Figure 2 shows the evolution of wages in two representative cities: New York and Las Vegas. Las Vegas was the city most affected during the Great Recession. Given high levels of household indebtedness and the importance of its service sector, predicted wages dropped by almost 15 percent. In contrast, New York City was affected by the Great Recession but at a level similar to the rest of the nation, if not slightly less. When the Great Recession hit, labelled as year 0 in the figure, wages dropped in every city, but they dropped disproportionately in cities like Las Vegas. After the shock, internal migration started to dissipate the shock across space. This meant that wages in Las Vegas recovered, while wages in New York dropped a little further. This is the process of wage convergence following the endogenous internal migration response.

Within 10 years, the economy had already almost reached a new steady state and a part of the initial shock had dissipated across space thanks to internal migration. If congestion forces were larger than those used in the calibration of this model, convergence would have been faster. Similarly, if the share of internal migrants in equilibrium had been larger or the response of internal migration to local shocks had been stronger, convergence would have been faster as well.

[Figure 2 goes here]

The lower part of Figure 2 shows how the evolution of wages shaped the evolution of the population. We see that in Las Vegas, wages dropped more than the national average and thus fewer people were attracted towards this city. This consequently decreased the city's population and partially mitigated the negative consequences of the crisis. The mechanism through which this occurred was, in this calibration, exclusively through reduced in-migration. This is shown in Figure 3.

[Figure 3 goes here]

Its apparent in Figure 2 that while wages recovered in the most affected locations, they did so to a lower levelthan the wage levels of the less affected locations. Thus, internal migration offered insurance to local shocks, but only partially. It is thus of great interest to evaluate to what extent the initial shock actually translated into permanent welfare losses at the local level. I investigate this question in the following section.

4.3 Welfare evaluation

The model provides a simple way to compute long run change in welfare across metropolitan areas resulting from the implied TFP loss during the Great Recession, while also taking into account all the endogenous migration responses. For this computation, we need only to know the long run population loss across metropolitan areas implied by the quantitative model and multiply the latter by the estimated parameter λ. That is, we can use:

$$\frac{\Delta \ln V_m - \Delta \ln V_{m'}}{\Delta \ln N_m - \Delta \ln N_{m'}} = \hat{\lambda}$$

By taking the median city in terms of population change implied by the model, we can plot the estimated change in welfare against measures of how hard the crisis affected a particular location.[28] This is done in Figure 4 using the debt to income ratio interacted with the share of non-tradable employment and with the initial drop in wages.

[Figure 4 goes here]

The top panel of Figure 4 shows that there is a tight negative correlation between change in welfare and a measure of how hard the crisis hit different metropolitan areas. This means that the shock has some persistence over time, even when internal migration is taken into account. The

[28] I consider only measures of relative welfare, as I can only obtain welfare measures relative to the value of amenities in a base location. It is difficult to know the value of amenities in this base location,and thus, hard to know the value of absolute welfare.

magnitude is easier to understand by comparing the initial drop in wages with long run change in welfare. The bottom part of Figure 4 plots the following regression:

$$\Delta^{2020-2005} \ln \mathrm{V}_m = \alpha + \beta \Delta^{2010-2005} \ln w_m + \varepsilon_m$$

The estimate of β translates initial wage drops into long-term consequences.[29] If $\beta = 1$ then the initial drop translates one for one into long run welfare change. Instead, $\beta = 0$ means that internal migration completely insures against local shocks. The fact that β is around .4 means that around 60 percent of the initial drop in wages are effectively dissipated (in terms of welfare) over time. This suggests that internal migration plays an important role.

5 Conclusion

This paper develops a parsimonious dynamic model with multiple locations in order to evaluate the speed of convergence and welfare consequences of shocks that affect different locations of an economy with different intensity.

The model is built to accommodate a very prevalent feature of internal migration in the United States: in-migration rates are more responsive to local shocks than out-migration rates. To capture this novel stylized fact, the model allows for the flows across any two locations to be decomposed between the share of workers who relocate and, among those, the share who choose each destination. This simple decomposition makes the study of population and wage dynamics much simpler than in prior work, even when agents are forward looking and when we consider key features of standard spatial equilibrium models. This modelling strategy can in fact be used in other settings where state variables evolve parsimoniously, such as prices in the sticky price literature.

Finally, I use the model to evaluate the long run consequences of the Great Recession across metropolitan areas. The model-based estimates suggest that the response of internal migration observed in the data can significantly dissipate initial local wage drops. Up to 60 percent of the initial wage shock is potentially dissipated across metropolitan areas in terms of welfare thanks to internal migration alone. Moreover, the convergence to the new equilibrium is reasonably fast. Tenable calibrations of the model suggest that the new steady state is reached within ten years of the initial shock.

[29] In a static model without other sources of income, wages determine the level of indirect utility, making the latter a nice benchmark to compare to with long-run welfare changes.

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6 Figures

Figure 1: Migration decision from an aggregate perspective

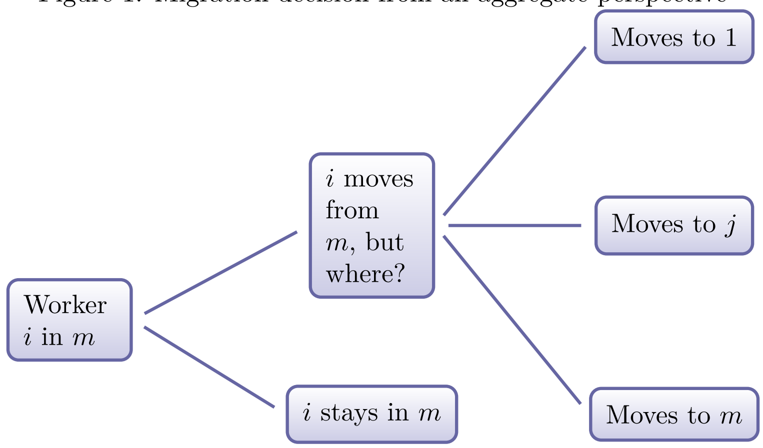
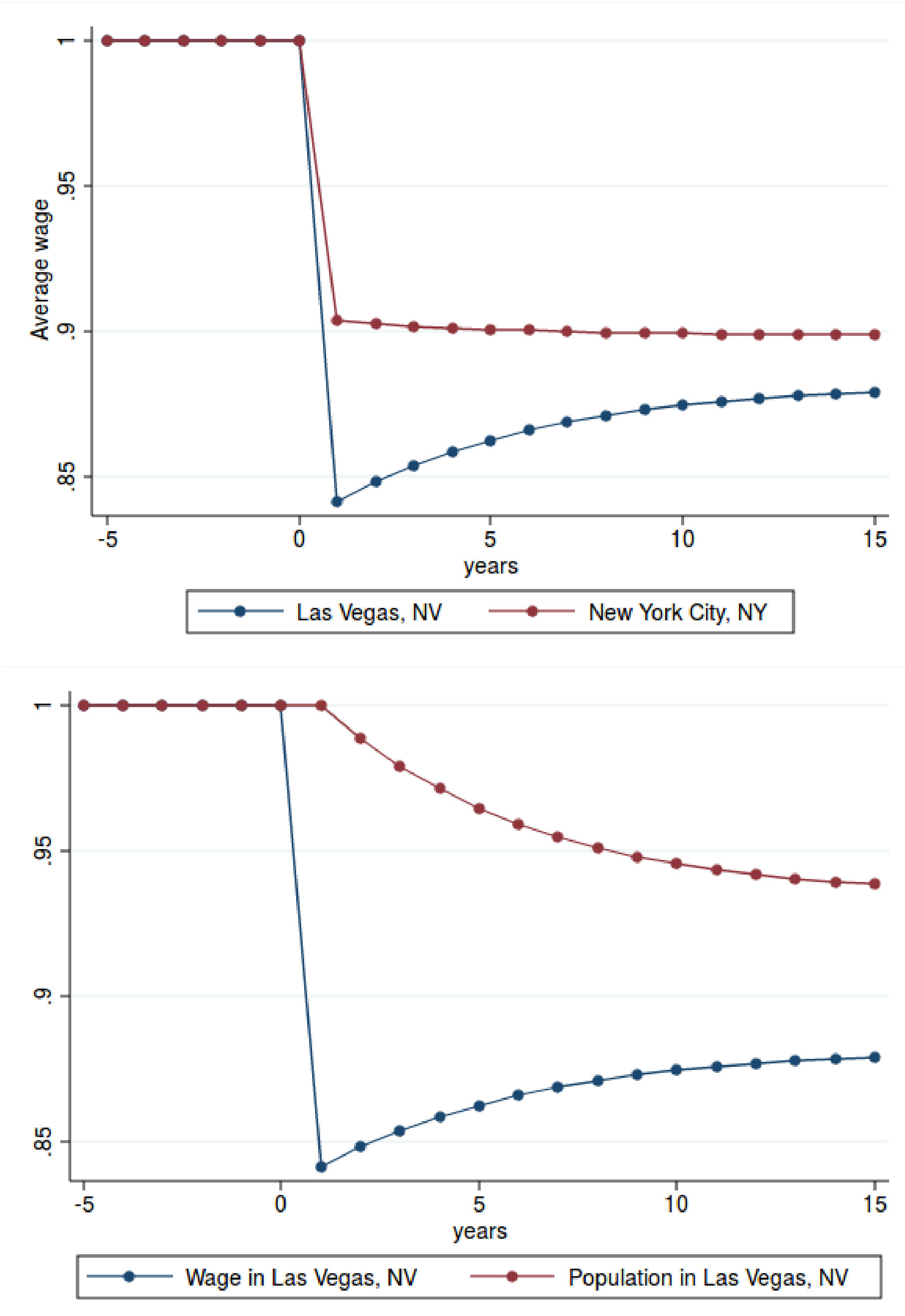
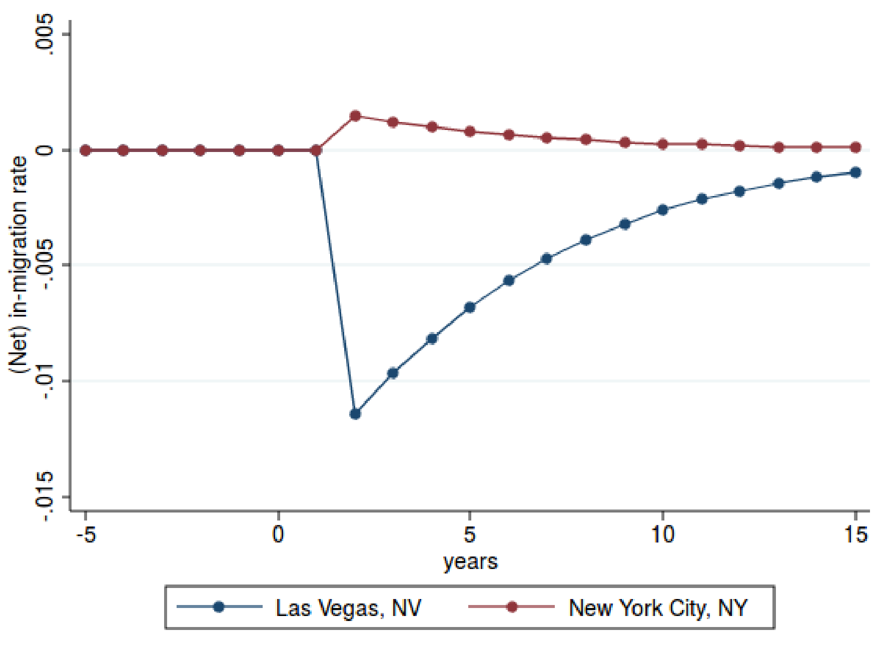


