

The Geography of the Great Recession^{*}

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Abstract

This paper documents, using county level data, some geographical features of the US business cycle over the past 30 years, with particular focus on the Great Recession. It shows that county level unemployment rates are spatially dispersed and spatially correlated, and that both these characteristics increase during recessions. It then shows that these features of county data can be generated by a model which includes simple channels of transmission of economic conditions from a county to its neighbors. The model also suggests that these local channels might matter a great deal for the amplification of aggregate shocks.

JEL Classification:

Keywords: Business Cycles, Economic Geography

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1 Introduction

This paper has two main objectives. The first is to document, using county level data, some geographical features of the US business cycle over the past 30 years, with particular focus on the Great Recession. The second is to argue that the geographical dimension is important in explaining the transmission and amplification of business cycles across time and across space.

Our main message is that, when seen from the geographical perspective, recessions are not a pure aggregate phenomenon. The local transmission of shocks plays an important role in the amplification and propagation of aggregate shocks. Recessions start in a few, localized, geographic areas and from here spread to nearby regions and, over time, to the rest of the country. This phenomenon translates into an inverted U-shaped dynamics for the standard deviation and spatial correlation of local unemployment rates. In this paper we first document these patterns and then propose a model of real business cycles that incorporates the geographic dimension and is able to generate patterns for local unemployment rates that are consistent with the time series as well as the geographic features of the data.

Using monthly data on unemployment rates at the county level, we analyze the onset and spreading of recessions over the last three decades. We show that unemployment initially rises sharply in some, but not all, counties. This implies that at the start of a recession the dispersion of unemployment rates across counties typically increases. Moreover, we find that the counties in which unemployment first rises tend to be located close to each other, generating clusters of counties characterized by high unemployment rates, which in turn drive up spatial correlation. As the recession progresses, the increase in unemployment becomes more generalized across counties, the dispersion in unemployment rates across counties decreases and this generates a fall in the spatial correlation. These patterns, resembling an inverted U, are observed for most recessions in our sample, with the exception of the 2001 recession and are only partially explained by common economic and demographic characteristics. The patterns also persists if one controls for cyclical movement in local unemployment that are attributable to similarity in industrial composition for counties that are clustered together.

These facts suggest that geographic transmission might play an important role in amplifying and propagating an aggregate shock. To explore this hypothesis more precisely, in the second part of the paper we develop a very simple model of business cycle across time and space. The engine of business cycle is an aggregate shock, but the shock initially hits different counties in a heterogeneous manner, depending on county specific conditions. For example a county which has a very favorable

local productivity condition might not be as severely affected by the aggregate shock.

In this environment we introduce two channels of geographic transmission. The first is that local conditions of neighboring counties might be contemporaneously correlated. For example, if demand is high in a given county because of high productivity in that county, that will keep unemployment low in that county and, through local trade, in neighboring counties. The second channel is the effect of unemployment in a given county today on future unemployment in neighboring counties through migration and commuting.

We then calibrate this model using several moments of aggregate employment and of county level unemployment. We go on to show that the calibrated version of the model can generate the patterns of spatial correlation and spatial dispersion mentioned above. We finally use the model to assess the importance of the two channels of geographic transmission for aggregate unemployment dynamics and find that both channels are responsible for a significant amplification of aggregate shocks. In particular an aggregate shock that causes an increase in unemployment of 3.5% with local transmission channels causes a far lower increases in unemployment without it, between 0.5% and 1.4%. The intuition for this result is that when local economic conditions are correlated, county idiosyncratic conditions tend to average out and to be more concentrated around the mean, and, as a consequence, aggregate shocks can have a more widespread effect.¹

In terms of literature this paper integrates two different lines of research: the macro literature on business cycles, that analyzes the factors leading to recessions and their consequences on macro aggregates, and the regional/urban literature, which analyzes the spatial properties of economic phenomena and focuses on explaining differences in local outcomes. Standard business cycle models ignore spatial heterogeneity, and standard spatial models ignore macroeconomic dynamics over the cycle and in this work we argue that establishing a connection between these two lines of research is fruitful.

Regarding the regional/urban literature the papers that are more related to our work are those which focus on the spatial structure of regional unemployment disparities and analyze the channels of interdependence among regions. This literature (see e.g. Molho, 1995; Burda and Profit, 1996; Petrongolo and Wasmer, 1999; Burgess and Profit, 2001; Overman and Puga, 2002; Elhorst 2003, Niebuhr, 2003) shows the existence of spatial dependence in unemployment rates, and explores the possible linkages between neighboring regions that can give rise to the observed degree of interdependence.

¹For a similar mechanism in a different context see Philippon, 2003

Regions are tightly linked by migration, commuting and interregional trade. These types of spatial interaction are exposed to the frictional effects of distance, possibly causing the spatial dependence of regional labor market conditions. Typically the papers in this literature estimate a significant degree of spatial correlation among unemployment rates in regional labor markets and analyze the role of these different channels in determining it.

Europe, Overman and Puga (2002) conclude that the unemployment rates of European regions are much closer to the rates of adjacent regions than to the average rate of other regions within the same EU country. The spatial concentrations of areas with similar skill composition or sectoral specialization are not found to be the primary cause of this spatial association. The analysis of Niebuhr (2003) also points to a significant spatial dependence in unemployment rates across European regions. Moreover, the evolution of regional unemployment is also marked by spatial effects. The results suggest that the change in regional unemployment between 1986 and 2000 was associated with an increasing concentration of high unemployment rates in spatial clusters. Using data on unemployment rates at the Travel-to-Work Areas (TTWAs) level for England, Scotland and Wales over the period 1985-2003, Patacchini and Zenou (2007) find a significant spatial dependence that has been growing over time and characterized by a low distance decay. They find that commuting flows are an important factor in generating spatial dependence, but other forces are responsible for the significant estimated coefficient on the spatially lagged unemployment rate, which remains significant even after commuting flows are controlled for. This result indicates that other factors such as mismatch between the supply and demand sides of the labor market, interregional trade or housing patterns might be at work.

For the U.S., Conley and Topa (2002) examine the spatial patterns of unemployment in Chicago between 1980 and 1990 at the Census Tract level. Their results indicate that there is a strong positive and statistically significant degree of spatial dependence in the distribution of raw unemployment rates, and that this is consistent with models in which agents' employment status is affected by information exchanged locally within their social networks.

Molho (1995) using 1991 British Census data on unemployment rates at the local labor market area level, find significant spillover effects. According to their estimates, a one-time local demand shock has an impact in the short run on the local unemployment rate, as well as ripple effects to neighboring areas. The immediate unemployment effect is strongest in the area where it originated; while the spillover effect is the strongest after a time lag. They interpret this pattern of behavior as being consistent with a (distributed) lagged migration response to a demand shock. Ultimately, the effects of the demand shock were spread evenly across the country.

Our model of spillovers and correlation of economic activity across location is going to be non-structural but it is inspired by a growing literature (non structural and structural) that studies how shocks to a specific location impact economic outcomes in other locations through migration and other channels (for example learning). See, among, others, Blanchard and Katz, (1992), Van Nieuwerburgh and Weill, (2010), Fogli and Veldkamp (2011), Davis et al. (2011). Still, none of these work have studied the effect of local transmission on business cycle dynamics.

There is also a literature that deals with the difference in long run economic development across locations For example Desmet and Rossi-Hansberg (2009) document that in the U.S. employment concentration and value added vary dramatically across space and so does the rate of growth. The same authors (2011) develop a dynamic model with endogenous investment in technology in which technology diffuses over space to nearby locations.

