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JEL Classification: J61, J20, J30, F22, J43, R23, R58

Keywords: Internal migration and local labor market dynamics

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Economic Shocks and Internal Migration

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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. The main goal of this paper is to accurately quantify the shape and importance of internal migration in dissipating local shocks.

To do so, I first document extensively that 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 fact using a number of alternative and complementary strategies. First, 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 more on their consumption and this in turn affected local non-tradable employment. Thus, metropolitan areas where households were indebted *and* where the share of employment in non-tradable sectors was high prior to the crisis 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 estimate is similar to what provided in Carrington (1996) using the Trans-Alaska Pipeline construction. Relative to Carrington (1996), and many other papers in the literature, I distinguish between the response in in- and out-migration rates. In this paper I document that this decrease in net in-migration was entirely driven by a decline in the in-migration rate, with little response of the out-migration rate. This distinction is important for how we should model internal migration, as I explain below.

The fact that in-migration explains most of the variation in internal migration is in fact 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 all publicly available datasets on Ipums for the US and a number of different 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 shocks and helps to establish a stylized fact.

The second and arguably main contribution of this paper is to develop a parsimonious quan-

[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 in that year. We can then use this to decompose population growth rates across location of the cohort surveyed at time t into in- and out-migration rates.

titative general equilibrium dynamic model with multiple locations around this stylized fact. The model assumes that in each period, each worker decides where to live given: a) current and future housing and labor market conditions in an arbitrary number of potential destinations, and b) an idiosyncratic taste shock. This idiosyncratic taste shock captures taste heterogeneity for mobility and is drawn from a nested logit distribution. This nesting structure captures the fact that the home location is special: workers in the model are more reluctant to substitute away the location where they currently live than to substitute among two potential alternative new destinations.

This assumption on how to model internal mobility allows to decompose the flows of workers between any two locations between the (endogenous) share of workers who move away from their original location and, among those, 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 a more likely candidate for the following period's location, something that is crucial in order to match the empirical regularity that in equilibrium internal migration is relatively low – only around 5 percent of the population relocates to a different metropolitan area each year. This modeling choice plays a similar role to the fixed costs of mobility introduced and estimated in Kennan and Walker (2011) but makes the model very tractable.[2]

Furthermore, there are a number of features of the model that make it attractive, both for analytical study and for estimation. 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.[3] In each location, the population in the following period is a weighted average between a) the indirect utility of living in that location relative to all other potential destinations, and b) the current size of the location. Thus, a simple equation per location fully characterizes (the sticky) population dynamics of the many locations in the economy and allows for an examination of the determinants of the speed of convergence to the new steady state. This simple equation allows me to show that the speed of convergence depends crucially both on the sensitivity of internal migration and on local congestion forces. The model makes very explicit the idea that reduced migration to one location is a labor supply shock – or increased competition for housing – in another location, as discussed in the seminal work of Topel (1986).

Second, the model is particularly suited to studying welfare. Long run changes in the value across locations can also be summarized in a simple and intuitive equation. The assumptions of the model imply that the change in the long run value of a location equals the change in the

[2]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. Papers using fixed costs of moving include the seminal contributions of Kennan and Walker (2011) and Artuc et al. (2010).

[3]Given the simplicity of the dynamics generated, this methodological innovation can potentially be used in a number of different contexts. For example, the model presented in this paper can be used to endogenise the share of firms that decide to set-up new prices in a sticky price model Calvo (1983). See also Clarida et al. (2000) and Gali (2015).

overall welfare in the economy plus the long run change in population in that location scaled by the sensitivity of internal migration to local shocks. It thus allows to study the importance of internal relocation in insuring locations against local shocks.[4]

Both for the transitional dynamics and the long-run welfare consequences, the sensitivity of in-migration to local shocks plays a crucial role. If in-migration rates are more responsive it means that different locations are more "substitutable" and thus shocks spread more quickly and dissipate better. I use the the local incidence of the Great Recession to estimate this parameter. Similar strategies can be used in future work in alternative contexts.

In the last part of the paper I use this quantitative model calibrated to the US economy to study the role of internal migration in dissipating the incidence of the 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. Considering only internal migration as a mechanism dissipating local shocks, I show that the model predicts that within 10 years the economy is back to the steady state and around 60 percent of the initial drop in value across locations dissipates. This is so even when only in-migration rates respond to local shocks while out-migration rates are constant. These estimates imply that internal mobility across locations in the US is well described as having a constant fraction of movers that strongly reacts to economic opportunities across destinations.

1.1 Related Literature

Many of the results reported in this paper are in-line with the seminal contribution of Blanchard and Katz (1992). For instance, Blanchard and Katz (1992) report that the economy returns to equilibrium across space within about 8 years, something that coincides with the model estimated in this paper and is also 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), particularly unemployment, something that I explain in the Appendix B.2. Relative to Blanchard and Katz (1992) and the large literature that followed it, I separately document the response of in- and out-migration rates something which I fully embed into a dynamic spatial equilibrium model. This was not done before. Hence, on the one hand, this model more realistically captures internal migration responses to local shocks. On the other hand, the internal migration part of the model can be estimated directly from short-run responses of in- and out-migration rates to local shocks. This last point is particularly valueable given that the persistence in local labor demand shocks complicates the estimation of Blanchard and Katz (1992) type models, as discussed in detail in Amior and Manning (2018).[5] Blanchard and Katz (1992) type

[4]Furthermore, I provide a simple metric for measuring insurance at the local level. Essentially, I compare the change in value of locations right after a shock hits the different local economies to the change in the long-run value of the locations once population adjusts.

[5]Amior and Manning (2018) propose instead to control for lagged employment rate. This is justified on a model similar to Blanchard and Katz (1992) with the added assumption that local labor supply equations are upward

frameworks or purely reduced form type strategies have also been used directly to study mobility during the Great Recession, see for example Mian et al. (2013), Dao et al. (2017), Cadena and Kovak (2016), and Yagan (2014), but none of this previous evidence can be interpreted through an (arguably) realistic model of internal migration.

More broadly, this paper advances the internal migration literature by showing how responses of internal migration to local shocks can be used to identify a dynamic location choice model. Previous literature, see the description in Greenwood (1997), can be divided between equilibrium and disequilibrium "perspectives". The disequilibrium perspective tends to view migration decisions from an individual perspective. Individuals need to decide where to move over their life cycle and this decision affects the level of present and future utility. This part of the literature estimates realistic life-cycle profiles of migration decisions, but these models are usually too complicated to also consider that different local labor markets are connected so that in equilibrium the marginal mover is indifferent between locations. Kennan and Walker (2011) is a seminal contribution in this stream of research, although a number of papers, like Dix-Carneiro (2014), Bayer et al. (2016), Bishop (2012), Murphy (2016) or Oswald (2016) add interesting aspects that go beyond Kennan and Walker (2011).

The equilibrium perspective, as explained in Greenwood (1997), emerged in part because internal migration studies using aggregate data showed that wages did not seem to play a major role in determining migrant flows. In a static sense, this is not surprising. In equilibrium, higher wages in a location probably compensate for lower amenities or higher housing costs, as has been emphasized in a large urban literature following Rosen (1974) and Roback (1982). Earlier studies, see Perloff et al. (1960), Lowry (1966) and Shaw (1985), showed empirically that conditions at origin play a smaller role in individual migration decisions than conditions at destination. This is in-line with the evidence presented in this paper. Relative to this earlier literature, this paper shows how we can map responses of in- and out-migration rates to identify a dynamic spatial equilibrium model that incorporates both a life-cycle profile of migration decisions and a notion of spatial equilibrium. I do so expanding tools from discrete choice theory (McFadden, 1974) that have been recently used to study the spatial equilibrium, see for example Redding and Sturm (2008), Ahlfeldt et al. (2015), Redding (2014), Albouy (2009), Notowidigdo (2013), Diamond (2015), and Monte et al. (2018). These papers, however, consider static models, and hence are not suited to study transitional dynamics.[6]

sloping (and common) across geographies.

[6]There is a growing literature on dynamic spatial equilibrium models that are well suited to study transitional dynamics that builds on Caliendo et al. (2018a, 2019). The model that these papers propose is similar to the one I present in this paper, except for the fact that their internal mobility part speaks only to population changes and not the responses of in- and out-migration rates. Caliendo et al. (2018a, 2019) use their framework to study how local labor markets adapt to trade and productivity shocks. Relative to this work, I provide a simple characterization of the evolution of population as a function of parameters that are easy to estimate given that I only need to rely on responses of in- and out-migration rates to estimate the migration part of the model.

2 Empirical evidence

2.1 Data

I employ four main data sources. 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 - 2011. 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.[7] 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.[8]

The second and third 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 al. (2013) and is used 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 $t-1$.[9]

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

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

[8]Sample selection does not drive any of the results. I prefer this sample selection because mobility between 18 and 25 is remarkably high, and thus, constitutes an important part of the people who potentially move for work related reasons.

[9]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.

the state of residence in the previous year. While this information can be used to define locations, metropolitan areas are a much better approximation of a local housing and 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.[10] Sample size is particularly important when studying yearly migration rates since the latter are usually below 6 percent of the population, or around 5 percent on average.

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 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; 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.[11]

[10] 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.

[11] I also follow Mian et al. (2013) in defining tradable and non-tradable sectors.

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

2.3.1 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, which is justified by the model that I introduce later:[12]

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

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.