Figure 2: The evolution of the wages and population in the model, selected metropolitan areas



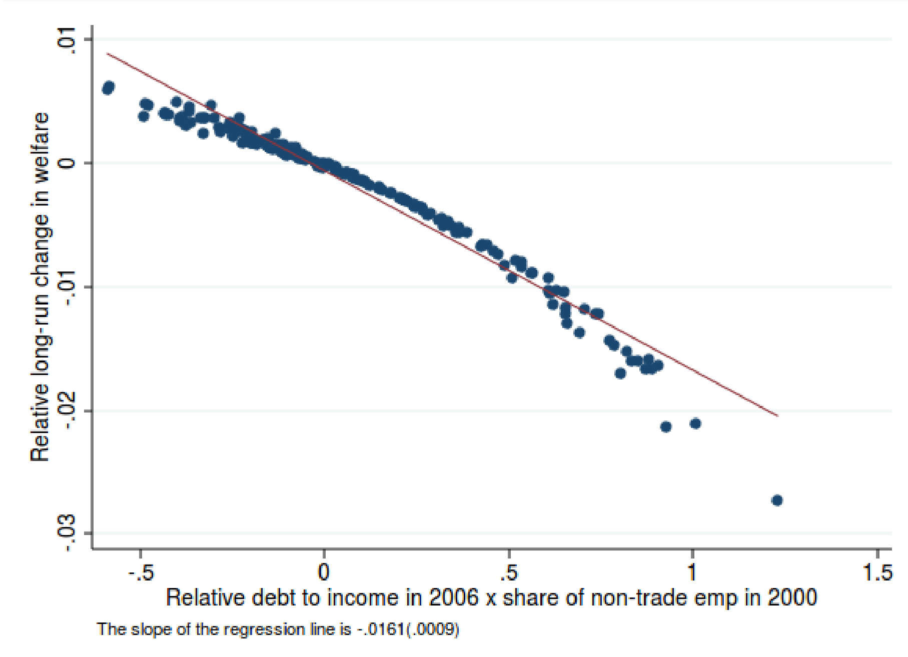
Notes: This graph shows the evolution of wages and population in a number of cities according to the model calibrated to match the implied productivity loss during the Great Recession. See more details in the text.

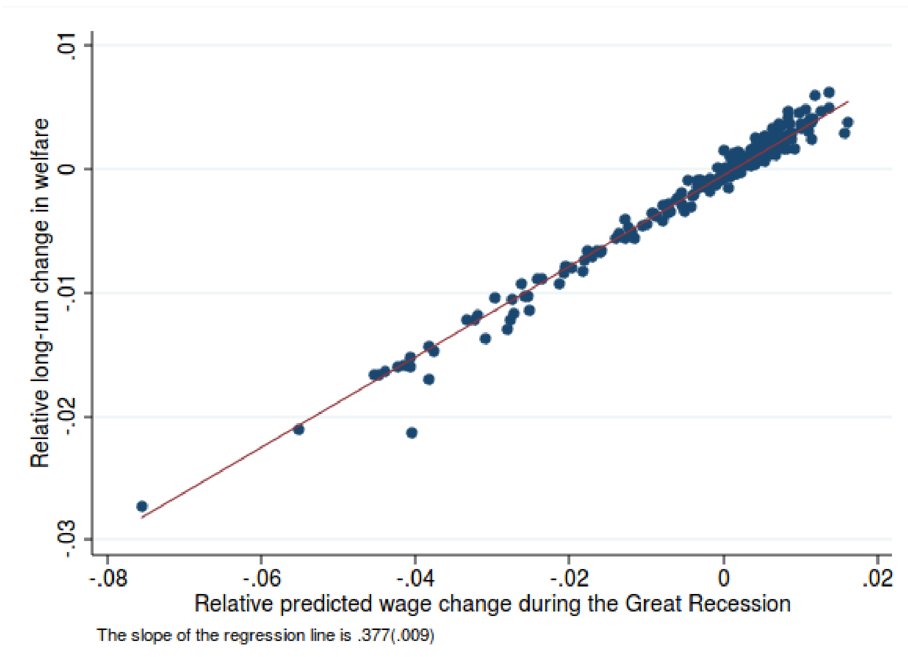
Figure 3: The evolution of the in-migration rate in the model, selected metropolitan areas



Notes: This graph shows the evolution of the in-migration rate in a number of cities according to the model calibrated to match the implied productivity loss during the Great Recession. See more details in the text.

Figure 4: The change in long-run welfare as a result of the Great Recession shock





Notes: This graph shows the change in welfare against a measure of the initial shock across metropolitan areas.