Finally in terms of empirical work, recently some authors have used county level data to identify the determinant of aggregate shocks (see, for example, Mian and Sufi, 2010 and Mian, Rao, and Sufi, 2011). This literature, however, abstracts from the role played by geography in the transmission of shocks across time and space, as counties are studied as isolated entities.

The paper is structured as follows. Section 2 contains the empirical analysis, Section 3 introduces the model, Section 4 discusses how we set the parameters and Section 5 presents our results. Section 6 concludes.

2 Empirical Evidence

The main goal of this section is to document several spatial properties of business cycles in the United States. Our main data-set is composed of the monthly unemployment rates for 3065 counties in the continental United States, starting in the first month of 1977 and ending in the last month of 2011, as provided by the Bureau of Labor Statistics (BLS). In the first part of the analysis we focus on the most recent recession, while in the second part of the section, to put things in perspective, we compare the spatial features of the recent cycle with those in previous cycles.

As data from the BLS is not seasonally adjusted we first apply the X12 census procedure to each county level data series to remove seasonal fluctuations. Then, as we want to highlight spatial features of unemployment that are connected to business cycles and not to permanent characteristics of a particular group of counties (for example a group of contiguous counties that are all rural), we remove county fixed effect (i.e. mean unemployment) from each county unemployment series.

So from now on, whenever we refer to county unemployment we always refer to data which is seasonally adjusted and in deviations from long run county mean.

2.1 Spatial Patterns of the Great Recession

In figure 1 we use our unemployment data to provide an informal but suggestive illustration of the spatial properties of the recent cycle by plotting several color coded unemployment maps for the counties in our sample. Each map depicts the deviation of unemployment within each county from its long term mean. The first map (the one in the Northwest corner) is for December 2007, the start of the recession, and the last one (the one in the Southeast corner) depicts the spatial distribution of unemployment in December 2009, when aggregate unemployment has reached its peak.² Next to each map we report three statistics: The first is simply the aggregate unemployment rate (from the BLS). The second is the standard deviation of unemployment across counties, which captures the spatial dispersion of unemployment deviations from the mean. The third statistic is the spatial autoregressive coefficient which is commonly used in geographical studies to measure the degree of spatial correlation i.e. the overall association between unemployment in each county and unemployment in all nearby counties.³

The first feature we want to highlight in the December 2007 map (at the start of the recession, when aggregate unemployment is still low), is that the majority of counties have unemployment close to or below their long term mean. As time goes by, unemployment does not increase in all counties simultaneously, rather it first increases in a few specific areas and then spreads from there to the rest of the country, following an epidemic pattern, i.e. increasing first in areas that are closer to areas of high unemployment. This pattern results in an inverse U shape for the spatial dispersion and the spatial correlation over the course of the recession. At the start of the recession unemployment is close or below historical average in most counties, so both spatial dispersion and spatial correlation are relatively low. In particular in December 2007 they are 1.54% and 0.737 respectively. In the midst of the recession unemployment is rising fast but in some concentrated areas is high while in others remains low, so there is higher dispersion and higher spatial correlation: in March 2009 both statistics have increased to 2.25% and 0.821. At the end of the recession unemployment is high in most counties and spatial correlation and dispersion revert to a lower level (2.18% and 0.778).

The evidence displayed in the maps indicates that the location of a given county might be an important determinant of its unemployment dynamics and in particular that its own unemployment

²For a similar visual analysis see also Egwuekwe, 2011

³See the appendix for details on how this coefficient is computed

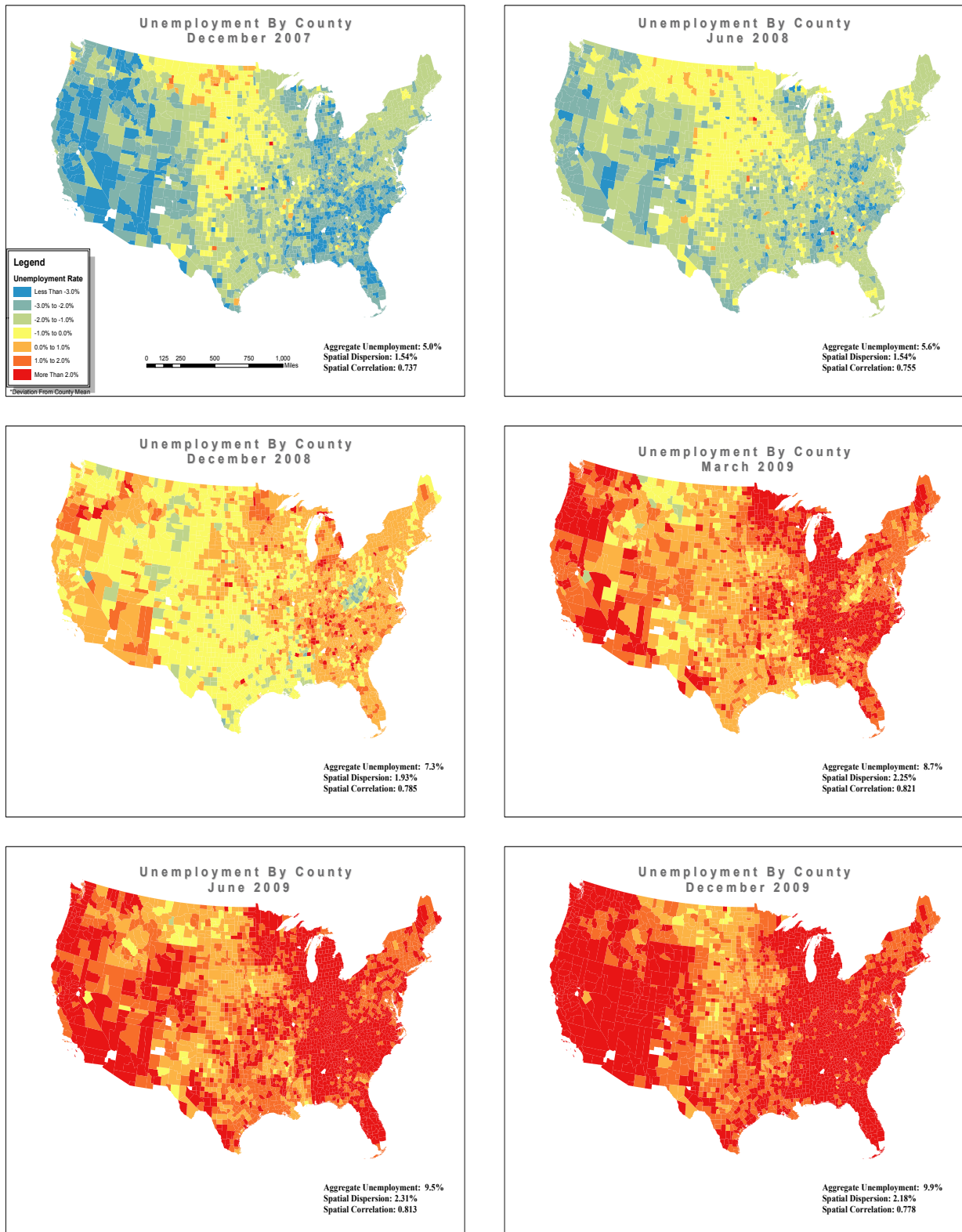


Figure 1: UNEMPLOYMENT MAPS

might be affected by (and affect) unemployment of its neighbors, suggesting a possible role of geography for the transmission and propagation of business cycle shocks. To better quantify this effect, it is necessary to control for a possible source of geographical correlation which arises from geographical specialization. To make a concrete example, think of the auto industry which is affected heavily by the recession, and which is also geographically concentrated around Detroit. This fact will be reflected in a high (and increasing in recession) indicator of spatial correlation; but this correlation does not reflect transmission of shocks from one county to the other, but rather a similarity of industrial structure in neighboring counties around Detroit. In order to control for this, in figures 2 and 3 we report time series, during the Great Recession, for spatial dispersion and spatial correlation computed first using county unemployment in deviations from mean (these are the same statistics reported in the maps) and then using the residuals from regressing, period by period, county unemployment on employment industrial composition in 1990 in each county.⁴ These controls will pick-up all the variation in county level unemployment that is due to similarity in industrial structure.

