A Spatial Investigation of Urban Labor Markets

A thesis

submitted by

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Abstract

This thesis considers two different methods of analyzing cross-sectional dependencies between city labor markets. First, it reports a spatial investigation of Okun's Law in a panel of 348 U.S. Metropolitan Statistical Areas (MSAs) using annual unemployment and GDP data from 2001-2010. Then, it considers a Global Vector Autoregressive (GVAR) model of various labor market variables for 34 of the Northeast Census Region cities. To the best of my knowledge, this is the first use of the GVAR framework in modeling interlinkages between U.S. cities.

Using spatial autoregressive models to estimate Okun's Law coefficients for MSAs, I find that moderate to high cross-sectional dependence exists between city labor markets, a result which is robust to a number of different spatial proximity measures. In fact, more importantly I find that the cross-sectional dependence increases as I change from distance- to economic-based measures. Lastly, in decomposing the total effect of changes in the growth rate of real GDP on the unemployment rate, I find that the indirect effect of growth in GDP in neighboring cities dominates the direct effect of growth in local GDP. This result is relevant for a discussion of whether or not place-based investment policies designed to alleviate high local unemployment rates provide an advantage over policy designed at the federal level.

The main result derived from the GVAR model is that notably positive contemporaneous relationships exist between cities in the Northeast for a number of labor market variables, but there is no evidence of statistically significant spillover effects following idiosyncratic shocks to the unemployment rates of the three largest MSAs by GDP (New York, Boston, and Philadelphia). In fact, only a global shock to the regional job openings rate has any statistically significant impact on city unemployment rates.

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I. Introduction

It is well-established in the macroeconomics literature that the recent 2007-2009 recession has been sluggish and has seen considerable variation in both the contraction and expansionary phases. In particular, aside from drastic variation in housing prices, the United States has seen considerable variation in employment dynamics across cities, states, and regions. One stylized fact that exemplifies the large differences in local labor market conditions is an increase at the start of the recession in the weighted standard deviation of metropolitan unemployment rates from an average of approximately 1.5% to an average of 2.75% (Valletta and Kuang, 2010; Daly et al., 2012; Karahan and Rhee, 2012).[1] Furthermore, the coefficient of variation, which was stable from 2005 to 2008, increased approximately 11% from 2008 to 2010 as the weighted standard deviation of the unemployment increased sharply. Valletta and Kuang (*op. cit*.) also document a drastic increase in dispersion of employment growth across industries and states, suggesting that job growth has been too slow in certain regions and sectors to reabsorb workers that lost their jobs during the recession.

Even with such great variation in unemployment rates and employment growth, the policy discussion at the federal level has taken place under the assumption that all regions face the same economic challenges, and policies designed to adapt to regional circumstances have largely been ignored (Rothwell, 2012). One of the reasons cited for this is that economists are often "suspicious of place based policies as they may create incentives to invest, work, and live in less productive and less hospitable areas" (Kline and Moretti, 2013). Another reason is that macroeconomic research has traditionally focused on describing economic fluctuations for the entire economy and on decomposing it into its different sectors, while ignoring an analysis of the

[1] This is illustrated in Figure 1 of the appendix. It is a reproduction with my data set of Figure 8 in Karahan and Rhee (*ibid*.) and is similar to Figure 4 in Valletta and Kuang (*op. cit*.).

economy at finer levels of spatial resolution. It is therefore unclear whether or not targeted regional economic policy would be any more effective than the current aggregate demand/supply policies.

In order to add to this policy discussion, the aim of this paper is to develop a basic understanding of spatial dependence that may exist across Metropolitan Statistical Areas (MSAs). More specifically, my interest is in capturing cross-sectional dependence across cities in order to assess the role that spillovers play in causing variation in employment dynamics. My approach to this spatial investigation is twofold: first, I consider a spatial panel model of Okun's Law, an empirical relationship linking the change in the unemployment rate to the growth rate of MSA Gross Domestic Product (GDP); second, I consider a global vector autoregressive model (GVAR) à la Pesaran, Schuermann, and Weiner (2004) and Dées, DiMauro, Pesaran, and Smith (2007), whom I shall refer to from hereon as PSW and DdPS, respectively.