7 Tables

Table 1: Summary statistics, period 2005-2010

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Debt to Income, 2006	1.977	0.595	0.865	3.784
Share of emp. in non-tradable sectors, 2000	0.221	0.032	0.163	0.432
Non-trade emp x Debt to Income	0.442	0.172	0.201	1.236
Years 2005-2006				
Total population	2,150,467	2,604,588	51,253	10,028,307
Sample size	4087.606	3921.324	124	15235
Average weekly wages	377.48	51.447	238.739	605.967
Unemployment rate	0.049	0.013	0.004	0.118
Employment rate	0.845	0.028	0.697	0.931
In-migration rate	0.054	0.019	0.006	0.126
Out-migration rate	0.053	0.019	0.005	0.259
Net in-migration rate	0.001	0.017	-0.2	0.093
Years 2007-2010				
Total population	2,233,383	2,679,241	47,997	10,176,648
Sample size	4051.202	3975.764	91	15362
Average weekly wages	357.875	51.535	209.414	580.365
Unemployment rate	0.071	0.029	0.008	0.172
Employment rate	0.834	0.039	0.635	0.947
In-migration rate	0.048	0.016	0	0.15
Out-migration rate	0.047	0.015	0.004	0.159
Net in-migration rate	0	0.009	-0.063	0.09

Notes: this table reports summary statistics for all the variables used in the regression analysis. All the summary statistics are computed using weighted averages across all 210 metropolitan areas. Sources: American Community Survey, 2005-2010, Mian et al. (2013), and 2000 US Census.

Table 2: Summary statistics: migration rates

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Metropolitan area migration				
	Pooled Censuses 1980-2000			
In-migration rate	0.177	0.083	0.065	0.618
Out-migration rate	0.175	0.043	0.049	0.433
	2000 Census			
In-migration rate	0.168	0.073	0.079	0.618
Out-migration rate	0.168	0.039	0.049	0.395
	1990 Census			
In-migration rate	0.187	0.09	0.069	0.466
Out-migration rate	0.183	0.045	0.113	0.433
	1980 Census			
In-migration rate	0.177	0.099	0.065	0.578
Out-migration rate	0.182	0.049	0.116	0.426
State migration				
	Pooled Censuses 1980-2000			
In-migration rate	0.114	0.053	0.046	0.645
Out-migration rate	0.11	0.03	0.074	0.419
	2000 Census			
In-migration rate	0.105	0.046	0.056	0.335
Out-migration rate	0.104	0.026	0.074	0.345
	1990 Census			
In-migration rate	0.114	0.052	0.055	0.385
Out-migration rate	0.113	0.033	0.077	0.321
	1980 Census			
In-migration rate	0.118	0.06	0.046	0.437
Out-migration rate	0.116	0.031	0.081	0.339
Regional migration				
	Pooled CPS 1982-2013			
In-migration rate	0.025	0.013	0.007	0.077
Out-migration rate	0.025	0.011	0.009	0.071

Notes: this table reports summary statistics for internal migration across metropolitan areas, states, and Census regions. Sources: US Censuses 1970 - 2000 and CPS 1982-2013. CPS data does not report migration decisions for 1985 and 1995. I use 148 metropolitan areas, 50 states plus DC, and 9 Census regions. With the US Census, it is possible to compute 5 year migration rates, while the CPS reports yearly migration.

Table 3: First stage and reduced form: household debt and the local consumption channel on employment and wages

Panel A: First Stage

VARIABLES	(1) Wages OLS	(2) Wages OLS	(3) Unemployment OLS	(4) Unemployment OLS	(5) Employment OLS	(6) Employment OLS
Debt to income x Post	-0.0174***		0.0120***		-0.0101***	
	(0.00374)		(0.00247)		(0.00290)	
Debt to income x Share non-trade x Post		-0.0726***		0.0453***		-0.0400***
		(0.0122)		(0.00917)		(0.00980)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes

Panel B: Reduced Form

VARIABLES	(1) Net migration OLS	(2) Net migration OLS	(3) In migration OLS	(4) In migration OLS	(5) Out migration OLS	(6) Out migration OLS
Debt to income x Post	-0.00328		-0.00378**		-0.000803	
	(0.00247)		(0.00159)		(0.00120)	
Debt to income x Share non-trade x Post		-0.0148**		-0.0160***		-0.00212
		(0.00704)		(0.00514)		(0.00349)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes

Notes: Panel A: The dependent variables are the average (log) wages, the employment and the unemployment rate in 2,010 metropolitan areas between 2005-2010. Panel B: The dependent variables are the net in-migration, the in-migration, and the out-migration rates in 2,010 metropolitan areas between 2005-2010. Regressions are weighted by the number of observations in each metropolitan area. 'Debt to Income' refers to the average debt to income ratio of households in the metropolitan area in 2006. 'Share non-trade' refers to the share of employment in non-tradable sectors in 2000, computed using 2000 US Census data. Number of observations: 210 metropolitan areas x 6 years = 1,260. Robust standard errors reported. * p<.1, ** p<.05 and *** p<.001.

Table 4: Migration response to the crisis: net in-migration rates

VARIABLES	(1) Net migration IV1	(2) Net migration IV2	(3) Net migration IV1	(4) Net migration IV2	(5) Net migration IV1	(6) Net migration IV2
(log) Weekly Wages	0.188**	0.205***				
	(0.0843)	(0.0640)				
Unemployment rate			-0.273***	-0.328***		
			(0.0990)	(0.0822)		
Employment rate					0.325***	0.371***
					(0.116)	(0.0936)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes
widstat	30.50	37.71	65.08	63.43	31.18	40.66

Notes: The dependent variable is the net in-migration rate in 2,010 metropolitan areas between 2005-2010. Regressions are weighted by the number of observations in each metropolitan area. ‘IV1’ refers to the interaction of the ‘Debt to Income’ ratio and a ‘Post’ 2007 dummy. ‘IV2’ refers to the interaction of the ‘Debt to Income’ ratio, the share of non-tradable employment,and a ‘Post’ 2007 dummy, see more details in Table 3. Number of observations: 210 metropolitan areas x 6 years = 1260. Robust standard errors reported. * p<.1, ** p<.05 and *** p<.001.

Table 5: Migration response to the crisis: in- and out-migration rates

Panel A: In-migration rates

VARIABLES	(1) In migration IV1	(2) In migration IV2	(3) In migration IV1	(4) In migration IV2	(5) In migration IV1	(6) In migration IV2
(log) Weekly Wages	0.217***	0.221***				
	(0.0593)	(0.0465)				
Unemployment rate			-0.315***	-0.354***		
			(0.0612)	(0.0563)		
Employment rate					0.374***	0.401***
					(0.0750)	(0.0668)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes
widstat	30.50	37.71	65.08	63.43	31.18	40.66

Panel B: Out-migration rates

VARIABLES	(1) Out migration IV1	(2) Out migration IV2	(3) Out migration IV1	(4) Out migration IV2	(5) Out migration IV1	(6) Out migration IV2
(log) Weekly Wages	0.0461	0.0293				
	(0.0443)	(0.0298)				
Unemployment rate			-0.0669	-0.0469		
			(0.0674)	(0.0498)		
Employment rate					0.0794	0.0531
					(0.0811)	(0.0568)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes
widstat	30.50	37.71	65.08	63.43	31.18	40.66

Notes: The dependent variable is the in-migration rate and the out-migration rate in 2,010 metropolitan areas between 2005-2010. Regressions are weighted by the number of observations in each metropolitan area. 'IV1' refers to the interaction of the 'Debt to Income' ratio and a 'Post' 2007 dummy. 'IV2' refers to the interaction of the 'Debt to Income' ratio, the share of non-tradable employment, and a 'Post' 2007 dummy, see more details in Table 3. Number of observations: 210 metropolitan areas x 6 years = 1260. Robust standard errors reported. * p<.1, ** p<.05 and *** p<.001.

Table 6: In- migration, out-migration and population growth

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Census data, metropolitan-level variation						
	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration rate	Out-migration rate	In-migration rate	Out-migration rate	In-migration rate	Out-migration rate
Population growth rate	1.099***	0.0985*	0.861***	-0.139**	0.829***	-0.171***
	(0.0542)	(0.0542)	(0.0617)	(0.0617)	(0.0432)	(0.0432)
Observations	444	444	444	444	444	444
R-squared	0.739	0.022	0.975	0.905	0.986	0.946
Panel B: Census data, state-level variation						
	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration rate	Out-migration rate	In-migration rate	Out-migration rate	In-migration rate	Out-migration rate
Population growth rate	1.044***	0.0440	0.857***	-0.143*	0.726***	-0.274***
	(0.0722)	(0.0722)	(0.0746)	(0.0746)	(0.0634)	(0.0634)
Observations	204	204	204	204	204	204
R-squared	0.671	0.004	0.964	0.891	0.980	0.939
Panel C: CPS data, regional variation						
	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration rate	Out-migration rate	In-migration rate	Out-migration rate	In-migration rate	Out-migration rate
Population growth rate	1.464***	0.464***	0.820***	-0.180	0.685***	-0.315***
	(0.154)	(0.154)	(0.211)	(0.211)	(0.0863)	(0.0863)
Observations	270	270	270	270	270	270
R-squared	0.340	0.049	0.476	0.246	0.925	0.892
Geography FEs	no	no	yes	yes	yes	yes
Time FEs	no	no	no	no	yes	yes

Notes: These regressions show the decomposition of population growth rates into in-migration rates and out-migration rates. The table shows 3 possible specifications, with various sets of fixed effects, that are presented in columns (1) and (2), (3) and (4), and (5) and (6). The coefficients for every pair of regressions need to add up to one. Panel A uses Census data at the metropolitan area level between 1980 and 2000. Panel B uses Census data at the state level between 1970 and 2000. Panel C uses CPS data at the regional level between 1982 and 2013. Robust standard errors reported. * p<.1, ** p<.05 and *** p<.001.