2.3.2 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 variation in wages across metropolitan areas that is independent of how internal migration reacts. The Great Recession offers 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 decrease 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

[12] In particular see Section 3.2.2 for the derivation of the model and see Section 4.1.1 for how β in this regression can easily be understood as a structural parameter.

households were heavily indebted *and* at the same time had high levels of employment in non-tradable goods were precisely the areas where the decrease in labor demand was largest.[13]

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.[14] 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.[15] I call these two alternative strategies IV1 and IV2. δ_m are metropolitan area fixed effects, while δ_t are year fixed effects.

Table 2 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.

[Table 2 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.

2.3.3 Second stage: internal migration rates and the crisis

In Table 3 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,

[13] Sectoral evolutions within cities tend to change relatively fast, as documented in Duranton (2007). There is, however, no systematic relationship in internal migration rates in high- relative to low- non-tradable sector employment cities prior to the Great Recession.

[14] 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 show 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.

[15] Employment rate is defined as the employed workers divided by working age population, while the unemployment rate is the number of unemployed divided by labor force participants.

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.[16]

[Table 3 goes here]

These responses of net migration rates are entirely due to the response of the in-migration rates, as shown in Table 4. A metropolitan area, which typically has 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. Another way to put it is that a 1 percent decrease in wages leads to around a 4 percent decrease in in-migration (.2 / 5). This magnitude is comparable to some estimates in previous literature. Previous literature oftentimes reports the percentage change in population for a 1 percent change in wages. This population elasticity can be directly compared to the change in (net) in-migration rate. Previous estimates cluster around .3 (see Carrington (1996) or more recently Caliendo et al. (2018b)). Table 4 shows that all the adjustment to the crisis took place through reductions in in-migration rates, as opposed to increases in out-migration rates. This had not been shown in prior literature.

[Table 4 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.

2.4 Population growth and internal migration

2.4.1 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 publicly available 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:

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

[16] These estimates are similar to the overall population response estimated in Carrington (1996).

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 that I observe in the data at time t but for which I have information on 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 5 shows internal migration rates for various data sets and geographic aggregations. 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 1980s and 1990s, on average around 18 percent of the workforce had changed metropolitan area in the preceding 5 years, a number that dropped to a bit under 17 percent in the 2000s. The same pattern is observed in cross-state migration.

[Table 5 goes here]

Table 5 similarly shows what 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.

2.4.2 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:[17]

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

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

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.

[17] Calling $\frac{N_{m,t}-N_{m,t-1}}{N_{m,t-1}} = Y$, $\frac{I_{m,t}}{N_{m,t-1}} = X$, and $-\frac{O_{m,t}}{N_{m,t-1}} = Z$, we have that $\beta_1 = \frac{Cov(X,Y)}{Var(Y)}$ and $\beta_2 = \frac{Cov(Z,Y)}{Var(Y)}$ and that $Y = X + Z$. It is easy to show that $\beta_1 + \beta_2 = 1$, given a straight application of the fact that $Y = X + Z$ and the properties of the covariance. Given that, we have that $1 = \frac{Cov(X,Y)}{Var(Y)} + \frac{Cov(Z,Y)}{Var(Y)}$, thus β_1 and β_2 can be interpreted as a decomposition of the variance of Y.

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.[18] 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.

Panel B of Table 6 shows the same results using state level 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. 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]

In sum, most of the internal migration adjustments take place through changes in in-migration rate patterns. This is similar to what Coen-Pirani (2010) shows. Relative to Coen-Pirani (2010) I show that not only in-migration rates have higher variance than out-migration rates, but that they better explain differential growth rates across states and metropolitan areas. In what follows I build a model around this stylized fact.

[18] 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.

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 housing and labor markets, guaranteeing the existence of an equilibrium. This simply means that if more workers move to a particular location, real wages – defined as nominal wages divided by housing prices – decline and thus the value of that location also decreases 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 that reacts to unexpected local shocks in particular places.

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.[19] There is also a non-tradable sector that, for simplicity I will call housing. The housing sector simply creates a positive relationship between housing prices and population that depends on the underlying shape of the local supply of housing. These generates congestion forces. There is also, potentially, a fixed factor of production, called land or capital, that can make the local labor demand downward sloping.[20] 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 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 location.

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

Workers live for many periods. At the beginning of each period and conditional on the distribution of workers across locations, firms maximize profits, and wages and housing prices are determined. At the end of the period and given current and future real wages in the economy and an i.i.d. idiosyncratic taste shock, workers decide where to live in the following period.

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

[20] If capital is flexible, then congestion forces necessary for an equilibrium to exist are a result of the housing market. If instead capital is not flexible, this generates extra congestion forces at the local market that can guarantee the existence of equilibrium.

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:

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

where N_m is labor or population and K_m is land or capital – which may be fixed or flexibly supplied.[21] 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 is the Total Factor Productivity (TFP) of each location. ρ is assumed to be the same across local labor markets and smaller than 1.

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.[22] Thus the labor market is determined by firms' behavior:

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

where $\sigma = 1/(1-\rho)$ is the elasticity of substitution between labor and capital. Conditional on the response of capital, this equation defines the (inverse) labor demand curve. Note that we can obtain a similar equation for the demand for capital, whose price is denominated by r_m. We can normalize the price of goods $p_m^g = 1$.[23] Free trade will guarantee that prices are the same across regions. We can re-express the (inverse) 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:

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

This is potentially one of the sources of congestion forces in this model.

[21] If fixed we tend to think about it as land, while if flexibly supplied we tend to call it capital.

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

[23] It is also possible to introduce more realistic models of internal trade. I discuss this point in Appendix B.3.

3.1.4 Housing market and demand for local goods

There is competition for land and an imperfectly elastic supply of housing. Workers spend a constant fraction of their income in housing (denoted by α). Price of housing is denoted by p_m. The local supply of housing is determined by the underlying housing supply elasticity. I assume that this takes the following form:

$$\ln p_m = \varepsilon_m^H \ln N_m \tag{3.3}$$

Note that ε_m^H may be location specific. There are remarkable differences in housing supply elasticities across US cities (Saiz, 2010).

Importantly, note also that p_m could represent, in a more general model, the price index of local non-tradable goods. This is, one can interpret the housing market as the non-tradable sector. To simplify the exposition of the model I will refer to p_m as the price of housing or local price index indistinctively.

A more general discussion of congestion and (potential) agglomeration forces is provided in Appendix B.1.

3.1.5 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 local housing prices $p_{m'}$, 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:[24]

$$v_{t,m,m'}^i = \ln V_{t,m'} + \epsilon_{t,m,m'}^i = \ln A_{m'} + \ln w_{t,m'} - \alpha \ln p_{t,m'} + \beta \mathrm{E}_t\{\ln V_{t+1,m'}\} + \epsilon_{t,m,m'}^i$$

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 $\epsilon_{t,m,m'}^i$ specific to each worker and her current residence.

Thus, for each period workers maximize:

$$\max_{m' \in M} \{\ln V_{t,m'} + \epsilon_{t,m,m'}^i\}$$

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, housing prices and valuations

[24] We can precisely define real wages as $\ln w_{t,m'} - \alpha \ln p_{t,m'}$. This is the indirect utility that is obtained from a Cobb-Douglas utility function with two goods, consumption and housing, without saving, and where α is the weight on housing.

of amenities $\mathbf{A}$, $\mathbf{w}_t$, $\mathbf{p}_t$ in each location.[25] 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':

$$P_{t,m,m'} = p_{m,m'}(\mathbf{A}, \mathbf{w}_t, \mathbf{p}_t) * N_{t,m} \tag{3.4}$$

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 the idiosyncratic taste shock determines the flows of workers across locations, not the final distribution. This is in contrast to what happens in static spatial equilibrium models. This is one of the crucial methodological innovations of this paper.

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:

$$I_{t,m} = \sum_{j \neq m} P_{t,j,m},\ O_{t,m} = \sum_{j \neq m} P_{t,m,j},\ N_{t+1,m} = \sum_{j} P_{t,j,m}$$

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 in line with migration patterns in the United States and cannot be captured by static spatial equilibrium models – where only net flows of people across locations can be studied.

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 and the productivity of each factor θ_m, and factor prices in each location to maximize profits. Second, labor and housing markets clear in each location. This equates the supply and the demand for housing and for labor and determines real wages in each local market. More formally:

[25] 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.

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, capital, and housing markets clear in each* $m \in M$ *so that* $\{w_{t,m}, r_{t,m}, p_{t,m}\}$ *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 or steady-state 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 we need to reduce the dimensionality of the migration matrix previously discussed. For that, I assume that the distribution of the idiosyncratic taste shocks is a nested logit, something that allows me to derive further properties. At the individual level, this means that the home location will be more likely to have a higher draw than any other destination, something that captures "home biased" preferences.

At the aggregate level, it will appear as if a representative worker decides as follows: first, she decides whether to stay in m or look for a new destination away from m; second, conditional on moving away from m, she decides where to go given all the possible destinations.[26]

A key feature of the model is that this nesting structure makes the home location special relative to all other locations. This is attained through 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).

[26] Figure A.1 shows this nested structure. The link between discrete choice theory and aggregate outcomes that "look like" a representative decision maker is described and analyzed in Anderson et al. (1992).

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:[27]

$$P_{t,m,m'} = N_{t,m}\eta_{t,m}\frac{V_{t,m'}^{1/\lambda}}{\sum_{j\in M} V_{t,j}^{1/\lambda}} \tag{3.5}$$

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. Note that a fraction $1-\eta_{t,m}$ of individuals decides not to move. This fraction responds *endogeneously* to local shocks, something that is governed by γ.