The goal of the Okun's Law investigation is to establish whether or not there exists cross-sectional dependence between city labor markets, and, if so, to determine its magnitude and properties. On the other hand, the GVAR model lends itself to an analysis of how idiosyncratic city-specific shocks propagate across cities. As suggested by PSW, this methodology is particularly suited for "models of inter-regional linkages, either through city-suburb economic ties (Voith, 1998) or linkages between cities as in the 'systems of cities' literature (Henderson, 1988)." Despite this recommendation, I am not yet aware of anyone who has applied a GVAR model in the context of the 'new economic geography' or regional and urban economics literature to capture economic inter-linkages across cities.[2]

[2] I interchange city and metropolitan statistical area for the remainder of the paper. A metro area contains an urban core of 50,000 or more population, and each "area consists of one or more counties and includes the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic

I focus my analysis on cities for two reasons: the first, more practical reason, is that the smallest level of disaggregation for which macroeconomic data exist at a business cycle frequency is that of the MSA; the second, which piques one's intellectual curiosities, is that the majority of economic and social activity in the United States is located within urban areas. In fact, metropolitan areas account for an astonishingly high 90% of national Gross Domestic Product (GDP), with nearly 72% of that generated by the largest 50 cities. For this reason alone, one cannot deny the importance of understanding the employment and output dynamics of cities in order to further our understanding of the national economy.[3]

II. Review of the Literature

There are few studies of the United States business cycle that explicitly allow for interdependencies amongst the nation's geographical subparts and the ones that do largely focus on modeling interactions between the national and sub-economies through the use of regime-switching models. For instance, Owyang, Piger, and Wall (2005) apply a regime-switching model to state-level coincidence index data from Crone (2002), based on Stock and Watson (1989), and find that states differ a great deal in the levels of growth they experience between recession and expansion phases. More specifically, they find that growth rates during recessions are related to industry mix, whereas growth rates during expansions are related to education and age composition. Further, they find that there are large differences across states in the timing of regime switches.

Taking this same idea in the context of urban business cycles, Owyang, Piger, Wall and Wheeler (2008) apply the Markov-switching approach of Hamilton (1989) to quarterly city

integration (as measured by commuting to work) with the urban core." Definition from the Office of Management and Budget (OMB) : http://www.census.gov/population/metro/

[3] Authors that have studied employment fluctuations in an urban setting include, but are not limited to, Gan and Li (2004), Zhang (2007), Gan and Zhang (2006), and Coulson (2004). I avoid further discussion of these papers because they do not specifically focus on cross-sectional aspects of the business cycle.

employment data from 1990-2002. They document similar results as in their state-level analysis in finding that growth in the high phase is related to human capital and industry mix, while growth in the low phase is related to industry mix and the relative importance of manufacturing. More recently, Owyang, Piger, and Wall (2010) use the same methodology to describe city-level employment cycles for 58 of the largest U.S. cities. They document substantial cross-city variation in the timing, lengths, and frequencies of contractions, and more importantly find that recessions follow underlying geographic patterns. In fact, in constructing a concordance index between employment cycles of each pair of cities over all time periods, they find that cities with sample-average similarities in high-school attainment and mean establishment should be in the same employment cycle phase 73.1 percent of the time, and that geographic similarity can raise the concordance by as much as 15.3 percentage points. They conclude that the U.S. employment and business cycles must have a spatial dimension that is independent of broad industry-level fluctuations.

Owyang, Rapach, and Wall (2009) take a different approach in allowing for interactions between the national and state economies by estimating a dynamic factor model for US state-level real income and employment growth for 1990:1-2006:3. They find that the national economy can be summarized with three common factors representing the national business cycle, core inflation, and the "dissonance" between employment growth and personal-income growth. The factor that they coin as dissonance is one which is correlated with both employment growth and personal-income growth, but with opposite signs for the correlation. They find that this dissonance factor helps to explain the "jobless" recovery following the 2001 recession in which income growth was relatively strong but employment growth was relatively weak. They also find that, according to the loadings that indicate the extent to which each state's economy is related to the corresponding factor, there is a great deal of heterogeneity in the nature of the links between state and national economies. To study the determinants of this heterogeneity, the authors estimate a series of spatial Durbin models in which the dependent variable is a vector of state factor loadings and the weight matrix is a 49 x 49 state contiguity matrix. Controlling for a number of industry and non-industry effects, the authors conclude that links between the state economies and the national business cycle are related to differences in industry mix, average establishment size, and agglomeration.