The figures show how controlling for industrial composition lowers both the level and the increase of serial correlation during the great recession; nevertheless, both spatial dispersion and serial correlation remain significantly different from zero and increase during the economic downturn, suggesting that geographic transmission of shocks might play an important role during the Great Recession.

2.2 Spatial Dispersion and Correlation in Previous recessions

In figures 4 and 5 we report, for all other recessions in our sample, the same statistics we reported for the great recession in figures 2 and 3. The main message we get from these two figures is that spatial dispersion and spatial correlation follow the same inverted U pattern highlighted for the Great Recession, for all past recessions in our sample, with the exception of the 2001 recession, where we register basically no change in spatial dispersion and spatial correlation. We conclude our empirical analysis summarizing its two main findings: the first is that at any point in time unemployment across counties is significantly spatially dispersed and spatially correlated. The

⁴We compute employment industrial composition in each county using Census Data in particular data from the publication "Historical, Demographic, Economic and Social Data: The United States, 1790-2000", ICPSR, Study No. 2896. The data reports employment in 1990 in the following categories: agriculture, mining, construction, manufacturing, transportation, communication and other public utilities, wholesale trade, retail trade, finance insurance and real estate, business and repair services, entertainment and recreation services, personal services, health services, educational services and public administration.

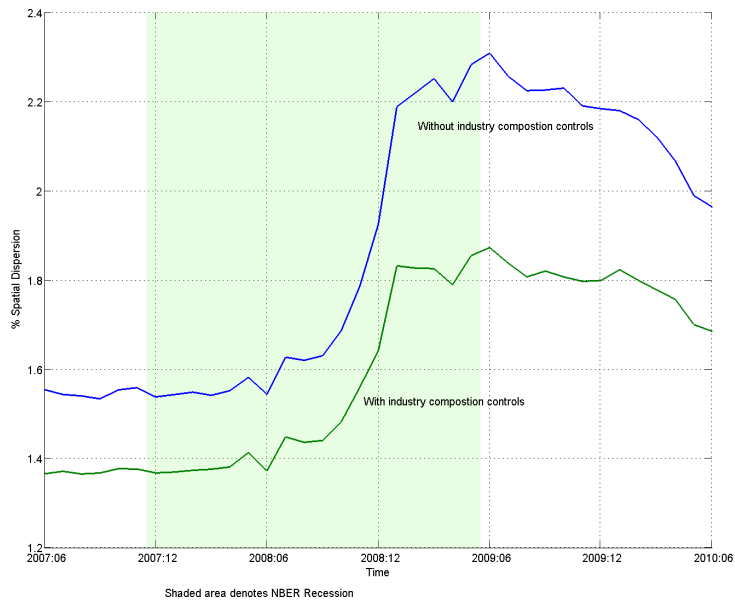


Figure 2: Spatial Dispersion During the Great Recession

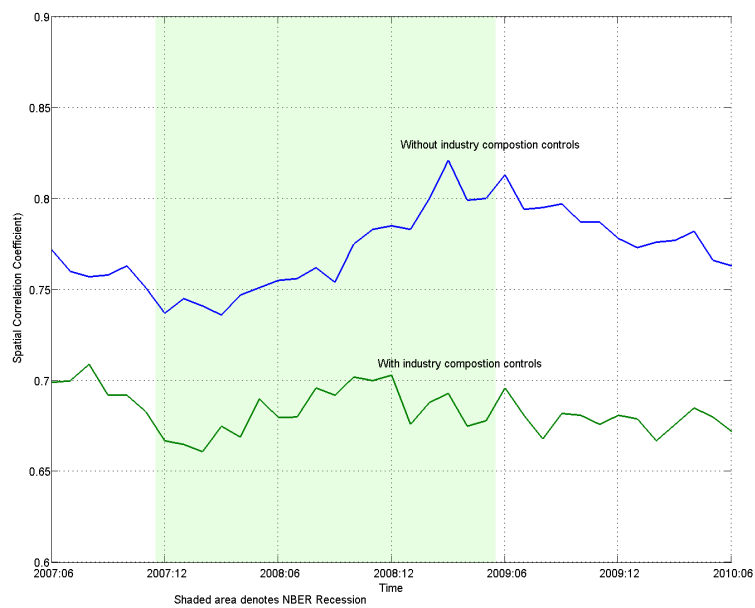


Figure 3: Spatial Correlation During the Great Recession

second is that during recession both spatial dispersion and correlation tend to increase. Neither of these patterns can be explained simply by differences in industrial composition across locations. In the next section we argue how these patterns can be important to understand the diffusion and the propagation of an aggregate business cycle shock.