Appendix, not for publication

A Empirical Evidence

A.1 Event type graphs

[Figure 5 goes here]

A.2 High- and low-skilled workers

Wozniak (2010) emphasizes that high-skilled workers are 5-15 percent more likely to take advantage of good labor market opportunities.[30] Her analysis does not, however, explain how sensitive this decision is when specific locations are hit by a negative shock.

An ideal experiment to answer whether in-migration rates respond differently to changes in local labor market conditions would be to have a shock that affects only one type of workers. In this paper, the selected shock affected both high and low-skilled workers.One can still, however, compare what happens to changes in wages or unemployment rates of specific groups, with changes in the internal migration of these respective groups. In this section I focus on in-migration rates, as all the action comes from this variable. The results are shown in Table 8.

[Table 8 goes here]

Table 8 shows that the internal migration response of low-skilled workers is very similar to that of the average population shown in Table 5. For example, the estimated elasticity of in-migration rates to wages is about 20 percent for the average population while it is around 19 percent for low-skilled workers. Table 8 also shows that this elasticity drops only slightly if we restrict the computation of in-migration rates to native workers. At first glance, this result seems to partially contradict the findings of Cadena and Kovak (2016), a subject that I discuss below.

Table 8 shows that the estimates do not change significantly if we restrict our attention to high-skilled workers. Again the elasticities are similar to those computed in Table 5.

A.3 Explaining some results of the literature

This section explains why the evidence reported in both Mian et al. (2013) and Cadena and Kovak (2016) do not contradict the findings reported herein. I also, however, challenge some of their conclusions.

Explaining Mian et al. (2013)

Mian et al. (2013) argue that people did not respond to the Great Recession by relocating geographically. To support this stance, they regress the population growth rate between 2007 and 2009 on a measure of the debt to income ratio at the county level. They find that population growth and debt to income ratios are not correlated, leading to their conclusion.

[30] Literature reviews on internal migration rates include Greenwood (1997).

To further investigate, I show that their findings do not change when, instead of counties, we use metropolitan areas as the unit of analysis, as seen in Figure 6. Here we can observe how the fitted values of the regression $\Delta \ln \text{pop}_c = \alpha + \beta \text{Economic Impact}_c + \varepsilon_c$ define a straight line between 2006 and 2010. This is true independent of the different measures of economic impact discussed above. Figure 6 also shows that the same regression used for the period between 2000 and 2006 gives a steep positive (and statistically significant) slope. In other words, before the crisis, metropolitan areas that were hit harder by the Great Recession grew more than others, coupled by an evident slowing of their population growth rates. This clearly suggests that there was an internal migration response during the Great Recession.

[Figure 6 goes here]

Explaining Cadena and Kovak (2016)

Cadena and Kovak (2016)instead investigate they ways people respond to local shocks by regressing the percent change in native population between 2006 and 2010 on a measure of how hard the crisis hit across locations. They then repeat this exercise for the percent change in Mexican population on the same measure of local economic shocks. They obtain a negative correlation in the second regression and a zero (or even slightly positive) coefficient in the first regression. This would suggest that the native population is not responsive to negative shocks (as concluded in Mian et al. (2013)) – while immigrants, particularly Mexicans, do respond to negative shocks. Unlike Mian et al. (2013), Cadena and Kovak (2016) focus on low-skilled workers.

This strategy misses, however, the fact that population trends can vary significantly between natives and Mexicans, something that needs to be controlled for. An easy way to further study this question is to retuilize the same regression employed by Cadena and Kovak (2016), but with population change between 2000 and 2006 as well. The change in trend between 2000-2006 and 2006-2010 is evident for both Mexicans and natives. This can be seen in Figure 7, which plots the fitted values of the regressions between 2000 and 2006 and between 2006 and 2010:

[Figure 7 goes here]

In particular, Figure 7 shows that if we relate the growth rate of the native population and the debt to income ratio computed in Mian et al. (2013), we observe that between 2000 and 2006 there was a strong positive relationship. This relationship became less strong between 2006 and 2010, precisely when the crisis hit in high debt metropolitan areas. If we look at Mexican immigrants alone, we observe that there was initially a slightly negative relationship, that became even more negative between 2006 and 2010. This change in trend is very similar between natives and immigrants. Understanding these different patterns is crucial to interpreting whether low-skilled immigrants alone respond to local shocks or whether natives do as well, despite the fact that the relationship between native population growth rates and debt to income ratio was not negative between 2006 and 2010.[31]

[31] I obtain similar results for the alternative measures of how hard the crisis hit across locations used in this paper.

A.4 Population size and internal migration

A natural consequence of the model is that, in equilibrium, internal migration rates in the cross-section are necessarily smaller in larger cities or regions. If this was not the case, bilateral flows across locations would not be equalized, and thus the economy would not be in spatial equilibrium as defined in the first section of the paper. This is an easy prediction to test.

In particular, one can run the following regression:

$$(\ln)\ \text{Migrants}_{mt} = \alpha + \beta (\ln)\ \text{Population}_{mt} + (\delta_t) + \varepsilon_{mt} \tag{A.1}$$

To test whether in-migration rates tend to be lower in larger locations, we need only to check whether $\beta < 1$.[32]

Table 9 shows the results of running this regression. It shows that when using either metropolitan areas or states, internal migration rates and population size are always negatively correlated. This remains true whether we weight the observations by the size of the location (to account for measurement error) or don't and instead assume that measurement error is non-existent. The magnitudes suggest that if we double the size of a location then its internal migration rate is around 7-20 percent smaller.

[Table 9 goes here]

It is worth noting that this result is true for the model presented herein, but need not hold in other spatial equilibrium models. More specifically, in spatial equilibrium, population levels need to be constant. This implies zero net in-migration rates. These zero net in-migration rates could be the result of any combination of in- and out-migration rates.

B Extensions to the Model

In this section I show how straightforward it is to introduce wealthier models of the labor market and of trade into the main model presented in the paper. More generally, it is easy to implement any static model for each of the periods that determines wage levels. These models need to have some congestion forces. Aside from this, the researcher can chose any static model of the economy and incorporate the dynamic discrete location choice model introduced earlier. In what follows I provide two examples: search and matching frictions and trade. For trade, I discuss some alternatives, relying heavily on Caliendo et al. (2015).

B.1 Unemployment

B.1.1 Labor market with unemployment

The local labor market equilibrium is determined by a search and match technology that takes place in each market (Pissarides, 2000).

Again, I simplify the intuitions by assuming standard functional forms of the various key variables. The constant returns to scale matching function is given by $m(u_m, v_m) = u_m^{\eta} v_m^{1-\eta}$. u_c is the unemployment rate, v_c is the vacancy rate. The probability of job loss is exogenous and given by δ. The revenue flow per worker is given by the expression $r_m = p_m(1-\theta_m)B_m Q_m^{\frac{1}{\sigma}} L_c^{-\frac{1}{\sigma}}$. Importantly, the fixed factor ensures that the revenue flow per worker is smaller when there are more workers in the local economy, other things being equal. The cost flow per vacancy is, as in the

[32] Note that one alternative would be to regress the (ln) of the migration rates on the (ln) population and test whether $\beta < 0$. This, obviously, delivers the same results.

rest of the literature, given by $r_m f$. Finally the unemployment benefits are specific to each location and given by b_m. I further assume that they are proportional to current wages $b_m = \tau_m w_m$.