It is important to note that in principle the value of the destination may depend on the distance between the origin and the destination. Including this feature is convenient for predicting the equilibrium bilateral flows of workers across locations, but it plays a very limited role in determining the *response* of in-migration rates to local shocks – which is the main focus of this paper – and it complicates (slightly) the algebra.[28] Thus, I present in this paper the simplified version of the model where distance between locations does not play a role.

The expected value of 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:[29]

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

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.

In order to gain intuition on the model, 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. However, this 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

[27] Anderson et al. (1992) provide an explicit derivation using the distribution of ϵ.

[28] The reason for this is that the value of the economy V_t becomes origin specific.

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

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 is also unrealistic because if half of the population decides 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 lower than the empirical fact that around 95 percent of the population stays where they are from one year to the next.

A simple intuitive assumption can address this latter issue. Assuming that the positive draw in the location of origin is $(1-\eta)/\eta$ times more likely than any other location implies that:[30]

$$\eta_{t,m} = \frac{\eta V_t^{1/\gamma}}{(1-\eta)V_{t,m}^{1/\gamma} + \eta V_t^{1/\gamma}} \tag{3.6}$$

This assumption can be interpreted as moving costs. It combines all the reasons why it may be costly to leave the current location, that can be related to either psychological costs or costs associated to selling the house or moving belongings to a new apartment or house. Instead of moving costs entering linearly, the specification in this paper makes the whole model much more tractable. See a discussion of this point in Appendix D.

In terms of the decision tree described in Figure A.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 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.

These assumptions make it particularly simple to solve the model forward, as is shown in Appendix C.

3.2.2 Mobility and labor relocation

In this section, 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

[30] This means that the distribution of ϵ takes the form of a generalized nested logit distribution, where the upper nests may take different weights which are captured by η. This assumption is similar to standard weights introduced in CES production functions or preferences that have been used to capture difference in productivity across factors (necessary for example in the literature on skilled biased technical change), or the relative importance of various sectors in overall consumption.

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, I 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. In- and out-migration rates are usually stationary series that are easier to analyze empirically.

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. □

Note that I used implicitly Corollary 3 in my estimation of the migration responses during the Great Recession. This is, in Section 2.3 I regress the in- and out-migration rates on wages before and after the shock. This is a continuous difference in difference estimate, i.e. it relates changes in in- and out-migration rates with changes in wages that are driven by the instrument. Thus, the estimates from the regressions in Section 2.3 are estimating the equations presented in Corollary 3.

3.2.3 Dynamics

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 changes in in-migration rates or out-migration rates. This, combined with congestion forces, is the source of spillovers across locations in this model. If congestion forces are strong, changes in the distribution of people across space will have consequences on real wages and thus valuations of non-affected locations. Fewer people will move to the shocked location or more will leave. In either case, the labor supply and the demand for housing in that location decreases. Reduced in-migration or increased out-migration translates into an increase in labor supply and an increase in the demand for housing in the non-affected locations, which tends to equalize the value across locations.

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

$$N_{t+1,m'} = (\sum_j P_{t,j,m'}) = \widetilde{\eta}_t \frac{V_{t,m'}^{1/\lambda}}{V_t^{1/\lambda}} N_t + (1-\eta_{m,t}) N_{t,m'} \tag{3.7}$$

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, since part of the current population is determined by the past number of workers in that location. When $1/\gamma = 0$, $\eta_{m,t}$ and $\widetilde{\eta}_t$ are independent of m and t and become the *same* parameter. In this case, the dynamic system simplifies even more.

The propagation of the shock through real wages and population is entirely determined by equation 3.7. To obtain the evolution of wages we simply need to combine equation 3.7 and the labor demand equation 3.2 such that:

$$Q_{t+1,m} w_{t+1,m}^{-\sigma} = \widetilde{\eta}_t \frac{V_{t,m}^{1/\lambda}}{V_t^{1/\lambda}} N_t + (1-\eta_{t,m}) Q_{t,m} w_{t,m}^{-\sigma} \tag{3.8}$$

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 periods.

A similar equation can be constructed for housing prices. Using the relationship between housing prices and population levels shown in equation 3.3 we obtain:

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

Finally, the evolution of the value of living in a location also evolves with a simple equation:

$$\ln V_{t,m'} = \ln A_{m'} + \ln w_{t,m'} - \alpha \ln p_{t,m'} + \beta\gamma(\ln[(1-\eta) V_{t+1,m'}^{1/\gamma} + \eta V_{t+1}^{1/\gamma}]) \tag{3.10}$$

where this equation is derived from the indirect utility and the expected continuation value in each location coming from the assumption on the distribution of ϵ as I make explicit in Appendix C. This equation also becomes simpler when $\frac{1}{\gamma} = 0$.

In fact, equations 3.7 and 3.10 define a system of two equations and two unknowns for each location that fully characterizes the dynamic system. For the system to converge, the crucial aspect is that, either through competition in the labor market or in the housing market, the value of a location is decreasing in population.

3.2.4 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:

$$\ln V_m \approx \frac{\beta}{1-\beta}\gamma\ln(1-\eta) + \frac{1}{1-\beta}\ln A_m + \frac{1}{1-\beta}\ln w_m - \frac{\alpha}{1-\beta}\ln p_m + \gamma\frac{\beta}{1-\beta}\frac{\eta}{1-\eta}(\frac{V}{V_m})^{1/\gamma} \quad (3.11)$$

This expression says that in the long run equilibrium, the value of each location can be expressed in terms of its current real wages and amenities.[31]

Furthermore, we can also obtain a very simple expression for the allocation of people across locations. Using 3.7 and the fact that $\widetilde{\eta_t} \approx \eta_{t,m}$ (especially for the average metropolitan area) we obtain:

$$N_m \approx \frac{V_m^{1/\lambda}}{V^{1/\lambda}}N \quad (3.12)$$

Thus, population is distributed across locations according to the location's share in the total value of the economy.[32] Another implication of this result is that in the long run equilibrium, bilateral flows 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 is *decreasing* in city size or that the elasticity of population to migrants is below 1. I show that this is indeed the case in the United States in Table A.2 discussed in Appendix A.4.

3.2.5 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 and the distribution of population is stable across space. The model collapses to a standard spatial equilibrium models, 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 we can obtain the unique dynamics that lead to the unique equilibrium.*

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

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

[32] When $\gamma = 0$ expression 3.12 is an identity.

Proof. See Appendix.

□

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 3.12.

We can also use equation 3.12 to evaluate long run welfare:

$$\Delta \ln V_{m'} \approx \lambda \Delta \ln N_{m'} + \Delta \ln V \tag{3.13}$$

This expression shows that the change in welfare between any two long run equilibria is determined by both changes in population ($\Delta \ln N_{m'}$) – which are specific to each location – and the overall change in the welfare of the economy ($\Delta \ln V$)– which affects everyone equally, independent of location. It also shows that there is some long-run relationship between population changes and welfare changes at the local level. While this is not directly testable, given the prominence of wages and housing prices in determining welfare levels, it is possible to look over long time horizons whether population changes are positively correlated with nominal or real wage changes. In this model they should be positively correlated, while in a model where immigration fully insures against local shocks (like in Blanchard and Katz (1992)) there should be no such correlation. In Appendix A.5 I show how long-run changes in population are indeed positively correlated to long-run changes in nominal and real wages (even after accounting for observable characteristics). 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 and housing prices in the affected location decrease relative to the rest of the economy and workers in that location lose in terms of welfare. In the long run, wages and housing prices in that location partially recover thanks to internal migration. In the long run, the lost welfare in each location is proportional to the lost population, where λ (i.e. the inverse of the elasticity of in-migration response to local shocks) 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 larger than that of out-migration rates. This explains how internal migration helps to dissipate local shocks, as made explicit in the model introduced in Section 3. In this section, I investigate quantitatively how these local shocks propagate through local markets using a calibrated version of the model where some of the key parameters were already estimated in Section 2.2.

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. It serves as an illustration of both the importance of internal migration and the simplicity with which the model can be brought to the data and used for welfare analysis.

4.1 Model estimation

4.1.1 Internal migration and local congestion forces

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 are (net) local congestion forces governed by ε_m. Since this parameter is not estimated in this paper, I rely on Saiz (2010). The fourth parameter is η, which determines the equilibrium internal migration rate in the economy and is computed in the summary statistics Table 1.

In Table 4 discussed in section 2.3 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 $\beta = .95$ which 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:[33]

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

[33] This estimate can be compared to Caliendo et al. (2018b) estimate of 2.3 in the context of a model similar to the one presented here, but where there is no distinction between the response in in- and out-migration rates.

To estimate local congestion forces, which can come from the housing or the labor markets, I start by using the local housing supply elasticities estimated in Saiz (2010). This assumes that the local labor demand elasticity is not a source of congestion. In Appendix E I show how the results change if I allow for congestion forces coming from local competition in the labor market. If congestion forces are larger, the speed of convergence is higher and the role of internal migration in insuring against local shocks is also larger. Thus, I present, in the main text of this paper, a *lower bound* of the potential importance of internal migration.

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 play a smaller 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. In particular I can re-write the system of equations so that it depends only on local productivities and amenities. For this, I use the long run equilibrium condition. This is, I assume that in 2005 the US economy was in long run spatial equilibrium, meaning that bilateral flows across locations are stable and cancel each other out, which necessarily implies that the distribution of people across space would have remained stable had it not been for the Great Recession.[34] In this case, I observe the population levels in all the locations in the US and I can infer the amenity-productivity levels that make the bilateral flows of workers across locations stable given the congestion forces coming from the housing market – a necessary and sufficient condition for the model to be in long run equilibrium.[35]

Assuming that the US is in long run equilibrium also allows me to compute the initial conditions of the dynamic system governed by equations 3.7 and 3.10. 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 3.10, which can be re-written as:

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

[34] 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.