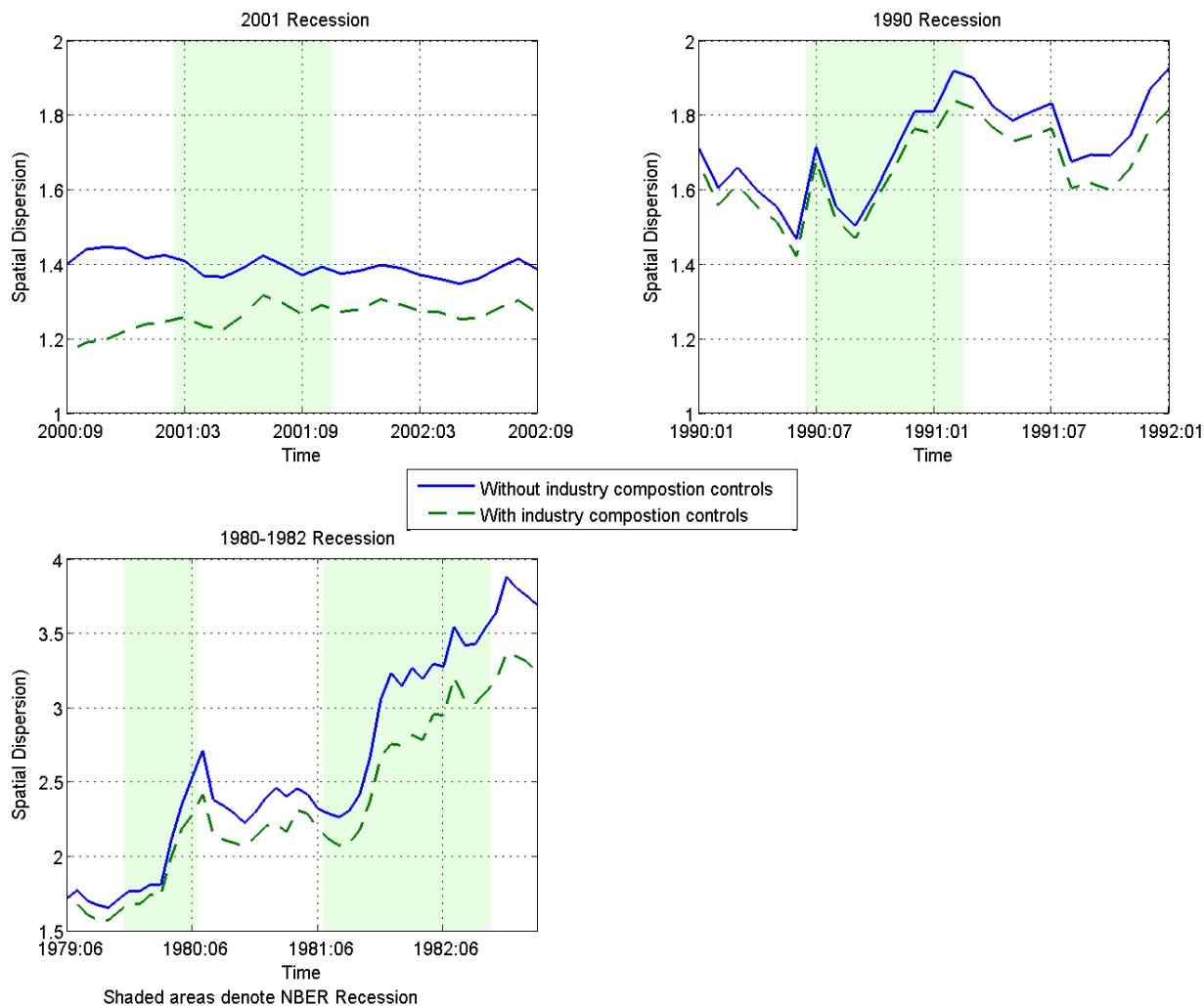


Figure 4: Spatial Dispersion During Past Recessions

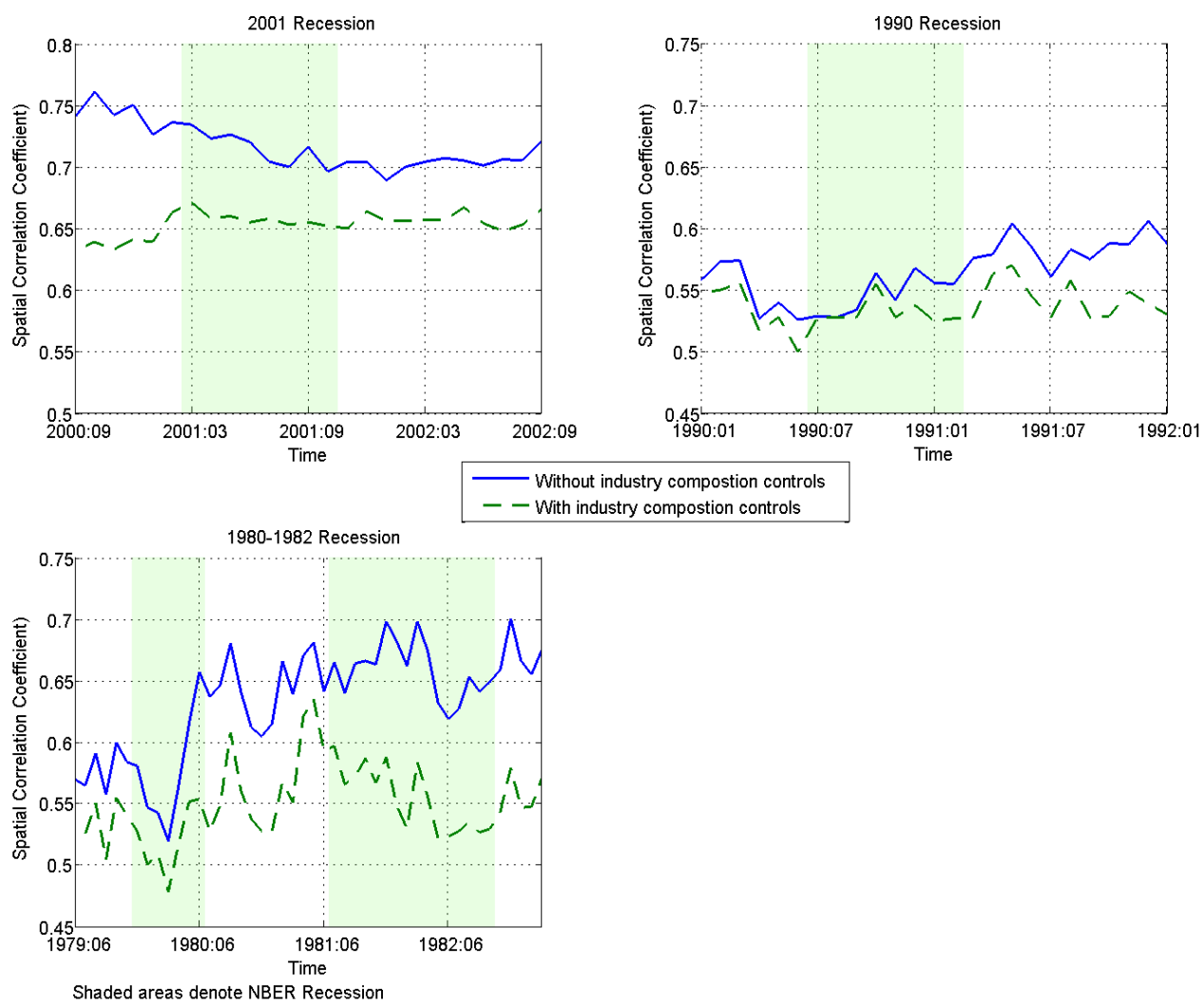


Figure 5: Spatial Correlation During Past Recessions

3 A mechanical model

In this section we present a simple (and mechanical) model of unemployment in a country with many counties. The purpose of the model is to illustrate and quantify, using the data presented in the previous section to discipline the model, the role of spatial transmission and spatial heterogeneity as a mechanism of amplification and propagation of aggregate shocks. Hence the key elements of the model are a basic geographic structure, a county specific shock, an aggregate shock and a mechanism of interaction between the two. We now describe these elements in detail

Spatial Structure

The economy consists of a finite number of contiguous counties (indexed by i) of equal size, located on a plane as depicted in Figure 6 where each square represent a county. Each county has a set of neighbors which are the counties which share a border with the given county. The county in black in the figure has all the grey counties as neighbors.