Under these conditions, we have the following three equilibrium conditions (before relocation across labor markets takes place):

Beveridge curve

The fact that in equilibrium, unemployment growth is 0 implies:

$$\delta(1 - u_m) = u_m^{\eta} v_m^{1-\eta}$$

So:

$$u_m = \frac{\delta}{\delta + \theta_m^{1+\eta}} \tag{B.1}$$

where $\theta_m = v_m / u_m$ is the labor market tightness.

Job creation

The zero profit condition determines the job creation equation:

$$r_m - w_m - \frac{(i_m + \delta) r_m f}{\theta_m^{\eta}} = 0 \tag{B.2}$$

Wage curve

Nash bargaining between firms and workers (with weight β) implies:

$$w_m = (1 - \beta) b_m + \beta r_m (1 + f \theta_m) \tag{B.3}$$

These 3 equations determine $\{u_m, \theta_m, w_m\}$ in each local labor market.

B.1.2 Location choice with unemployment

The indirect utility of the workers is given by the local wage $w_{m'}$ and unemployment rate $u_{m'}$, the amenities $A_{m'}$ and the idiosyncratic draw they get for location m', given that they live in m:

$$v_{m'}^i = \ln V_{m'} + \epsilon_{m,m'}^i = \ln A_{m'} + \ln((1 - u_{m'}) * \omega_{m'} + u_{m'} * b_{m'}) + \epsilon_{m,m'}^i$$

where $u_{m'}$, $b_{m'}$ and $\omega_{m'}$ are the respectively the unemployment rate, unemployment benefits and wages in region m'. The intuition is straightforward. If an individual i moves to m', the probability that she will be unemployed is $u_{m'}$. She will then receive the unemployment benefit $b_{m'}$. Meanwhile, the probability that she will be employed and receive the wage $\omega_{m'}$ is $1 - u_{m'}$.

This expression can be simplified even further by using the assumption that unemployment benefits are proportional to wages $b_{m'} = \tau_{m'} w_{m'}$. We then have

$$v_{m'}^i = \ln A_{m'} + \ln((1 - u_{m'}) * w_{m'} + u_{m'} * \tau_{m'} w_{m'}) + \epsilon_{m,m'}^i \approx \ln A_{m'} + \ln w_{m'} - u_{m'}(1 - \tau_{m'}) + \epsilon_{m,m'}^i = \ln V_{m'} + \epsilon_{m,m'}^i \tag{B.4}$$

This expression has a simple interpretation. Indirect utility is higher if amenities are higher, (ln) wages are higher, and unemployment rates are lower. The more this is the case, the lower unemployment benefits are.

Note that the indirect utility has a common component to all workers $\ln V_{m'}$ that depends on variables at destination and an idiosyncratic component $\epsilon^i_{m,m'}$ specific to each worker. It is also important to note that workers decide on future location given current wages across locations. This is an optimal behavior if two things hold. First, workers do not expect shocks to happen in any location in the near future. Second, workers do not form expectations about how many people will move to each location (Kennan and Walker, 2011).

Thus, workers maximize:

$$\max_{s' \in M} \{\ln V_{m'} + \epsilon^i_{m,m'}\} \tag{B.5}$$

The general solution to this maximization problem gives the probability that an individual i residing in location m moves to m', given current wages and valuations of amenities $\mathbf{A}$, $\mathbf{w}, \mathbf{u}$:[33]

$$p^i_{m,m'} = p_{m,m'}(\mathbf{A}, \mathbf{w}, \mathbf{u}) \tag{B.6}$$

This idiosyncratic taste shock shapes the flows of workers across locations, as I discuss in detail in the paper.

By the law of large numbers we can then use equation (B.6) to obtain the flow of people between m and m':

$$P_{m,m'} = p^i_{m,m'} * N_m \text{ for } s \neq s' \tag{B.7}$$

where N_m is the population residing in m. Note that this defines a matrix that represents the flows of people between any two locations in the economy.

B.1.3 Equilibrium with unemployment

The definition of the equilibrium has two parts. I start by defining the equilibrium in the short run,satisfying two conditions. First, firms take as given productivity B_m, the productivity of each factor θ_m, and factor prices in each location to maximize profits. Second, labor markets clear in each location. This equates the supply and demand for labor and determines wages in each local labor market. More formally:

Definition III. *A short run equilibrium is defined by the following decisions:*

- *Given $\{\theta_m, B_m, K_m, \sigma, w_m, r_m\}_{m \in M}$ firms maximize profits.*
- *Labor and land markets clear in each $s \in M$ so that $\{w_m, u_m, \theta_m, r_m\}$ is determined.*

Note that in the short run, the two factors of production are fixed. At the end of the period relocation takes place, determining the distribution of workers across space in the following period. We can define the long run equilibrium by adding an extra condition to the short run definition. That is, the economy is in long run equilibrium when bilateral flows of people are equalized across regions. More specifically,

Definition IV. *Given $\{\theta_m, B_m, K_m, \sigma, A_m\}_{m \in M}$, a long run equilibrium is defined as a short run equilibrium with a stable distribution of workers across space, i.e. with $N_{t+1,m} = N_{t,m}$ for all $m \in M$.*

B.2 Trade

We can easily introduce wealthier models of internal trade in the model presented above. For this we need only a static theory of trade that determines the price of goods across space. With this in hand, we can go back to the

[33] I use bold to denote the vector of all the locations in the economy.

migration choice model, where we need to take into account differences in prices across locations. These differences are usually understood as variations in price indexes, which reflect the location of production in the economy.

Caliendo et al. (2015) reach their results using an Eaton and Kortum (2002) model of international trade. There are, however, many alternatives.[34] Trade could also be determined by the relative endowments of land and labor in each location, or by productivity differences and specializations, if more than one sector exists. Some of the standard theories of international trade lead to factor prize equalization. If this is the case, we would need other congestion forces asthe local labor market would no longer be a source of of the latter. We can , however, attain this through competition for land.

C Solving the Model Forward

We start from the expression:

$$\ln V_{t,m'} = \ln A_{m'} + \ln w_{t,m'} + \beta\gamma(\ln[V_{t+1}^{1/\gamma} + (\eta-1)V_{t+1,m'}^{1/\gamma}])$$

which can be re-expressed as:

$$\ln V_{t,m'} = \beta\gamma\ln(\eta-1) + \ln A_{m'} + \ln w_{t,m'} + \beta\ln V_{t+1,m'} + \beta\frac{\gamma}{(\eta-1)}(\frac{V_{t+1}}{V_{t+1,m'}})^{1/\gamma}$$

Now, note that if η is sufficiently big the last term is quite small. Then,

$$\ln V_{t,m'} = \beta\gamma\ln(\eta-1) + \ln A_{m'} + \ln w_{t,m'} + \beta\ln V_{t+1,m'} + \beta\ln\nu_{t+1,m'}$$

At t+1:

$$\ln V_{t+1,m'} = \beta\gamma\ln(\eta-1) + \ln A_{m'} + \ln w_{t,m'} + \beta\ln V_{t+2,m'} + \beta\ln\nu_{t+2,m'}$$

So,

$$\ln V_{t,m'} = \beta\gamma\ln(\eta-1)+\ln A_{m'}+\ln w_{t,m'}+\beta(\beta\gamma\ln(\eta-1)+\ln A_{m'}+\ln w_{t+1,m'}+\beta\ln V_{t+2,m'}+\beta\ln\nu_{t+2,m'})+\beta\ln\nu_{t+1,m'}$$

After many iterations:

$$\ln V_{t,m'} = \sum_{k=1}^{\infty}\beta^k\gamma\ln(\eta-1) + \sum_{k=0}^{\infty}\beta^k\ln A_{m'} + \sum_{k=0}^{\infty}\beta^k\ln w_{k,m'} + \sum_{k=0}^{\infty}\beta^k\ln\nu_{k,m'}$$

Which can be simplified to:

$$\ln V_{t,m'} = \frac{\beta}{1-\beta}\gamma\ln(\eta-1) + \frac{1}{1-\beta}\ln A_{m'} + \sum_{k=0}^{\infty}\beta^k\ln w_{k,m'} + \sum_{k=0}^{\infty}\beta^k\ln\nu_{k,m'}$$

D Moving Costs

In this section I establish the mapping between the fixed costs of moving and the η.