[35] More specifically, to obtain the productivity-amenity levels we need to use the long run equilibrium. This is:

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

which holds for every m. From that we have:

$$\frac{A_m B_m}{A_0 B_0} = \frac{N_{0,m}^{\lambda(1-(1-\eta)\beta))+\varepsilon_m}}{N_{0,0}^{\lambda(1-(1-\eta)\beta))+\varepsilon_0}}$$

Thus, we obtain the value of the amenity-productivity in each location relative to a base location.

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

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

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 for each location:

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

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

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

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

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

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

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

Note that it is particularly simple to solve this model numerically despite the large number of locations and the forward looking behavior of agents. First, to determine initial conditions, we obtain an estimate of unobservable amenity-productivity ($A_m B_m$) as a simple explicit function of parameters already estimated and observable population levels. For this we only need to assume that initially the system is at its steady state. Second, to obtain a the new short-run value of the locations when there is a shock, we only need to know how much the shock changes amenity-productivity levels and use the multiple iterations of equation 4.2 holding population constant. This is a contraction mapping that converges to the new valuation of each location. Third, we can also obtain the long-run valuation and population levels using the steady state conditions of the model with the new amenity-productivity levels. And fourth, given the new short-run value of each location we can use the dynamic system to characterize the full transitional dynamics. I describe this in more detail in Appendix F.

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 productivity (B_m) of cities of various magnitudes. This might reflect the functioning of the financial systems in these different localities or the importance of particular sectors that were more affected by the crisis. This change in B_m is, however, unobservable. However, it can be predicted from the short run change in wages during the Great Recession. In other words, we can compare the wages in 2005 with those of 2010, assume that population levels are stable throughout this period, and infer the new B_m that justifies the wages in 2010. I can then feed these changes in B_m back into the model and obtain the new long run equilibrium and the full transition dynamics for valuation 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 local valuations and population levels across locations if nothing else is changing in the economy. In this respect, it isolates the contribution of internal migration to the mitigation of real 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 left panel of Figure 1 shows the evolution of normalized valuations in two representative cities: New York and Las Vegas.[36] Las Vegas was one of the cities most affected during the Great Recession. Given high levels of household indebtedness and the importance of its service sector, predicted productivity dropped by almost 19 percent, as shown in Table A.4. 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, labeled as year 0 in the figure, the value of each location dropped, but, relative to the average in the economy, the value of New York increased, while the value of Las Vegas decreased. After the shock, internal migration starts to dissipate the shock across space. This means that real wages and thus the value of Las Vegas recovers, while the value of New York decreases. This is the process of real wage convergence following the endogenous internal migration response.

Within 20 years in the case of Las Vegas, and within very few years in the case of New York, their value and population levels are back to the steady state. In Table A.3 in the Appendix, I show that in this calibration it takes around 13 years for the average city to be back to the long-run equilibrium. This table also shows that there is a lot of heterogeneity across locations. Some are back to the long-run equilibrium very quickly, while the most affected metropolitan areas take as much as 30 years.

[36] I normalize the value of each location to 1 in the pre-shock period so that it is easy to see the dynamics in a graph.

[Figure 1 goes here]

The top right part of Figure 1 shows how the evolution of local valuation shapes the evolution of the population. We see that in Las Vegas, valuations dropped more than the national average and thus fewer people were attracted towards this city. This consequently decreases the city's population which partially mitigates the negative consequences of the crisis. The mechanism through which this occurs is, in this calibration, almost exclusively through reduced in-migration. This is shown in the bottom of Figure 1. In-migration rates in Las Vegas drop to 3 percent from a pre-shock level of 5 percent.[37] This graph neatly shows the asymmetry in the response of in- and out-migration rates that the model captures and that is absent in previous work.

It is apparent in Figure 1 that while the value of locations recovers in the most affected locations, it does so to a lower level than the value of the location prior to the shock. Thus, internal migration offers insurance to local shocks, but only partially – in contrast to the implications in the seminal contribution of Blanchard and Katz (1992). It is thus of great interest to evaluate to what extent the initial shock actually translates into permanent welfare losses at the local level. I investigate this question in the following section.

4.3 Internal migration and insurance

The model provides a simple way to compute how much insurance internal migration provides. For this we can relate the initial change in local valuations to the change in local valuations between the immediate post-shock period and the long-run valuations. This is, we can run the following regression:

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

The estimate of β translates initial valuation changes into long-term consequences. If $\beta = -1$ then the initial drop is fully dissipated in the long-run. Instead, if $\beta = 0$ then the short-run shock becomes permanent.

Figure 2 shows these results. In the top panel I show that the estimate of the change in local productivity, perfectly explains the short-run change in local valuations.

[Figure 2 goes here]

The bottom part of Figure 2 shows that locations that in the short-run lost more value gained more value over time. The estimate of β is around -.67. This means that 67 percent of the initial

[37]Note that in this figure the both the denominator and numerator change, which explains the particular shape that the series takes.

shock is dissipated across space thanks to internal migration alone. This is so even when people do not out-migrate from hard hit locations in higher proportions after the shock. Again, this highlights that it is important to take into account both in- and out-migration to think about how much insurance migration provides. The variance in the figure reflects the fact that housing supply elasticities differ across metropolitan areas, and so the rate at which metropolitan areas absorb population.

In Table A.3 I show how sensitive these results are to alternative congestion forces. As can be seen in the Table, if I increase the level of congestion forces – for instance by assuming positive local labor demand elasticities – this tends to accelerate the convergence to the new equilibrium and tends to make internal migration a more powerful insurance mechanism against local shocks.

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 real 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. I view this as an important methodological contribution that goes beyond models of internal migration. For example, this modeling 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. At least 60 percent of the initial shock is potentially dissipated across metropolitan areas thanks to internal migration alone. Moreover, the convergence to the new equilibrium is reasonably fast. Reasonable calibrations of the model suggest that the new steady state is reached within ten years of the initial shock for most metropolitan areas. The model also shows that there is substantial heterogeneity in how fast each metropolitan area reaches the new long-run equilibrium.

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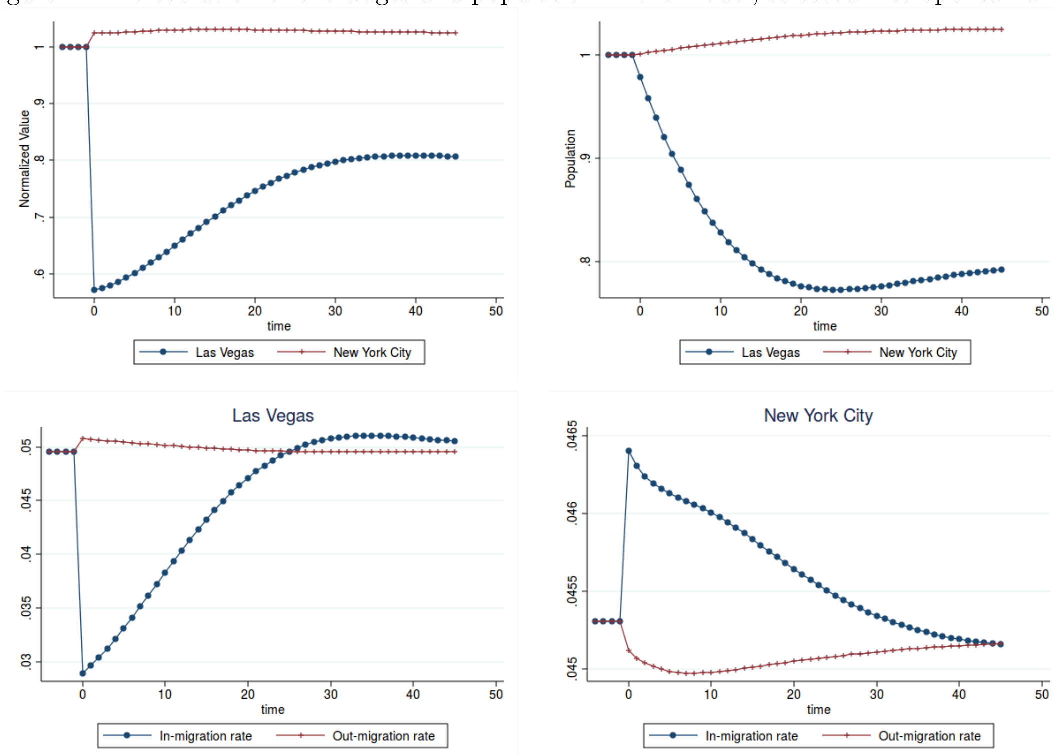
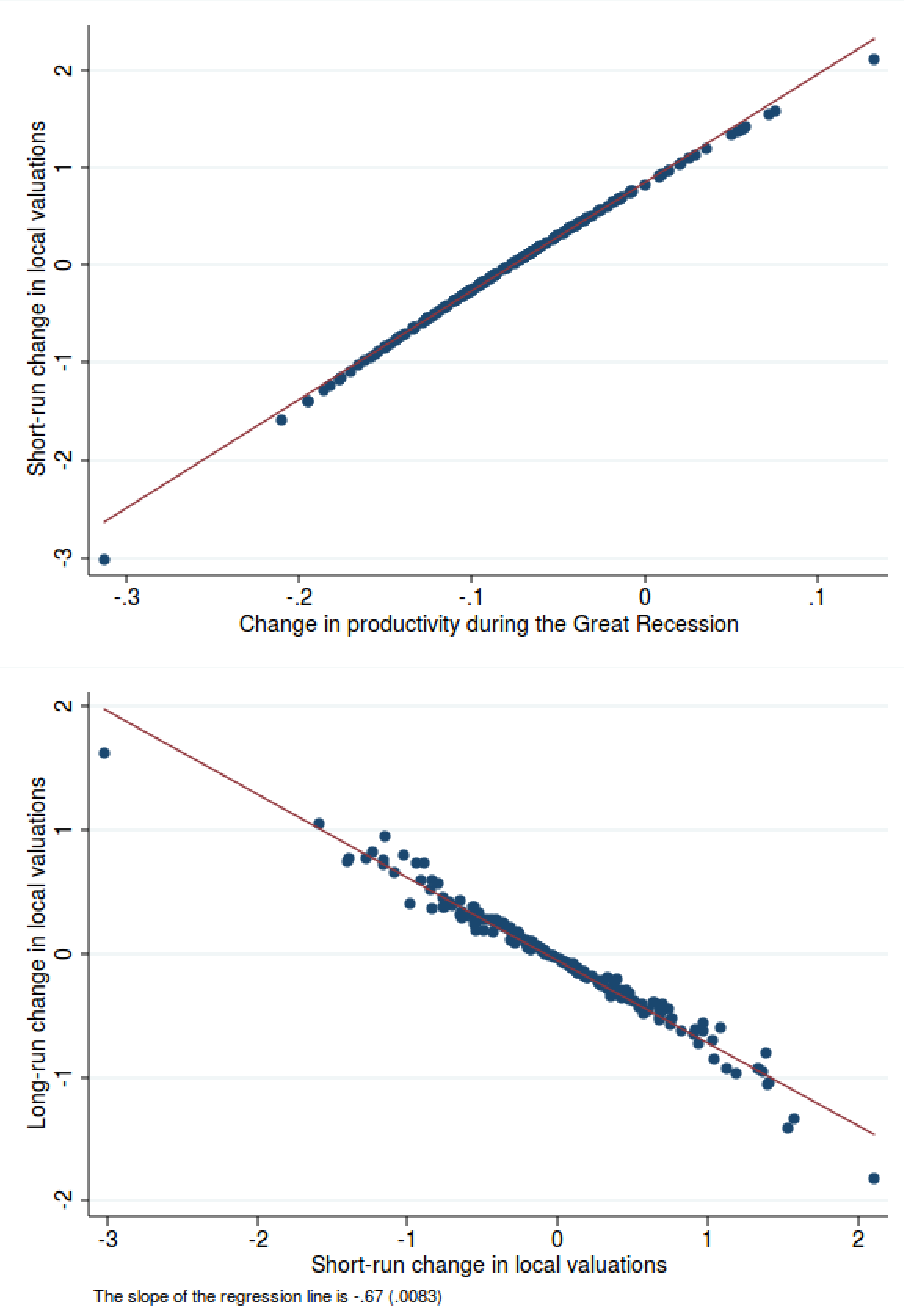
6 Figures