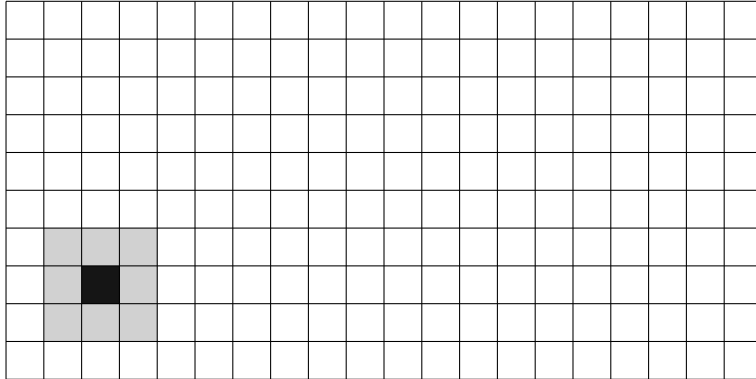


Figure 6: MAP OF THE MODEL ECONOMY

County specific shocks

Unemployment in county i in period t , denoted by u_{it} is modeled as a Markov chain that can take two values, u_h and u_l , with $u_h > u_l$. In each period, each county draws a fundamental county specific shock that we denote by ε_{it} . With these shocks we want to capture the effects of county specific conditions (i.e. local labor market frictions, local productivity or local demand, etc.) on the dynamics of local unemployment, *ceteris paribus*. A higher value of the shock here indicates better conditions and, as we'll see later, it pushes down unemployment in that county. We assume that these shocks are independently and identically distributed across counties and across time, according to a uniform distribution with support on the unit interval. We introduce the possibility

of spatial transmission by defining an "effective" shock for county i , given by

$$\hat{\varepsilon}_{it} = (1 - \lambda)\varepsilon_{it} + \lambda \frac{1}{N_i} \sum_{j \neq i} w_{ij} \varepsilon_{jt}$$

where λ is a key parameter that captures the simultaneous impact of shocks in its neighbors on county i unemployment. N_i is the number of neighbors of county i and w_{ij} is equal to 1 if county j is a neighbor of i and 0 otherwise. The special case in which shocks in neighboring counties do not have any effect on local unemployment dynamics is captured by $\lambda = 0$.

We now specify how effective shocks $\hat{\varepsilon}_{it}$ affect unemployment transitions by defining a vector of cut-offs, specific for each county, given by

$$\Gamma_{it} = \begin{bmatrix} p + d(s_t) + \phi \sum_{j \neq i} w_{ij} u_{jt-1} \\ 1 - q + d(s_t) + \phi \sum_{j \neq i} w_{ij} u_{jt-1} \end{bmatrix}$$

The first term of the vector represents the cutoff for a county which currently has high unemployment: if the county draws an effective shock $\hat{\varepsilon}_{it} \leq p + d_t + \phi \sum_{j \neq i} w_{ij} u_{jt-1}$ then the county will stay in the high unemployment state and if $\hat{\varepsilon}_{it} > p + d(s_t) + \phi \sum_{j \neq i} w_{ij} u_{jt-1}$ the county will switch to low unemployment. The second term of the vector represents the cutoff for a low unemployment county: if the county draws an effective shock $\hat{\varepsilon}_{it} \geq 1 - q + d_t + \phi \sum_{j \neq i} w_{ij} u_{jt-1}$ then the county will stay in the low unemployment state and if $\hat{\varepsilon}_{it} < q + d_t + \phi \sum_{j \neq i} w_{ij} u_{jt-1}$ the county will switch into high unemployment.

These cutoffs have three terms which serve three purposes: the first terms (p and $1 - q$) are fixed parameters are there to introduce persistence in the county state (i.e. county unemployment) and they are different as, to be consistent with data, we will want to make the high unemployment state less persistent than the low unemployment employment state ($q > p$).

The second term $d(s_t)$ captures aggregate shocks which affect all counties while the third term $\sum_{j \neq i} w_{ij} u_{jt-1}$ captures the spillover effect that lagged unemployment in neighboring county can have on current unemployment in any given county. We now describe how we model them in more detail.

Aggregate shocks

The second term of the cutoff $d(s_t) \geq 0$, is a random variable that is a function of the aggregate state of the economy s_t . Notice that when $d(s_t)$ is high the whole economy will have higher unemployment as all counties that are in the high unemployment state are more likely to remain in that

state, while all counties with low unemployment are more likely to switch into high unemployment. We assume that s_t can be either 1 (expansion) or 0 (recession) and we model the joint statistical processes for $d(s_t)$ and s_t as follow

$$\begin{aligned} \text{If } s_t = 1 \text{ then } & \begin{cases} s_{t+1} = 1 & \text{and } d(s_{t+1}) = \rho d(s_t) & \text{with probability } \eta \\ s_{t+1} = 0 & \text{and } d(s_{t+1}) = d(s_t) + x_t & \text{with probability } (1 - \eta) \end{cases} \\ \text{If } s_t = 0 \text{ then } & \begin{cases} s_{t+1} = 1 & \text{and } d(s_{t+1}) = \rho d_t & \text{with probability } (1 - \gamma) \\ s_{t+1} = 0 & \text{and } d(s_{t+1}) = d(s_t) + d(s_t) - d(s_{t-1}) & \text{with probability } \gamma \end{cases} \end{aligned}$$

This process is flexible enough to capture recession phases in which the probability of high unemployment can increase sharply for each county, followed by expansion phases in which the same probability gradually declines at a rate governed by the parameter $0 < \rho < 1$. Note that if the economy is in an expansion phase in t it will remain in that state with probability η and in that case the term $d(s_{t+1})$ will fall to $\rho d(s_t)$. With probability $1 - \eta$ the economy will switch into a recession in which case $d(s_t)$ will increase by x_t , which is a random variable which uniformly distributed on the support $[0, d_{\max}]$.

Similarly if the economy is in a recession in period t ($s_t = 0$) then it will stay in the recession state with probability γ and in that case $d(s_{t+1})$ will increase to $d(s_t) + d(s_t) - d(s_{t-1})$ which is the state last period plus the original x which was the amplitude of increase in d at the beginning of the recession. With probability $1 - \gamma$ the economy exit recession and $d(s_{t+1})$ starts falling at rate ρ .

Figure 7 below plots a typical sample path realization that arises from this process for aggregate shock.

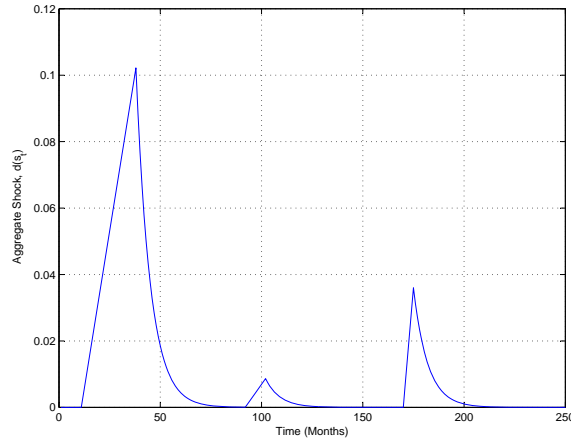


Figure 7: AGGREGATE SHOCKS

Spillovers

The third term of the cut-off $\phi \sum_{j \neq i} w_{ij} u_{jt-1}$ captures the influence that unemployment in a given county has on the probability of future unemployment in neighboring counties. We now have all the elements to characterize numerically, given an initial distribution of unemployment rates across counties, the evolution of unemployment across counties and across time.

Before we present our results we would like to stress that here both the contemporaneous and the lagged effect of a county on its neighbors are determined by two reduced form parameters λ and ϕ . Ideally one will want to write down a structural model of a local job market where, because of labor mobility, unemployment in one country can affect future unemployment of its neighbors (see, for example, Patacchini and Zenou, 2006) and where common structural shocks (like, for example, technology or preference shocks) can affect contemporaneously unemployment in both counties. So the contribution of this part is not so much to provide a serious attempt to model the interaction of local labor market with aggregate shocks, but rather to provide a simple evaluation tool to assess whether this interaction can be important.