The flows implied by a model with moving costs can be written as:

[34] See for instance the work by Redding (2014)

$$P_{m,m'} = N_m * \frac{V_{m,m'}^{1/\lambda}}{\sum_{j\in M} V_{m,j}^{1/\lambda}}$$

where

$$\ln V_{m,m'} = \ln A_{m'} + \ln \omega_{m'} - \ln F_m = \ln V_{m'} - \ln F_m$$

Using this expression we obtain:

$$P_{m,m'} = N_m * \frac{(V_{m'}/F_m)^{1/\lambda}}{V_m^{1/\lambda} + \sum_{j\neq m'}(V_j/F_m)^{1/\lambda}}$$

We need to compare this expression to what we derived in the model:

$$P_{m,m'} = N_m * \frac{\eta V^{1/\gamma}}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}} \frac{V_{m'}^{1/\lambda}}{V^{1/\lambda}}$$

For these expressions to represent the same flows we need them to be equal, so:

$$\frac{(V_{m'}/F_m)^{1/\lambda}}{V_m^{1/\lambda} + \sum_{j\neq m'}(V_j/F_m)^{1/\lambda}} = \frac{\eta V^{1/\gamma}}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}} \frac{V_{m'}^{1/\lambda}}{V^{1/\lambda}}$$

if and only if:

$$\frac{(1/F_m)^{1/\lambda}}{V_m^{1/\lambda} + \sum_{j\neq m'}(V_j/F_m)^{1/\lambda}} = \frac{\eta V^{1/\gamma}}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}} \frac{1}{V^{1/\lambda}}$$

if and only if:

$$\frac{(1/F_m)^{1/\lambda}}{V_m^{1/\lambda} + (1/F_m)^{1/\lambda}\sum_{j\neq m'}(V_j)^{1/\lambda}} = \frac{\eta V^{1/\gamma - 1/\lambda}}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}}$$

if and only if:

$$\frac{1}{(V_m F_m)^{1/\lambda} + \sum_{j\neq m'}(V_j)^{1/\lambda}} = \frac{\eta V^{1/\gamma - 1/\lambda}}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}}$$

if and only if:

$$(V_m F_m)^{1/\lambda} + \sum_{j\neq m'}(V_j)^{1/\lambda} = \frac{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}}{\eta V^{1/\gamma - 1/\lambda}}$$

if and only if:

$$(V_m F_m)^{1/\lambda} = \frac{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}}{\eta V^{1/\gamma - 1/\lambda}} - \sum_{j\neq m'} V_j^{1/\lambda}$$

So we would need:

$$F_m^{1/\lambda} = \frac{\frac{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}}{\eta V^{1/\gamma - 1/\lambda}} + V_{m'}^{1/\lambda} - V^{1/\lambda}}{V_m^{1/\lambda}}$$

Note that if $1/\gamma = 0$ then:

$$F_m^{1/\lambda} = \frac{\frac{(1-\eta)}{\eta}V^{1/\lambda} + V_{m'}^{1/\lambda}}{V_m^{1/\lambda}} = \frac{(1-\eta)}{\eta}(V/V_m)^{1/\lambda} + (V_{m'}/V_m)^{1/\lambda}$$

These two last expressions show that there isn't a direct mapping between the model presented in this paper and a similar model with logit error terms and fixed costs of moving. It also shows, however, that fixed costs of moving are roughly similar to $\frac{\eta V_m^{1/\lambda}}{(1-\eta)V^{1/\lambda}}$, and thus roughly proportional to the value in each location, which in turn is proportional to the size of the location, all scaled by η.

This expression also highlights the high value of previous estimates of moving costs. We established that η is around 5 percent, and λ is around 2.56, and we can assume that $V_{m'}/V_m$ is roughly 1, for similarly sized cities.

Then:

$$F_m^{1/2.56} = \frac{0.95}{0.05}(V/V_m)^{1/2.56} + (V_{m'}/V_m)^{1/2.56}$$

So

$$F_m \approx (\frac{0.95}{0.05})^{2.56}(V/V_m) + 1 \approx 1878 * (V/V_m) + 1 \approx 1878 * M + 1$$

That is, the fixed costs of moving for the average city are almost 2,000 times the number of locations M in the economy. With 200 metropolitan areas, this is a value of about 375,600 dollars, in line with that estimated in Kennan and Walker (2011) and in subsequent work.

E Sensitivity Analysis

In this section, I analyze the sensitivity of the results on the speed of adjustment to alternative local labor demand elasticity estimates. Until now, I have assumed that equation 3.1 was Cobb-Douglas, here I use alternative CES production functions.

To study the influence of these various production functions on convergence, I examine how far apart wages and population levels are from the steady state 5, 10, and 15 years after the shock. To do so, I first compute the absolute percentage difference between these years and the long run equilibrium values for every metropolitan area.[35] I then compute the average of these differences across all the metropolitan areas. These numbers are reported in Table 7. For example, if $\sigma = 0.5$, 10 years after the shock wages are almost (99 percent) in the long-run equilibrium. Population levels are also very close to their long run equilibrium (99 percent) after 10 years.In fact population and wages follow very similar dynamics to the steady state, as can be observed in equation 3.8 and equation 3.9.

[Table 7 goes here]

More generally, Table 7 shows that the stronger spatial convergence induced by internal migration is, themore inelastic the local labor demand elasticity is. However, even for an elasticity of substitution between land and labor of 1.5, Table 7 reports that after 10 years wage levels are already 80 percent of those in the long run equilibrium. This shows that the high responsiveness of internal migration to local shocks estimated in this paper is likely to be important for all reasonable estimates of the local labor demand elasticity.

[35] The long run equilibrium is assumed to be 30 years after the shock. After this, variation is quite minimal for all σ.

F Proofs

F.1 Proof of lemma 1

In what follows I proof lemma 1:

Proof. We start with:

$$\ln P_{j,m} = \ln N_j + \frac{1}{\gamma}\ln \eta V - \ln(\eta V^{1/\gamma} + (1-\eta)V_j^{1/\gamma}) + \frac{1}{\lambda}\ln V_m - \frac{1}{\lambda}\ln V$$

and

$$\ln V_m = \ln A_m + \ln w_m + \beta\gamma(\ln[(1-\eta)V_{+1,m}^{1/\gamma} + \eta V_{+1}^{1/\gamma}])$$

Let's find the derivative with respect to each of these terms.
First we need to realize that:

$$\frac{\partial \ln V_{t,m}}{\partial \ln w_m} \approx 1 + \beta\frac{\partial \ln V_{t+1,m}}{\partial \ln w_m}(1 - \frac{\eta}{1-\eta}(\frac{V_{t+1}}{V_{t+1,m}})^{1/\gamma}) = \frac{1}{(1-\beta_m)}$$

Note also that $\frac{\partial \ln V_j}{\partial \ln w_m} \approx 0$ if $j \neq m$.

$$\frac{\partial \ln V}{\partial \ln w_m} = \frac{\partial \lambda \ln(\sum_j V_j^{1/\lambda})}{\partial \ln w_m} = \frac{\lambda}{V^{1/\lambda}}\frac{\partial V_m^{1/\lambda}}{\partial \ln w_m} = \frac{\lambda V_m^{1/\lambda}}{V^{1/\lambda}}\frac{\partial 1/\lambda \ln V_m}{\partial \ln w_m} = \frac{V_m^{1/\lambda}}{V^{1/\lambda}} = \frac{V_m^{1/\lambda}}{V^{1/\lambda}}\frac{1}{(1-\beta_m)}$$

Now, note that $\sum_m \frac{V_m^{1/\lambda}}{V^{1/\lambda}} = 1$ so $\frac{V_m^{1/\lambda}}{V^{1/\lambda}}$ is small if there are many locations. Thus we can use:

$$\frac{\partial \ln V}{\partial \ln w_m} \approx 0$$

Thus we also have that:

$$\frac{\partial \ln(\eta V^{1/\gamma} + (1-\eta)V_j^{1/\gamma})}{\partial \ln w_m} \approx 0$$

Using all of this,

$$\frac{\partial \ln P_{j,m}}{\partial \ln w_m} \approx \frac{1}{\lambda(1-\beta_m)}$$

For the second equation we start by:

$$P_{m,m} = N_m[\eta_m \frac{V_m^{1/\lambda}}{V^{1/\lambda}} + (1-\eta_m)] = N_m[\frac{\eta V^{1/\gamma}}{\eta V^{1/\gamma} + (1-\eta)V_m^{1/\gamma}}\frac{V_m^{1/\lambda}}{V^{1/\lambda}} + \frac{(1-\eta)V_m^{1/\gamma}}{\eta V^{1/\gamma} + (1-\eta)V_m^{1/\gamma}}]$$