Figure 1: The evolution of the wages and population in the model, selected metropolitan areas



Notes: The top two graph show the evolution of normalized valuations and population in Las Vegas and New York City according to the model calibrated to match the implied productivity loss during the Great Recession. The bottom two graphs show the evolution of the in- and out-migration rates in Las Vegas and New York City according to the model calibrated to match the implied productivity loss during the Great Recession. See more details in the text.

Figure 2: The change in sort- and long-run local valuations as a result of the Great Recession shock



Notes: The top graph shows the percentage change in local valuations as a function of the implied change in local productivities during the Great Recession, without population adjustments. The bottom graph shows the long-run change in local valuations once population adjusts. A slope of -1 in the bottom graph means that internal migration fully insures against local shocks, while a slope of 0 means that internal migration does not contribute to insuring against local shocks.

7 Tables

Table 1: Summary statistics, period 2005-2010

Variable	Mean	Median	Std. Dev.	Min.	Max.
Debt to Income, 2006	1.977	1.858	0.595	0.865	3.784
Share of emp. in non-tradable sectors, 2000	0.221	0.213	0.032	0.163	0.432
Non-trade emp x Debt to Income	0.442	0.380	0.172	0.201	1.236
Years 2005-2006					
Total population	2,150,467	1,083,765	2,604,588	51,253	10,028,307
Sample size	4,087.606	2,760	3,921.324	124	15,235
Average weekly wages	377.48	372.63	51.447	238.739	605.967
Unemployment rate	0.049	0.048	0.013	0.004	0.118
Employment rate	0.845	0.846	0.028	0.697	0.931
In-migration rate	0.054	0.051	0.019	0.006	0.126
Out-migration rate	0.053	0.050	0.019	0.005	0.259
Net in-migration rate	0.001	0.001	0.017	-0.2	0.093
Years 2007-2010					
Total population	2,233,383	1,138,118	2,679,241	47,997	10,176,648
Sample size	4,051.202	2,709	3,975.764	91	15,362
Average weekly wages	357.875	352.144	51.535	209.414	580.365
Unemployment rate	0.071	0.065	0.029	0.008	0.172
Employment rate	0.834	0.839	0.039	0.635	0.947
In-migration rate	0.048	0.045	0.016	0	0.15
Out-migration rate	0.047	0.045	0.015	0.004	0.159
Net in-migration rate	0.000	0.000	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: First stage and reduced form 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 210 metropolitan areas between 2005-2010. Panel B: The dependent variables are the net in-migration, the in-migration, and the out-migration rates in 210 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 3: 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 210 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 2. 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: 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 210 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 2. Number of observations: 210 metropolitan areas x 6 years = 1,260. Robust standard errors reported. * p<.1, ** p<.05 and *** p<.001.

Table 5: 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 1980 - 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 6: In- migration, out-migration and population growth

Panel A: Census data, metropolitan-level variation

	(1) In-migration rate	(2) Out-migration rate	(3) In-migration rate	(4) Out-migration rate	(5) In-migration rate	(6) 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) In-migration rate	(2) Out-migration rate	(3) In-migration rate	(4) Out-migration rate	(5) In-migration rate	(6) 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) In-migration rate	(2) Out-migration rate	(3) In-migration rate	(4) Out-migration rate	(5) In-migration rate	(6) 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, for Online Publication

A Empirical Evidence

A.1 Event type graphs

A simple way to understand exactly where local labor market and migration results come from is to run the difference in difference specification introduced in the first stage of equation 2.1 but splitting the post period dummy into year dummies and plot these year dummies interacted with the measure of local shocks. I plot these coefficients in Figure A.2. The Figure shows the dramatic change that takes place after 2007. After 2008 local labor market conditions deteriorate and internal migration responds accordingly.

[Figure A.2 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.[38] 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 A.1.

[Table A.1 goes here]

Table A.1 shows that the internal migration response of low-skilled workers is very similar to that of the average population shown in Table 4. 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 A.1 also shows that this elasticity drops only slightly if we restrict the

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

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 A.1 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 4.

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.

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 A.3. 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 A.3 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 A.3 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 use 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 A.4, which plots the fitted values of the regressions between 2000 and 2006 and between 2006 and 2010:

[Figure A.4 goes here]

In particular, Figure A.4 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.[39]

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 $\beta < 1$.[40]

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

[40] 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.

Table A.2 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 A.2 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.

A.5 Long run wage and real wage convergence

The model suggests that in the long run, the valuations across location permanently change as a consequence of local shocks. The intuition for this results is linked to the reason why internal migration rates are decreasing in city size as discussed in Appendix A.4. In the long run equilibrium, bilateral flows between any two metropolitan areas exactly cancel each other out. Thus, for a city to be larger, it must have a higher value. Part of this value is reflected in wages in the city.

This is why when a location loses population the average wage in the location never recovers the previous level. In other words, the model predicts that there is a positive correlation between population and wage growth. If instead, internal migration fully dissipated wage differences across space, we would obtain a 0 correlation between population and wage growth. This is, thus, an empirical question. The simplest possible test is the following regression:

$$\Delta \ln wage_m = \alpha + \beta \Delta \ln pop_m + \varepsilon_m \tag{A.2}$$

where $wage_m$ is the average wage (which can be composition adjusted if we run first a mincerian regression) in metropolitan area m and where pop_m is the working population. Furthermore, we can take into account that maybe only house prices adjust by using real wages, i.e. nominal wage minus 25 percent of the local housing price index. I compute local price indexes following Moretti (2013).

In this context, if $\beta > 0$ it means that there may be some persistence in local shocks. If instead $\beta = 0$ it means that internal migration potentially equilibrates the value across locations fully.

[Figure A.5 goes here]

Results are shown graphically in Figure A.5 and some robustness is provided in Table A.5.

[Table A.5 goes here]

Figure A.5 and Table A.5 show that there is a positive and statistically significant relationship between wages and real wages and population growth. This is true for each and every decade, for 20 years year intervals, when controlling for metropolitan area trends, and when controlling for decade changes in wage and population growth. Thus, the data clearly suggests that there is some degree of wage and real wage persistence. Note that this evidence is inconsistent with Blanchard and Katz (1992) and the large literature that follows their estimation strategy.

B Extensions to the Model

In this section I show how straightforward it is to introduce wealthier models of the labor market, of trade and on other congestion and agglomerations forces 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 first present a general discussion of congestion and agglomeration forces and I then discuss two potential extensions of the mode using search and matching frictions and trade. For trade, I discuss some alternatives, relying heavily on Caliendo et al. (2019).