4 Calibration

In order to characterize the path for local and aggregate unemployment in the economy described above we perform simple simulations. We first assume that the model economy is comprised of $100 \times 30 = 3000$ counties which approximate the US counties (3065) in our data set. We then need to specify values for 10 parameters, which are calibrated to match the 13 moments we report in table 1. We chose as calibration targets what we view as key statistics for characterizing unemployment and unemployment dynamics at the aggregate and county level. In general, with the exception of one target⁵, all targets depend on all parameters so we use a global search algorithm to try to hit all targets. We find that the model does a reasonable job in matching several moments with the possible exception of the autocorrelation at the county level (0.93 in the data and 0.72 in the model), which is possibly due to our approximation of county unemployment rate as a two state Markov Chain. After all parameters are set we can use the model to assess the impact of spatial transmission on the impact and propagation of aggregate shocks. The actual parameter values used in the simulations below are reported in Table 2.

⁵This is the frequency with which a recession starts, conditional of not being in one, which is uniquely pinned down by the parameter η .

Table 1. Calibration Targets

Moment	Data	Model
Aggregate Moments (1948.1-2011.12)		
Average unemployment	5.8%	5.8%
Standard deviation of unemployment	1.7%	1.7%
Autocorrelation of unemployment	0.99	0.99
Standard deviation of unemployment changes	0.21%	0.15%
Skewness of unemployment changes	0.32	0.22
Frequency of months in which a recession start	1.4%	1.4%
Duration of unemployment increase (avg across recessions)	15.5 mos.	15.0mos
Max unemployment Increase (avg across recessions)	3.0%	2.9%
County Level Moments (2000.1-2011.12)		
Spatial Dispersion (Avg. across time)	1.4%	1.9%
Spatial Correlation (Avg across time)	0.68	0.68
Lagged Spatial Correlation ⁶ (Avg. across time)	0.05	0.08
Standard deviation unemployment (Avg. across counties)	2.4%	2.67%
Autocorrelation unemployment (Avg. across counties)	0.93	0.72

Note: Aggregate moments are computed on aggregate unemployment data from the BLS. County Level moments are computed using seasonally adjusted county level unemployment with

Table 2. Parameter values

Parameter	Description	Value
u_h	High unemployment	11.2%
u_l	Low unemployment	4.3%
p	Persistence of high unemployment	0.46
q	Persistence of low unemployment	0.77
λ	Contemporaneous transmission of shocks	0.62
ϕ	Spatial Impact of Lagged unemployment	2.0
η	Probability of starting a recession conditional on not being in one	0.014
γ	Probability of continuing a recession conditional on being in one	0.94
ρ	Rate of decline of high unemployment probability in expansions	0.87
d_{Max}	Maximum possible one period increase in unemployment	0.023

⁶To obtain this coefficient we regress, in the data and in the data generated by the model, county level unemployment on its own lagged value and on the lagged value of the neighbors unemployment. The Lagged spatial conditional correlation is the estimated coefficient on lagged neighbor unemployment.

5 Results

Our first result is about the ability of the model of replicating the pattern of spatial dispersion and spatial correlation during recessions (reproduced in figures 2,3,4 and 5). Note that the model is calibrated to match average spatial correlation and dispersion but not their movement over the cycle. To assess this we feed the model aggregate shocks so to generate a typical US recession, i.e. one in which unemployment increases by about 3% over the course of the recession and the increase lasts about 16 months. In figure 8 we plot the path of unemployment, spatial correlation and spatial dispersion during the recession. Note that interestingly the model generates an increase in spatial dispersion and in spatial correlation during the recession. The increase in spatial dispersion is easy to understand. the aggregate shock here is modelled as an increase in probability of switching in to high unemployment (from low unemployment) and a fall in the probability of switching into low unemployment (for counties which are in high unemployment). This implies that when the recession hits, the fraction of counties with high unemployment will increase and this will in general increase spatial dispersion.

The increase in spatial correlation is more subtle and it comes from the fact that there are more counties in recession and counties in recession are more sensitive to idiosyncratic shock and thus more sensitive to the impact of their neighbors. The reason why counties in recession are more sensitive to idiosyncratic shock is that recession is a less persistent state than expansion and thus there is a higher probability that an idiosyncratic shock will cause the county to change state.

Our second result concerns with the importance of the local transmission effects for the impact of aggregate shocks. In order to evaluate this we feed our model the same aggregate shock we used in the previous figure and then we evaluate the aggregate unemployment response to the shock first reducing the local contemporaneous correlation of idiosyncratic shocks (i.e. setting the parameter $\lambda = 0$) and then eliminating the local spillover effect from unemployment today in neighboring counties to unemployment tomorrow (i.e setting the parameter $\phi = 0$). Figure 11 shows the path of unemployment under these two assumption. The figure shows clearly that in both cases the local transmission effect has a significant amplification on the aggregate shock.

The intuition for this result is that when local economic conditions are correlated, county idiosyncratic conditions tend to average out i.e. the relevant idiosyncratic shock for a county is an average of the shocks of all its neighbors. As a consequence the distribution of aggregate shocks is less disperse and aggregate shocks, which we model as a change in threshold, can have a more widespread effect, i.e. it can trigger more counties to switch.