Thus,

$$P_{m,m} = N_m \frac{V_m^{1/\lambda}}{\eta V^{1/\gamma} + (1-\eta)V_m^{1/\gamma}}[\eta V^{1/\gamma - 1/\lambda} + (1-\eta)]$$

$$\ln P_{m,m} = \ln N_m + \frac{1}{\lambda}\ln V_m - \ln(\eta V^{1/\gamma} + (1-\eta)V_m^{1/\gamma}) + \ln[\eta V^{1/\gamma - 1/\lambda} + (1-\eta)]$$

We can use what we derive above to obtain:

$$\frac{\partial \ln(\eta V^{1/\gamma} + (1-\eta)V_m^{1/\gamma})}{\partial \ln w_m} = \frac{1}{\gamma} \frac{1}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}} (\eta V^{1/\gamma} \frac{\partial \ln V}{\partial \ln w_m} + (1-\eta)V_m^{1/\gamma} \frac{\partial \ln V_m}{\partial \ln w_m}) =$$

$$\approx \frac{1}{\gamma(1-\beta_m)} \frac{(1-\eta)V_m^{1/\gamma}}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}} = \frac{1}{\gamma(1-\beta_m)} \frac{(1-\eta)V_m^{1/\gamma}}{(1-\eta)V_m^{1/\gamma} + \eta V^{1/\gamma}} = \frac{1}{\gamma(1-\beta_m)}(1-\eta_m)$$

Thus,

$$\frac{\partial \ln P_{m,m}}{\partial \ln w_m} \approx \frac{1}{(1-\beta_m)}(\frac{1}{\lambda} - \frac{1}{\gamma}(1-\eta_m))$$

For the third equation:

$$\ln P_{j,m} = \ln N_j + \frac{1}{\gamma} \ln V - \ln(V^{1/\gamma} + V_j^{1/\gamma}) + \frac{1}{\lambda} \ln V_m - \frac{1}{\lambda} \ln V$$

we follow the same steps as before, to obtain:

$$\frac{\partial \ln P_{j,m}}{\partial \ln w_j} \approx -\frac{1}{\gamma(1-\beta_m)}(1-\eta_j)$$

For the last equation:

$$\ln P_{j,m} = \ln N_j + \frac{1}{\gamma} \ln V - \ln(V^{1/\gamma} + V_j^{1/\gamma}) + \frac{1}{\lambda} \ln V_m - \frac{1}{\lambda} \ln V$$

Again, as before:

$$\frac{\partial \ln P_{j,m}}{\partial \ln w_{m'}} \approx 0$$

□

F.2 Proof of proposition 2

Proof. From $I_m = \sum_{j \neq m} P_{j,m}$ we obtain:

$$\frac{\partial \ln I_m}{\partial \ln w_m} = \frac{1}{\sum_{j \neq m} P_{j,m}} \sum_{j \neq m} \frac{\partial P_{j,m}}{\partial \ln w_m} = \frac{1}{\sum_{j \neq m} P_{j,m}} \sum_{j \neq m} P_{j,m} \frac{\partial \ln P_{j,m}}{\partial \ln w_m}$$

So, we need to know $\frac{\partial \ln P_{j,m}}{\partial \ln w_m}$, which we know from lemma 1:

$$\frac{\partial \ln I_m}{\partial \ln w_m} \approx \frac{1}{(1-\beta_m)} \frac{1}{\lambda}$$

Similarly, from $O_m = \sum_{j \neq m} P_{m,j}$ we obtain:

$$\frac{\partial \ln O_m}{\partial \ln w_m} = \frac{1}{\sum_{j \neq m} P_{m,j}} \sum_{j \neq m} \frac{\partial P_{m,j}}{\partial \ln w_m} = \frac{1}{\sum_{j \neq m} P_{m,j}} \sum_{j \neq m} P_{m,j} \frac{\partial \ln P_{m,j}}{\partial \ln w_m}$$

Again, using lemma 1:

$$\frac{\partial \ln P_{s,j}}{\partial \ln w_m} \approx -\frac{1}{(1-\beta_m)}\frac{1}{\gamma}(1-\eta_m)$$

□

F.3 Proof of corollary 3

Proof. We only need to realize that:

$$\frac{\partial (I_m/N_m)}{\partial \ln w_m} = \frac{\partial I_m}{N_m \partial \ln w_m} = \frac{I_m}{N_m}\frac{\partial \ln I_m}{\partial \ln w_s}$$

The out-migration rate is analogous.

□

F.4 Proof of proposition 5

Proof. The law of motion of the economy is given by:

$$N'_{t+1} = N_t \text{ x } P_t$$

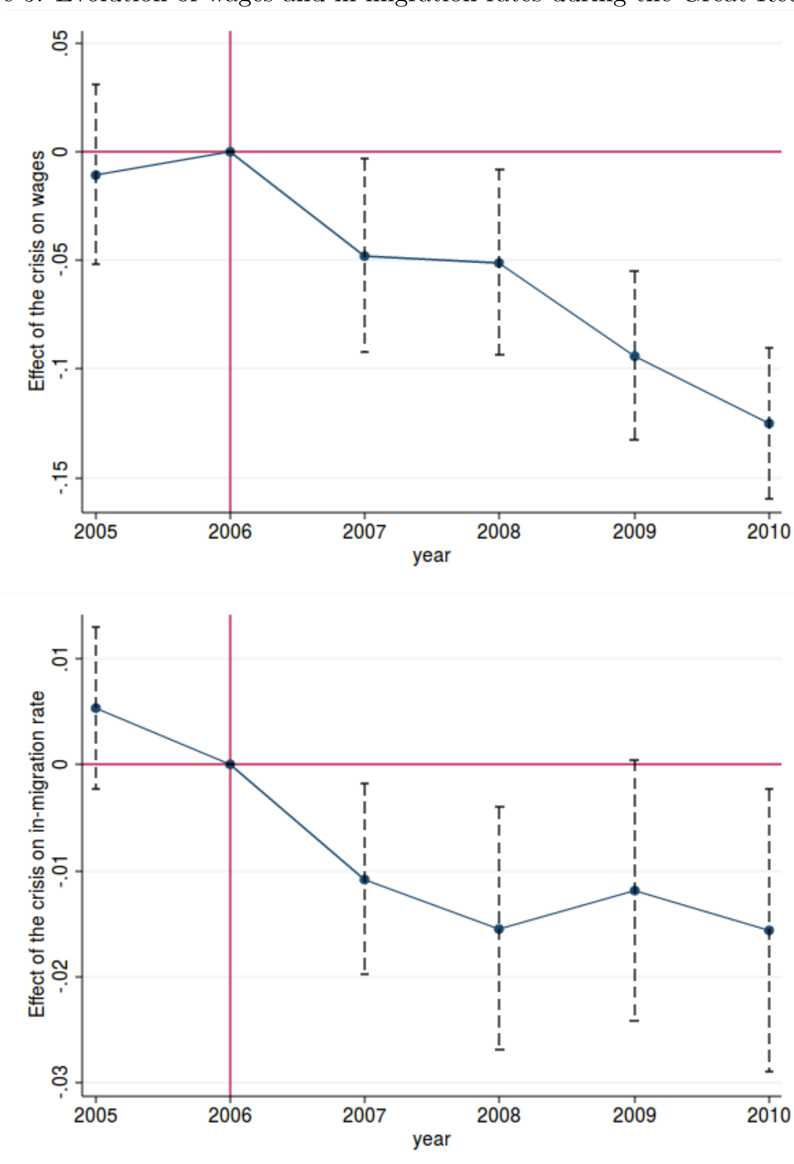
where P_t is the matrix of bilateral flows at time t.

Given an initial distribution of people across space (N_0), we can easily compute the long run equilibrium.