B.1 Agglomeration and congestion forces

Before moving into the next section and bringing the model to US data it is convenient to show clearly why congestion forces need to dominate. A simple way to think about congestion and (potentially) agglomeration forces is to substitute prices in the value of each location. This is we can re-write $\ln V_{t,m'} = \ln A_{m'} + \ln w_{t,m'} - \alpha \ln p_{t,m'} + \beta \mathrm{E}_t\{\ln V_{t+1,m'}\}$ as follows:

$$\ln V_{t,m'} = \ln(1-\theta_{m'}) + \ln A_{m'} + \ln B_{m'} - (\varepsilon^D_{m'} + \alpha\varepsilon^H_{m'} - \varepsilon^A_{m'} - \varepsilon^B_{m'}) \ln N_{t,m'} + \beta \mathrm{E}_t\{\ln V_{t+1,m'}\}$$

This equation shows the various congestion forces of the model and show simple ways in which agglomeration forces could have been introduced. For example, it shows that labor market competition reduces the (instantaneous) value of the location by ε^D_m. Similarly, competition in the housing market decreases the value of the location by $\alpha\varepsilon_m^H$ which is the share of income spent on housing times the local housing supply elasticity. There could also have been agglomeration forces. For instance, a location can become more productive if the are more people. This could be captured by ε_m^B, reflecting agglomeration forces identified in the literature (see Duranton and Puga (2004)) related to the local productivity increasing in local population. There could also have been endogenous agglomeration forces coming from consumption amenities, which could have been captured with ε_m^A (see Diamond (2015)). While in the model these agglomeration forces are ignored, this equation shows that it is very simple in this framework to introduce elements explored in prior literature.

More generally, the equation also shows that we can also introduce various trends in the value of the different locations. Locations that become more attractive can be thought of as locations where $A_{m'}$ is increasing. Similarly, locations may become more attractive if their local productivity increases $B_{m'}$ or the technology biases towards labor $1-\theta_{m'}$.

We can combine these various agglomeration and congestion forces into a simple equation:

$$\ln V_{t,m'} = \ln(1-\theta_{m'}) + \ln A_{m'} + \ln B_{m'} - \varepsilon_{m'} \ln N_{t,m'} + \beta \mathrm{E}_t\{\ln V_{t+1,m'}\} \tag{B.1}$$

where I allowed for various sources of congestion and (potential) agglomeration forces that are summarized in the parameter $\varepsilon_{m'}$. It is important to note, though, that this parameter needs to be positive *for every metropolitan area*. If this is not the case, then population would ultimately concentrate in the metropolitan area with the most negative $\varepsilon_{m'}$.

B.2 Unemployment

B.2.1 Labor market with unemployment

In this section I consider the case in which the local labor market equilibrium is determined by a search and match technology that takes place in each market (Pissarides, 2000) and I abstract from the housing market.

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

$$u_m = \frac{\delta}{\delta + \tilde{\theta}_m^{1+\eta}} \tag{B.2}$$

where $\tilde{\theta}_m = v_m/u_m$ is the labor market tightness.

Job creation

The zero profit condition determines the job creation equation:

$$r_m - w_m - \frac{(i_m+\delta)r_m f}{\tilde{\theta}_m^{\eta}} = 0 \tag{B.3}$$

Where i_m is the interest rate.

Wage curve

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

$$w_m = (1-\beta)b_m + \beta r_m(1+f\tilde{\theta}_m) \tag{B.4}$$

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

B.2.2 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:

$$v^i_{m'} = \ln V_{m'} + \epsilon^i_{m,m'} = \ln A_{m'} + \ln((1-u_{m'}) * \omega_{m'} + u_{m'} * b_{m'}) + \epsilon^i_{m,m'}$$

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

$$v^i_{m'} = \ln A_{m'} + \ln((1-u_{m'}) * w_{m'} + u_{m'} * \tau_{m'} w_{m'}) + \epsilon^i_{m,m'} \approx \ln A_{m'} + \ln w_{m'} - u_{m'}(1-\tau_{m'}) + \epsilon^i_{m,m'} = \ln V_{m'} + \epsilon^i_{m,m'} \tag{B.5}$$

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:

$$\max_{s' \in M} \{\ln V_{m'} + \epsilon^i_{m,m'}\} \tag{B.6}$$

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 $\mathbf{A}$, $\mathbf{w}, \mathbf{u}$:[41]

$$p^i_{m,m'} = p_{m,m'}(\mathbf{A}, \mathbf{w}, \mathbf{u}) \tag{B.7}$$

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.7) to obtain the flow of people between m and m':

$$P_{m,m'} = p^i_{m,m'} * N_m \text{ for } s \neq s' \tag{B.8}$$

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.2.3 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

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

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* $\{w_m, u_m, \tilde{\theta}_m, r_m\}$ *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.3 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 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. (2019) reach their results using an Eaton and Kortum (2002) model of international trade. There are, however, many alternatives.[42] 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 as the 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

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

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

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

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

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

This expression says that the value of location m' is the value of its amenities and real wages ($\ln w_{t,m'} - \alpha \ln p_{t,m'}$) 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 real wages and amenities.

We start from the expression:

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

which can be re-expressed as:

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

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

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

At t+1:

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

So,

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

After many iterations:

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

Which can be simplified to:

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

Now, note that $\ln \nu_{t+k,m'} = \beta\gamma\frac{\eta}{(1-\eta)}(\frac{V_{t+1}}{V_{t+1,m'}})^{1/\gamma}$, which, given that η is close to 0, means that $\ln \nu_{t+k,m'}$ is a small residual. So, we have:

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

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

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

which iterating forward can be written as:

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

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 real wages, and the current and future state 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.

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:

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

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. In the main text I assumed that the only congestion force in the model was competition in the housing market and I used the housing supply elasticity estimated in Saiz (2010) to parametrize the competition in the housing market in the various metropolitan areas.

However, there could also be other sources of competition at the local level. In particular if capital takes time to adjust, an increase in labor supply at the local level likely decreases wages. To see how sensitive are the speeds of convergence presented in the main text to alternative sources of congestion forces I report in Table A.3 the speed of convergence to the new steady state of the average city under various assumptions. I also report the time to convergence of location that converges to the new steady state fastest and slowest.

[Table A.3 goes here]

The results are shown in Table A.3. The Table shows that increasing the size of local congestion forces tends to increases spillovers and, thus, increase the speed of convergence. For example when congestion forces are a combination of local competition for housing and a local labor demand elasticity of 1, the average city takes 8 years to converge to the new steady state, i.e. 5 years faster than if I don't consider competition in the labor market.

Table A.3 also shows that there is quite a lot of heterogeneity in how fast different metropolitan areas converge to the new steady state. There are always metropolitan areas where the shock of the Great Recession is such that they are already at population levels of equilibrium. Instead, the hardest hit metropolitan areas take as much as 20 to 30 years to return to equilibrium.

The final piece of information reported in Table A.3 estimates the degree of insurance provided by internal migration. This is the regression line shown in Figure 2. It shows that the degree of insurance provided by internal migration is relatively high, always above 60 percent. This is, given the difference in valuations of different locations at the onset of the Great Recessions, 60 percent of this difference is dissipated through internal migration.

F Numerical solution of the model

F.1 Steady state

The steady state of the system is given by:

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

$$V_0 = (\sum_j V_{0,j}^{1/\lambda})^{\lambda}$$

$$\frac{N_{0,m}}{N} = (\frac{V_{0,m}}{V_0})^{1/\lambda}$$

F.2 Dynamics

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

$$V_{t+1,m} = (A_m B_m N_{t,m}^{-\varepsilon_m})^{\frac{-1}{\beta(1-\eta)}} V_{t,m}^{\frac{1}{\beta(1-\eta)}} V_{t+1}^{\frac{-\eta}{(1-\eta)}}$$

$$V_{t+1} = (\sum_j V_{t+1,j}^{1/\lambda})^{\lambda}$$

where the last equation comes from inverting $V_{t,m} = A_m B_m N_{t,m}^{-\varepsilon_m} (V_{t+1,m}^{1-\eta} V_{t+1}^{\eta})^{\beta}$.

We can also use the definition of $V_{t+1,m}$ into the definition of V_{t+1} to obtain:

$$V_{t+1,m} = (A_m B_m N_{t,m}^{-\varepsilon_m})^{\frac{-1}{\beta(1-\eta)}} V_{t,m}^{\frac{1}{\beta(1-\eta)}} ([\sum_j [(\frac{V_{t,j}}{A_j B_j N_{t,j}^{-\varepsilon_j}})^{\frac{1}{\beta}}]^{\frac{1}{\lambda(1-\eta)}}]^{\lambda(1-\eta)})^{\frac{-\eta}{(1-\eta)}}$$

F.3 Estimation of initial conditions

$N_{0,m}$ is data. Select $A_m B_m$ such that the steady state holds. This is:

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

which holds for every m. From that we have:

$$\frac{A_m B_m}{A_0 B_0} = \frac{N_{0,m}^{\lambda(1-(1-\eta)\beta))+\varepsilon_m}}{N_{0,0}^{\lambda(1-(1-\eta)\beta))+\varepsilon_0}}$$

Thus, we obtain the value of the amenity-productivity in each location relative to a base location.

F.4 Estimation of final conditions

Given a change in $A_m B_m$, we can use the steady state conditions to find $N_{\infty,m}$. This is from:

$$V_{\infty,m} = (A_m B_m N_{\infty,m}^{-\varepsilon_m} V_{\infty}^{\eta\beta})^{\frac{1}{1-(1-\eta)\beta}}$$

$$V_{\infty} = (\sum_j V_{\infty,j}^{1/\lambda})^{\lambda}$$

$$\frac{N_{\infty,m}}{N} = (\frac{V_{\infty,m}}{V_{\infty}})^{1/\lambda}$$

So we can use this to obtain the value of each location in the new steady state:

$$V_{\infty,m}^{1-(1-\eta)\beta+\frac{\varepsilon_m}{\lambda}} = A_m B_m N^{-\varepsilon_m} V_{\infty}^{\eta\beta+\frac{\varepsilon_m}{\lambda}}$$

$$V_{\infty} = (\sum_j V_{\infty,j}^{1/\lambda})^{\lambda}$$

These equations define $V_{\infty,m}$ and V_{∞}. They are globally stable. So that can be solved in the computer with an initial guess and an iterative process.