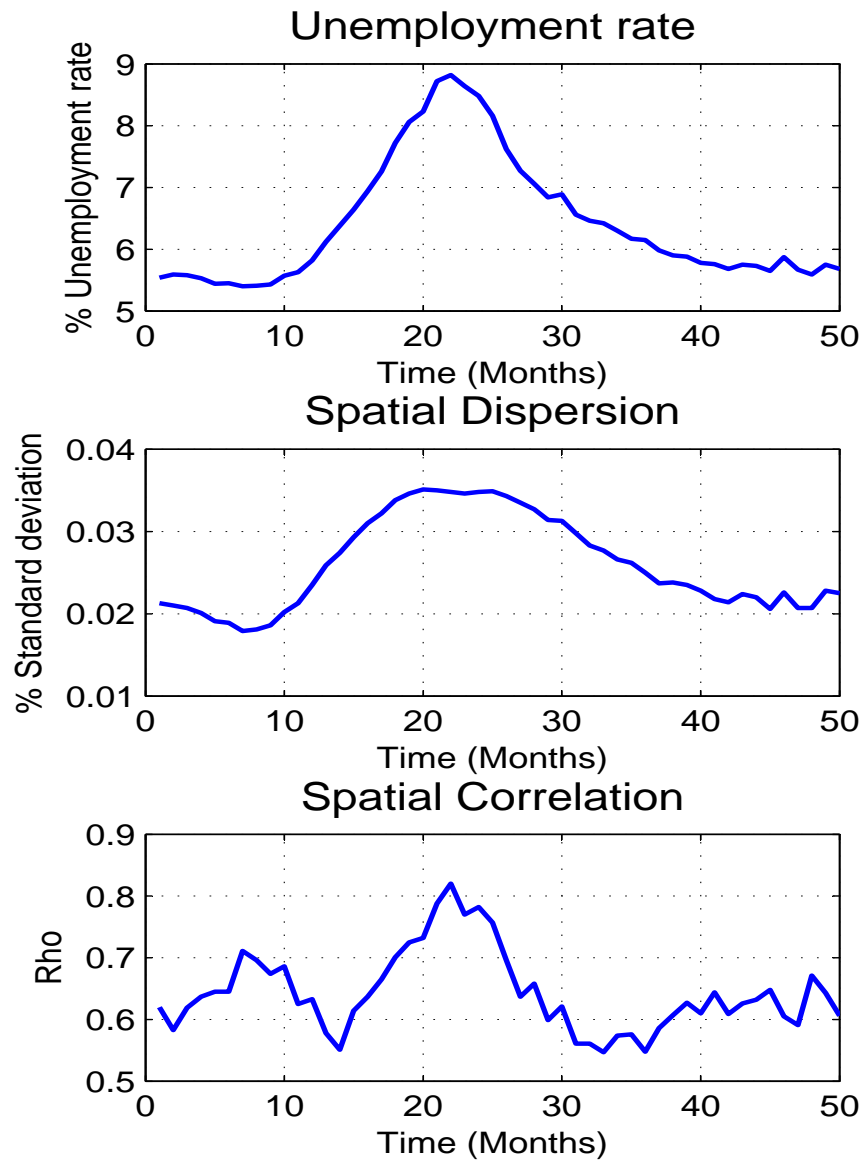


Figure 8: MODEL'S PREDICTION FOR SPATIAL DISPERSION AND CORRELATION DURING RECESSIONS

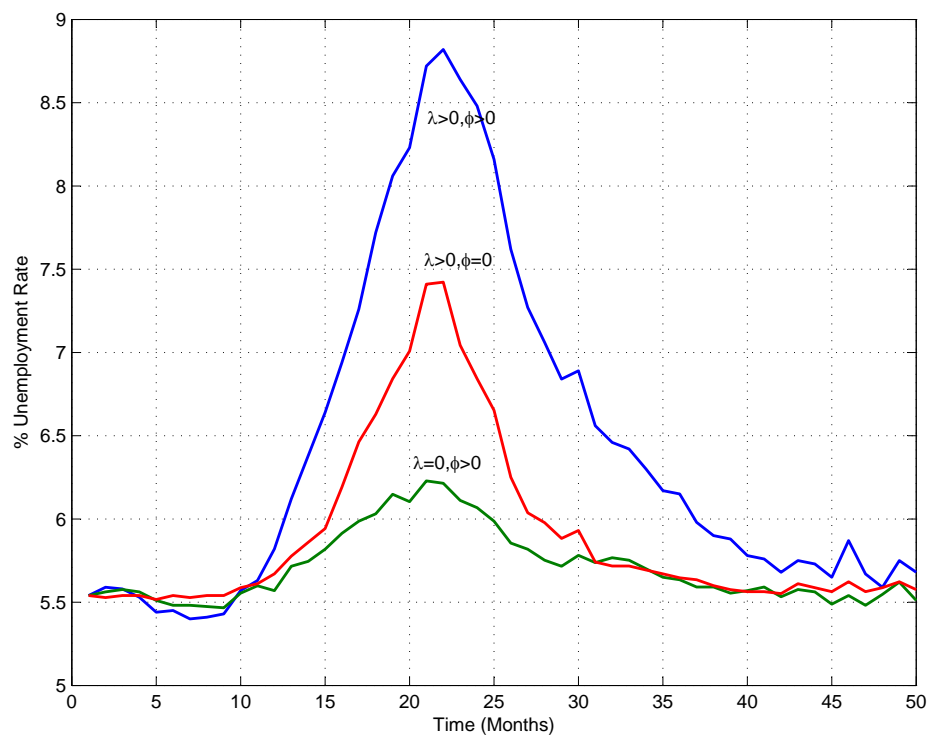


Figure 9: AMPLIFICATION OF THE SAME AGGREGATE SHOCK

Obviously these results do not necessarily prove the existence of spatial transmission effects in the data, as results are dependent on the model. However, they suggest that local transmission mechanisms can have big amplification effects on the magnitude and duration of unemployment cycles. Also, importantly, our simple model includes a reduced form mechanism through which high unemployment can transmit from one county to another but it is silent on the source of the transmission. We would like to conclude this section by exploring a plausible mechanism, namely housing prices, which might be relevant for the geographic transmission of unemployment, especially during the Great Recession. The underlying idea is that changes in housing prices in a given county can affect unemployment in that county (for a specific channel that can cause this see Mian, Rao and Sufi, 2011). At the same time, through mobility of households, it is plausible to think that changes in housing prices in a given county will affect changes in housing prices in neighboring counties (see for example the work of Campbell, Giglio and Phatak, 2011). It follows that, through housing prices, high unemployment can transmit from one county to its neighbor.

Using county level monthly price data provided by Zillow⁷, we examine the geographic properties of the evolution of housing prices. Figure 10 shows the progression of the deviation of housing prices from their long term mean over time in all in the counties in Florida for which we have data, from early 2007 (when prices were at their peak) to early 2009 (as they reached their bottom). The main point of the figure is to show that housing prices decline seem to follow the same spatial patterns as unemployment. In early 2007 prices fall in sparse location around the coasts and over time price fall in nearby locations until they reach a uniformly low level across the state.

Figure ?? summarizes this pattern (including also the period of housing prices boom) displaying the graph for spatial correlation in housing prices, and it compares to the spatial correlation of unemployment for the same set of counties in Florida. The figure shows that the spatial diffusion of housing prices and unemployment are strikingly similar across the whole period of housing boom and bust, suggesting that housing prices might indeed be an important factor in the spatial transmission of unemployment.

6 Conclusions

The main contribution of this paper is to argue that local, geographical factors, which are usually not used in macro analysis might be very important to understand aggregate business cycle dynamics. It suggests that a more detailed study of the exact channels through which economic activity is