□

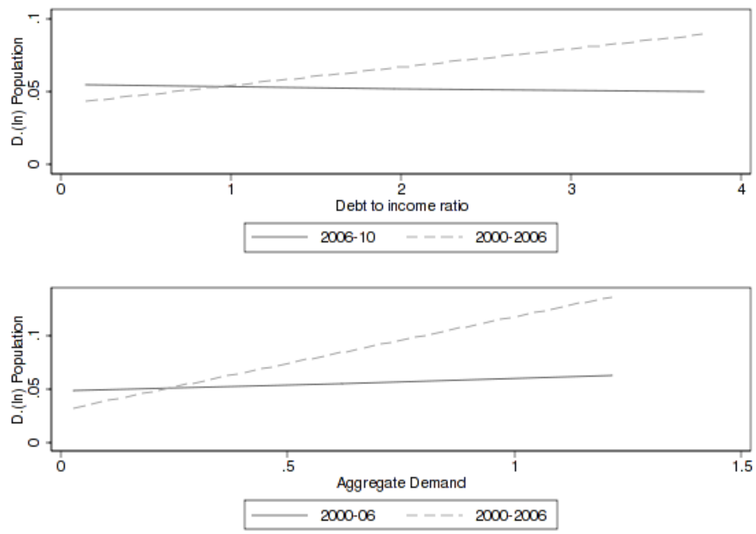
G Appendix Figures

Figure 5: Evolution of wages and in-migration rates during the Great Recession



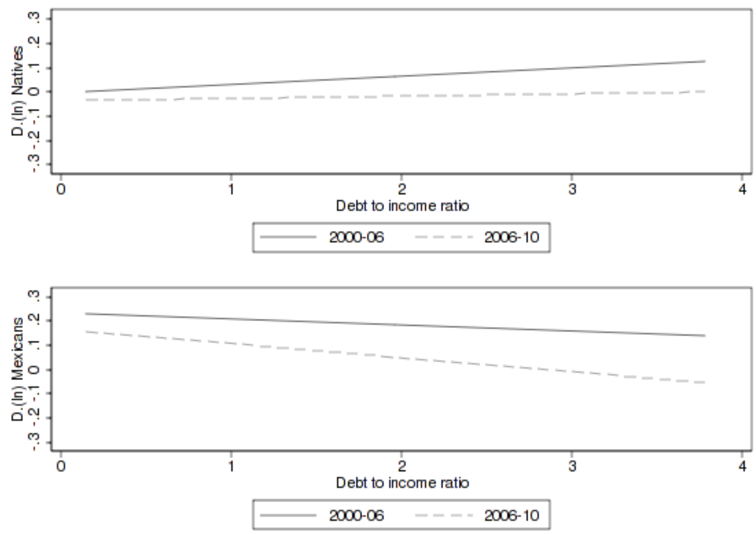
Notes: This figure reports the estimate of the interaction of year dummies with the Debt to income x share of employment in non-tradable sectors, controlling for metarea and year fixed effects. 95 percent confidence intervals are reported.

Figure 6: Pre-trends in population growth rates



Notes: This graph shows the pre-trends in population growth rates relative to a measure of how hard the crisis hit at the local level.

Figure 7: Differential trends between low-skilled natives and immigrants



Notes: This graph shows the different trends in native and immigrant low-skilled populations relative to a measure of how hard the crisis hit at the local level.

H Appendix Tables

Table 7: Time to convergence, sensitivity analysis

Time	Wage convergence	Population convergence
	$\sigma = 0.5$	
5 years	0.828	0.828
10 years	0.991	0.991
15 years	1.000	1.000
	$\sigma = 0.7$	
5 years	0.700	0.700
10 years	0.961	0.961
15 years	0.995	0.995
	$\sigma = 0.9$	
5 years	0.607	0.608
10 years	0.919	0.919
15 years	0.984	0.984
	$\sigma = 1.1$	
5 years	0.540	0.541
10 years	0.876	0.877
15 years	0.967	0.967
	$\sigma = 1.3$	
5 years	0.489	0.491
10 years	0.836	0.837
15 years	0.949	0.949
	$\sigma = 1.5$	
5 years	0.450	0.452
10 years	0.801	0.802
15 years	0.930	0.930
	$\sigma = 1.7$	
5 years	0.420	0.421
10 years	0.770	0.771
15 years	0.911	0.912

Notes: This table shows some sensitivity analysis to the speed of spatial convergence of wages and population under alternative local labor demand elasticities, parametrized by the CES parameter in equation 3.1. The reported values compare the outcomes 'Time', up to 30 years after the shock, which is assumed to be the long run equilibrium. An entry equal to .9 means that 90 percent of the long-run change already occurred 'Time' years after the shock, on average across all the metropolitan areas.

Table 8: The migration response to the crisis by skill

Panel A: In-migration rates, low-skilled

VARIABLES	(1) In migration IV1	(2) In migration IV2	(3) In migration IV1	(4) In migration IV2	(5) In migration IV1	(6) In migration IV2
(log) Weekly Wages	0.185***	0.189***				
	(0.0482)	(0.0439)				
Unemployment rate			-0.256***	-0.257***		
			(0.0464)	(0.0419)		
Employment rate					0.301***	0.277***
					(0.0574)	(0.0462)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes
widstat	32.04	27.59	62.98	51.08	32.35	40.35

Panel B: In-migration rates, native low-skilled

VARIABLES	(1) In migration IV1	(2) In migration IV2	(3) In migration IV1	(4) In migration IV2	(5) In migration IV1	(6) In migration IV2
(log) Weekly Wages	0.140***	0.146***				
	(0.0430)	(0.0391)				
Unemployment rate			-0.170***	-0.186***		
			(0.0413)	(0.0405)		
Employment rate					0.176***	0.178***
					(0.0418)	(0.0380)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes
widstat	32.04	27.59	62.58	39.05	54.29	52.48

Panel C: In-migration rates, high-skilled

VARIABLES	(1) In migration IV1	(2) In migration IV2	(3) In migration IV1	(4) In migration IV2	(5) In migration IV1	(6) In migration IV2
(log) Weekly Wages	0.260**	0.286***				
	(0.108)	(0.0786)				
Unemployment rate			-0.433***	-0.595***		
			(0.137)	(0.142)		
Employment rate					0.559***	0.845***
					(0.196)	(0.259)
Observations	1,260	1,260	1,260	1,260	1,260	1,260
year FE	yes	yes	yes	yes	yes	yes
metarea FE	yes	yes	yes	yes	yes	yes
widstat	11.92	21.38	40.12	48.64	16.47	16.20

Notes: The dependent variable is the in-migration rate and the out-migration rate in 2,010 metropolitan areas between 2005-2010. Regressions are weighted by the number of observations in each metropolitan area. 'IV1' refers to the interaction of the 'Debt to Income' ratio and a 'Post' 2007 dummy. 'IV2' refers to the interaction of the 'Debt to Income' ratio, the share of non-tradable employment and a 'Post' 2007 dummy, see more details in Table 3. Number of observations: 210 metropolitan areas x 6 years = 1260. Robust standard errors reported. * p<.1, ** p<.05 and *** p<.001.

Table 9: Internal migration and population size

Panel A: Census data, metropolitan-level variation

VARIABLES	(1) (ln) In migrants OLS	(2) (ln) Out migrants OLS	(3) (ln) In migrants OLS	(4) (ln) Out migrants OLS	(5) (ln) In migrants OLS	(6) (ln) Out migrants OLS
(ln) Population	0.785***	0.918***	0.787***	0.920***	0.800***	0.899***
	(0.0365)	(0.0200)	(0.0373)	(0.0201)	(0.0277)	(0.0162)
Observations	444	444	444	444	444	444
R-squared	0.857	0.955	0.858	0.956	0.945	0.975
MSA FEs	no	no	no	no	yes	yes
Time FEs	no	no	yes	yes	yes	yes
Weights	yes	yes	yes	yes	yes	yes

Panel B: Census data, state-level variation

VARIABLES	(1) (ln) In migrants OLS	(2) (ln) Out migrants OLS	(3) (ln) In migrants OLS	(4) (ln) Out migrants OLS	(5) (ln) In migrants OLS	(6) (ln) Out migrants OLS
(ln) Population	0.748***	0.826***	0.755***	0.827***	0.587***	0.704***
	(0.0428)	(0.0211)	(0.0461)	(0.0216)	(0.184)	(0.0937)
Observations	204	204	204	204	204	204
R-squared	0.816	0.947	0.825	0.948	0.982	0.987
State FEs	no	no	no	no	yes	yes
Time FEs	no	no	yes	yes	yes	yes
Weights	yes	yes	yes	yes	yes	yes

These regressions show the relationship between internal migration and population size. Standard errors are clustered at the level of the geographic aggregation. Panel A uses Census data at the metropolitan area level between 1980 and 2000. Panel B uses Census data at the state level between 1970 and 2000. * p<.1, ** p<.05 and *** p<.001 indicates whether the coefficient is significantly smaller than 1.