We can also use these expressions to analytically obtain results. To do so it is simpler to analyze them by taking logs:

$$(1-(1-\eta)\beta+\frac{\varepsilon_m}{\lambda})\ln V_{\infty,m}=\ln A_m B_m-\varepsilon_m\ln N+(\eta\beta+\frac{\varepsilon_m}{\lambda})\ln V_\infty$$

$$\ln V_\infty=\lambda\ln(\sum_j V_{\infty,j}^{1/\lambda})$$

Now, taking derivatives we have:

$$(1-(1-\eta)\beta+\frac{\varepsilon_m}{\lambda})\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}=1+(\eta\beta+\frac{\varepsilon_m}{\lambda})\frac{\partial\ln V_\infty}{\partial\ln B_m}$$

$$\frac{\partial\ln V_\infty}{\partial\ln B_m}=(\frac{V_{\infty,m}^{1/\lambda}}{\sum_j V_{\infty,j}^{1/\lambda}})\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}$$

Or

$$\frac{\partial\ln V_\infty}{\partial\ln B_m}=(\frac{V_{\infty,m}}{V_\infty})^{1/\lambda}\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}$$

So:

$$(1-(1-\eta)\beta+\frac{\varepsilon_m}{\lambda}-(\eta\beta+\frac{\varepsilon_m}{\lambda})(\frac{V_{\infty,m}}{V_\infty})^{1/\lambda})\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}=1$$

Thus

$$\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}=\frac{1}{1-(1-\eta)\beta+\frac{\varepsilon_m}{\lambda}-(\eta\beta+\frac{\varepsilon_m}{\lambda})(\frac{V_{\infty,m}}{V_\infty})^{1/\lambda}}$$

We can now use the fact that:

$$\frac{\partial\ln N_{\infty,m}}{\partial\ln B_m}=\frac{1}{\lambda}(\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}-\frac{\partial\ln V_\infty}{\partial\ln B_m})=\frac{1}{\lambda}(1-(\frac{V_{\infty,m}}{V_\infty})^{1/\lambda})\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}$$

To obtain:

$$\frac{\partial\ln N_{\infty,m}}{\partial\ln B_m}=\frac{1}{\lambda}(\frac{\partial\ln V_{\infty,m}}{\partial\ln B_m}-\frac{\partial\ln V_\infty}{\partial\ln B_m})=\frac{1}{\lambda}(\frac{1-(\frac{V_{\infty,m}}{V_\infty})^{1/\lambda}}{1-(1-\eta)\beta+\frac{\varepsilon_m}{\lambda}-(\eta\beta+\frac{\varepsilon_m}{\lambda})(\frac{V_{\infty,m}}{V_\infty})^{1/\lambda}})$$

F.5 Transitional dynamics

We have the final distribution of $V_{\infty,m}$, $N_{\infty,m}$, but we **only** have $N_{0,m}$. We also know the equations governing dynamics. We need to find the sequence of $V_{t,m}$ and $N_{t,m}$ such that $N_{t,m}$ starts from the initial condition and we get to $N_{\infty,m}$ in the limit.

However, we can use the fact that $V_{t+1,m} = (A_m B_m N_{t,m}^{-\varepsilon_m})^{\frac{-1}{\beta(1-\eta)}} V_{t,m}^{\frac{1}{\beta(1-\eta)}} V_{t+1}^{\frac{-\eta}{(1-\eta)}}$ is a contraction to obtain the new valuation across locations by using the population levels $N_{0,m}$ and the new $A_m B_m$ to obtain the new valuation of each location before population adjusts. Once we have this, we simply use the system to obtain the full transitional dynamics.

G Proofs

G.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:

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

□

G.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:

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

□

G.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.

□

G.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.

□

H Appendix Figures

Figure A.1: Migration decision from an aggregate perspective

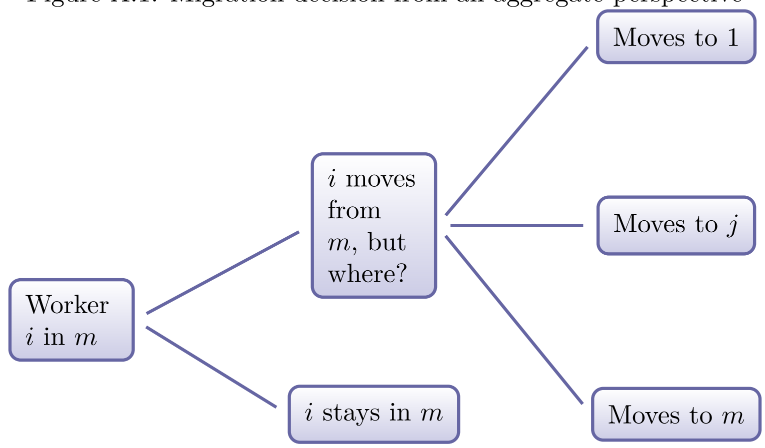
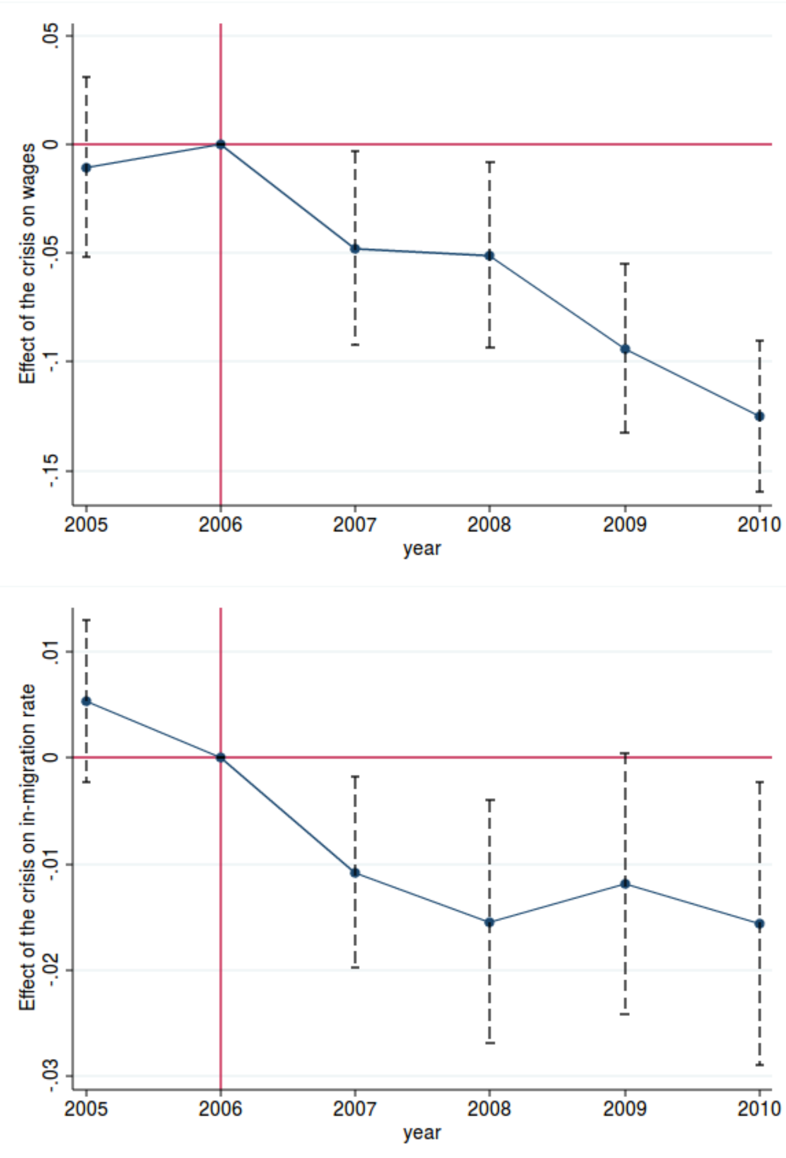
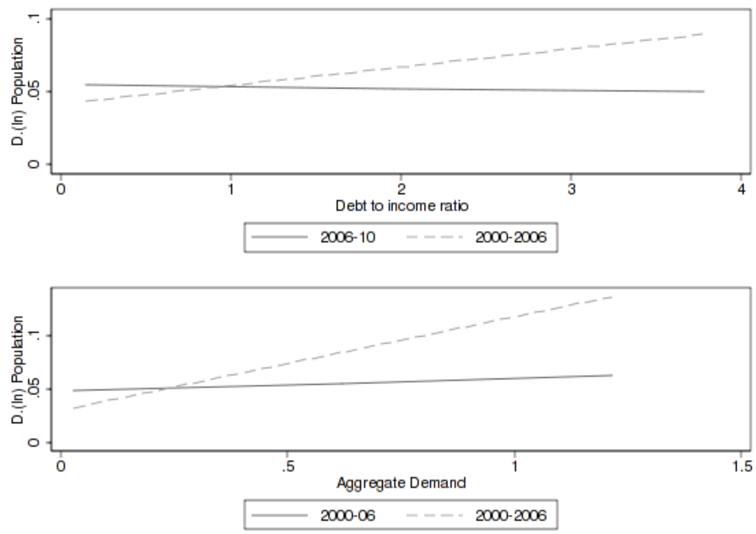