⁷Additional information on the Zillow data is provided in the Appendix

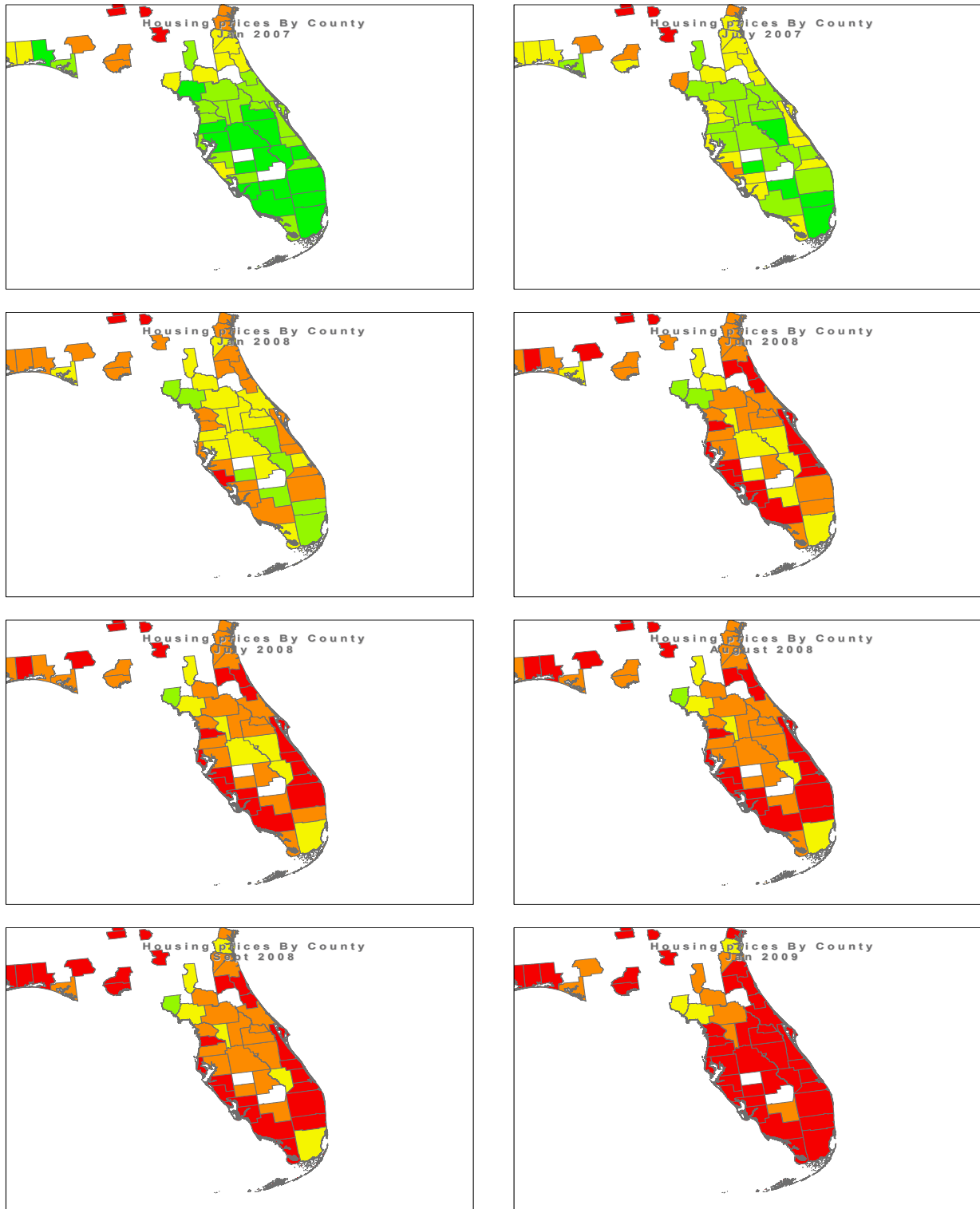


Figure 10: THE SPATIAL DIFFUSION OF HOUSING PRICES BUST IN FLORIDA
 Note: Darker colors correspond to lower housing prices

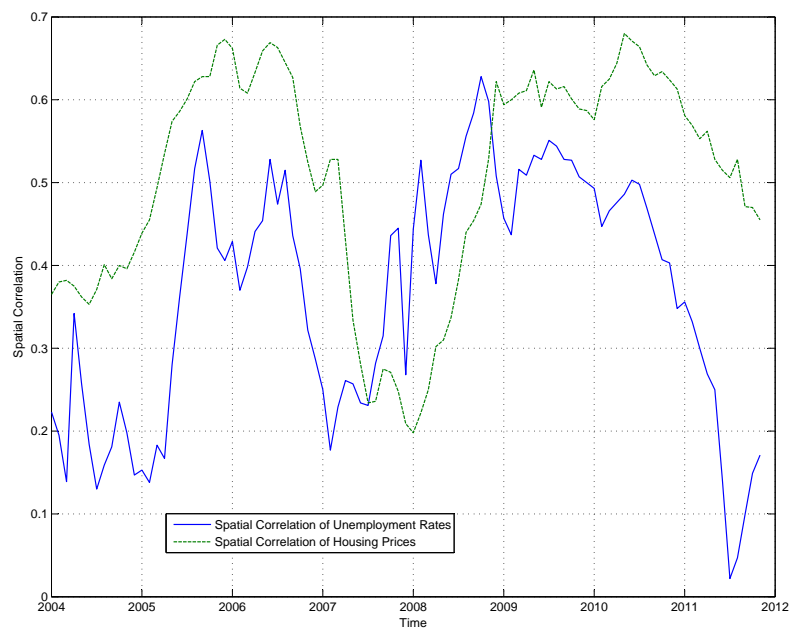


Figure 11: SPATIAL CORRELATION OF UNEMPLOYMENT AND OF HOUSING PRICES: FLORIDA 2004-2011

transmitted locally (see for example the recent work of Fogli and Veldkamp, 2011 who focus on learning in labor markets and the work of Campbell and al., 2011 who focus on the effect of foreclosures on local housing prices) might also have a big macro payoff.

Appendix

A The Spatial Autoregressive Model

To measure the association between unemployment in one county and its neighbors we use the following so-called spatial lag model.⁸

$$u_{it} = \rho_t \frac{1}{N_i} \sum_{j \neq i} w_{ij} u_{jt} + X_{it} \beta_t + \varepsilon_{it}$$

$$\varepsilon_{it} \sim N(0, \sigma^2 I_n)$$

where u_{it} represents the de-meaned unemployment rate for county i in period t and ρ_t is called the spatial autoregressive coefficient and describes the overall association between unemployment in each county and unemployment in all nearby counties. Here w_{ij} is an element of a spatial weights matrix W in which the element in column j of row i equals 1 if counties j and i share a border and 0 otherwise, note that $w_{ii} = 0$ for all i . X_{it} is a standard matrix of (optional) control variables and ε_{it} is assumed to be a normally distributed error term.

As demonstrated in LeSage (1999), the inclusion of a spatially lagged dependent variable introduces an endogeneity which biases standard OLS estimation of ρ_t . To help further illustrate this endogeneity, consider a large positive shock in ε_{it} . This shock increases the unemployment rate u_{jt} of bordering county j by the amount $\rho_t \frac{1}{N_j} w_{ji} \varepsilon_{it}$ which in turn reflects a portion back to county i . This transmission across counties violates the strict exogeneity assumption required by OLS (i.e. $E \left[\varepsilon_{it} \mid \frac{1}{N_i} \sum_{j \neq i} w_{ij} u_{jt} \right] \neq 0$). In order to correct for this bias we employ the maximum likelihood procedure outlined in Anselin (1988). Note we slightly modify the use of W here in that the rows have been normalized to sum to 1 (i.e. rows have already been multiplied by $\frac{1}{N_i}$). The steps of the procedure are as follows:

1. perform OLS for the model: $u = X\beta_0 + \varepsilon_0$

⁸Elhorst, Spatial Panel Data Models; LeSage, Applied Econometrics Using MATLAB; Anselin et al. 2006

2. perform OLS for the model $Wu = X\beta_L + \varepsilon_L$
3. compute residuals $\varepsilon_0 = u - X\hat{\beta}_0$ and $\varepsilon_L = Wu - X\hat{\beta}_L$
4. given ε_0 and ε_L , find ρ that maximizes the concentrated likelihood function:

$$L_c = -(n/2)\ln(\pi) - (n/2)\ln(1/n)(\varepsilon_0 - \rho\varepsilon_L)'(\varepsilon_0 - \rho\varepsilon_L) + \ln|I - \rho W|$$
5. given $\hat{\rho}$ that maximizes L_c , compute $\hat{\beta} = (\hat{\beta}_0 - \hat{\rho}\hat{\beta}_L)$ and

$$\hat{\sigma}_\varepsilon^2 = (1/\eta)(\varepsilon_0 - \hat{\rho}\varepsilon_L)'(\varepsilon_0 - \hat{\rho}\varepsilon_L)$$

which provides an unbiased estimate of the spatial autoregressive coefficient ρ .

B Zillow

We use a monthly time series of county level housing data from the Zillow Home Value Index time series which runs from April 1996 through November 2011. The index seeks to provide an unbiased estimate of the monthly median level home value by county⁹. Excluding Hawaii and Alaska, the final dataset provided by Zillow includes complete time series for 623 counties and partial time series for an additional 16 counties. The 639 counties included in the index were admitted based on a rubric of five criteria including sparseness of data and unreasonable temporal volatility¹⁰.

⁹Additional information on how the index is created is provided on the Zillow Research site and can be found at <http://www.zillow.com/blog/research/2012/01/21/zillow-home-value-index-methodology/>

¹⁰A complete list of the criteria for inclusion can be found at <http://www.zillow.com/blog/research/2012/01/21/zillow-home-value-index-methodology/>

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