Figure A.2: Evolution of wages and in-migration rates during the Great Recession



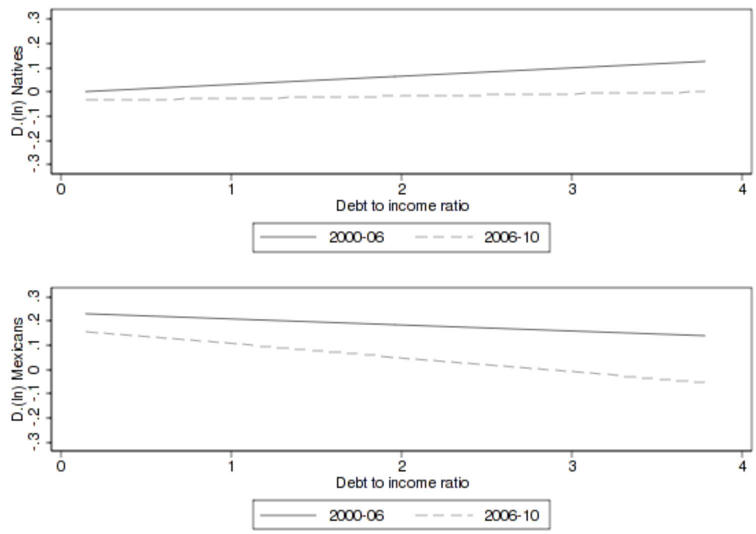
Notes: This figure reports the estimate of the interaction of year dummies with the Debt to income x share of employment in non-tradable sectors, controlling for metarea and year fixed effects. 95 percent confidence intervals are reported.

Figure A.3: Pre-trends in population growth rates



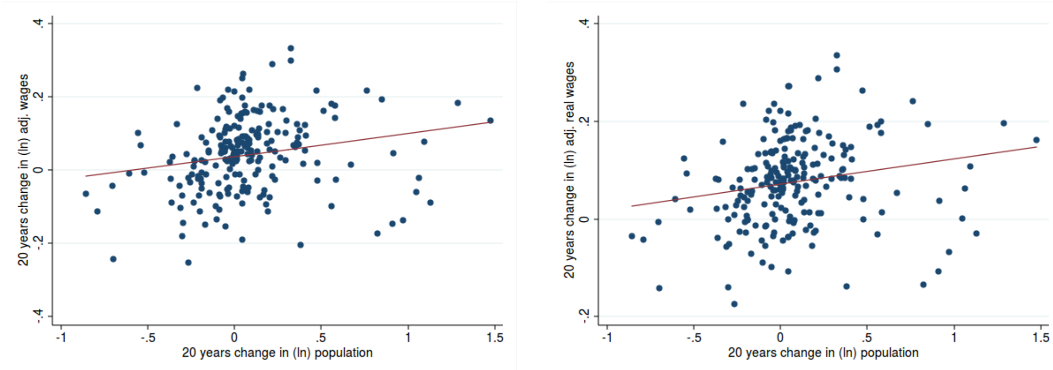
Notes: This graph shows the pre-trends in population growth rates relative to a measure of how hard the crisis hit at the local level.

Figure A.4: 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.

Figure A.5: Long run wage convergence in the data, 1980 to 2000



Notes: This figure shows the long run correlation between real and nominal wage changes and population changes. The data used for these figures comes from the US Censuses of 1980 and 2000.

I Appendix Tables

Table A.1: 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 2. Number of observations: 210 metropolitan areas x 6 years = 1260. Robust standard errors reported. * p<.1, ** p<.05 and *** p<.001.

Table A.2: 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.

Table A.3: Time to convergence, sensitivity analysis

Elasticity	Years to convergence			Degree of
Labor Demand	Average	Minimum	Maximum	migration insurance
0	13	0	31	.67
.2	15	0	33	.58
.4	13	0	24	.66
.6	11	0	19	.74
.8	9	0	16	.8
1	8	0	32	.83
1.2	8	0	27	.86
1.4	8	0	25	.88
1.6	7	0	24	.89
1.8	7	0	23	.9

Notes: This table shows the speed of convergence as a function of the local labor demand elasticity. Congestion forces are in each case, the combination of housing price costs and local competition for labor. The Degree of insurance is the regression coefficient showing how much of the initial shock is dissipated across space through internal migration.

Table A.4: Summary statistics for simulated data

CMSA name	Implied Change in Productivity	Short-run change in local valuations	Long-run change in local valuations	Long-run change in population	Rank
san luis obispo-atascad-p robles, ca	-.31	-3.02	1.63	-.55	1
dover, de	-.21	-1.59	1.05	-.19	2
fort myers-cape coral, fl	-.2	-1.4	.75	-.24	3
las vegas, nv	-.19	-1.39	.77	-.23	4
ocala, fl	-.19	-1.28	.77	-.18	5
ann arbor, mi	-.18	-1.24	.82	-.14	6
myrtle beach, sc	-.18	-1.16	.71	-.16	7
lacrosse, wi	-.18	-1.16	.76	-.14	8
fargo-morehead, nd/mn	-.18	-1.15	.94	-.07	9
chico, ca	-.17	-1.09	.65	-.15	10
mansfield, oh	-.17	-1.03	.8	-.07	11
new orleans, la	-.16	-.98	.4	-.22	12
topeka, ks	-.16	-.94	.73	-.07	13
grand rapids, mi	-.16	-.9	.59	-.1	14
alexandria, la	-.15	-.88	.73	-.04	15
trenton, nj	-.15	-.84	.51	-.11	16
billings, mt	-.15	-.84	.59	-.08	17
sarasota, fl	-.15	-.83	.36	-.17	18
abilene, tx	-.15	-.8	.56	-.07	19
fort walton beach, fl	-.14	-.77	.45	-.11	20
albany-schenectady-troy, ny	-.01	.76	-.52	.11	159
sharon, pa	0	.83	-.63	.09	160
mobile, al	.01	.91	-.65	.12	161
erie, pa	.01	.92	-.61	.13	162
lincoln, ne	.01	.94	-.72	.1	163
bremerton, wa	.01	.97	-.62	.15	164
galveston-texas city, tx	.01	.98	-.57	.18	165
redding, ca	.02	1.03	-.71	.14	166
amarillo, tx	.02	1.05	-.85	.09	167
jacksonville, nc	.03	1.09	-.6	.21	168
sumter, sc	.03	1.12	-.93	.09	169
bloomington-normal, il	.04	1.19	-.96	.1	170
greenville, nc	.05	1.34	-.92	.17	171
reading, pa	.05	1.37	-.96	.17	172
provo-orem, ut	.06	1.38	-.8	.25	173
lexington-fayette, ky	.06	1.4	-1.05	.15	174
brownsville-harlingen-san benito, tx	.06	1.41	-1.04	.16	175
columbia, mo	.07	1.54	-1.41	.07	176
iowa city, ia	.08	1.58	-1.33	.11	177
sioux city, ia/ne	.13	2.11	-1.82	.14	178

Notes: This table shows the top 20 and bottom 20 metropolitan areas in terms of implied productivity losses during the Great Recession. Implied productivity losses are derived from wage changes between 2007 and 2010. The table also shows the change in short-run and long-run local valuations, and long-run changes in population implied by the model. Short-run change in local valuations are defined as the difference in pre-crisis valuations and post-crisis valuation before any population responses. Long-run change in local valuations are defined as the difference in post crisis valuations without population adjustment and with population adjustment. * p<.1, ** p<.05 and *** p<.001 indicates whether the coefficient is significantly different than 0. Robust standard errors clustered at the metropolitan area are reported.

Table A.5: Long run wage convergence in the data

Panel A

VARIABLES	(1) Δ ln adj wage OLS	(2) Δ ln adj wage OLS	(3) Δ ln adj wage OLS	(4) Δ ln adj wage OLS	(5) Δ ln adj wage OLS
Δ ln pop	0.116***	0.116***	0.146***	0.108***	0.127***
	(0.0201)	(0.0201)	(0.0453)	(0.0267)	(0.0355)
Observations	438	438	438	219	219
R-squared	0.131	0.131	0.414	0.191	0.104
State FEs	no	no	yes	no	no
Time FEs	no	yes	yes	no	no
Years	1980-2000	1980-2000	1980-2000	1990 and 2000	1980 and 1990

Panel B

VARIABLES	(1) Δ ln real adj wage OLS	(2) Δ ln real adj wage OLS	(3) Δ ln real adj wage OLS	(4) Δ ln real adj wage OLS	(5) Δ ln real adj wage OLS
Δ ln pop	0.0979***	0.0974***	0.110***	0.0961***	0.0990***
	(0.0174)	(0.0162)	(0.0350)	(0.0229)	(0.0303)
Observations	438	438	438	219	219
R-squared	0.106	0.279	0.508	0.203	0.089
State FEs	no	no	yes	no	no
Time FEs	no	yes	yes	no	no
Years	1980-2000	1980-2000	1980-2000	1990 and 2000	1980 and 1990

Notes: This table shows the relationship between real and nominal wage growth and population growth across metropolitan areas. The data used in the table comes from the US censuses of 1980, 1990, and 2000. There are 219 metropolitan areas in the sample. Adjusted wages refer to nominal wages adjusted to 4 education groups and age dummies separately for each census year. Real wages are computed using local price indexes computed following Moretti (2013), and using a weight of .25 as this is the weight of housing in consumption (see Davis and Ortalo-Magne (2011)).