A forthcoming paper by Karahan and Rhee (2012) also tackles explaining dispersion of unemployment across MSAs during the recent 2007-2009 recession by constructing and calibrating a directed search model of local housing, labor markets, and migration. Their model accounts for 88% of the increase in dispersion of unemployment across MSAs and the entire decline in net migration during the recession. Furthermore, they find that the decline in net migration explains approximately 17% of the rise in unemployment after accounting for the fall in labor productivity. Their model supports the hypothesis that the housing bust decreased geographic mobility and thus exacerbated unemployment during the Great Recession.[4]

Although the original motivation behind the GVAR framework developed first in PSW (2004) and then further in DdPS (2007) was to have a consistent model for macro-based risk management for commercial banks, researchers have since applied it to a number of different areas. Three broad categories that di Mauro and Pesaran (2013) fit the existing GVAR literature into are: international transmission and forecasting; finance applications; and regional applications. Vansteenkiste and Hiebert (2009) is an example of the third, which is the closest in similarity to my research agenda. These authors empirically assess the prospects for house price

[4] Although I do not currently control for how variation in housing prices across cities may explain variation in employment dynamics, it is something I plan to examine in the future.

spillovers across euro area countries. Their application involves three housing demand variables (real house prices, real per capita disposable income, and the real interest) on a quarterly basis for 10 euro area countries over the period 1989-2007. Their results suggest that while spillovers result from country-specific house price shocks in the euro area, they are of a relatively low magnitude.

In what follows, I present a spatial investigation of Okun's Law. In Section IV, I introduce the GVAR model and discuss key identification assumptions. In part A, I summarize the data and aggregation weight matrix. In parts B-D, I present unit root tests, discuss the model specification, and test a weak exogeneity assumption. Lastly, in parts E-G, I present the results of the city-specific models, average pair-wise cross-section correlations of the endogenous variables, and a diagnostic impulse response analysis. In Section V, I recapitulate my results and provide suggestions for future research.

III. Okun's Law: A Spatial Investigation

Before developing the Global VAR framework, I first estimate a panel model of Okun's Law with and without controls for spatial correlation in order to assess whether or not spatial dependence exists across MSAs. This baseline model motivates the reasons for why spatial correlation must be accounted for, while also exploring a topic that has gained considerable attention since the onset of the Great Recession. The reason for the recent popularity of Okun's Law is due to the fact that there has been a sustained level of high unemployment during the recovery, even though real output growth has recovered. This so-called jobless recovery has brought up the general concern of whether or not the correlation between different measures of unemployment and fluctuations in output has weakened over time. In fact, some authors have already provided evidence negating Okun's Law stability over the business cycle, and have arn argued that it "should not be taken too seriously but rather as an approximation to be taken with a grain of salt" (Owyang and Sekhposyan, 2012).

These authors in many ways are justified in their assessment given their empirical results and given that there is no set theory explaining why a 2- to 3-percentage point decrease in real output growth should be associated with an approximate 1-percentage point increase in unemployment. On the other hand, it is difficult for one to disregard such a simple rule of thumb in economics, especially given that not many exist. Another group of authors argue similarly in their 50th anniversary assessment of Okun's Law, and state that while "it is rare to call a macroeconomic relationship a 'law' … we believe that Okun's Law has earned its name" (Ball et al., 2012). Although I recognize both perspectives regarding the usefulness of Okun's Law, I lean towards the side of the latter argument. Although it may not be the most robust rule, proponents of its usefulness in macroeconomic policy still exist, and it is with this in mind that I present this study.[5]

Rather than focusing on the traditional aggregate unemployment and output relationship though, I estimate a metropolitan area panel model of Okun's Law. The reason for this is because, when it comes to policy issues, a difference in Okun's coefficient between metropolitan areas and rural areas, between metropolitan areas and the aggregate U.S., or across metro areas in general, may inform the need for a mix of region-specific policy with the traditional aggregate demand/supply policies.

A. Empirical Model and Tests for Stationarity

In his seminal work, Arthur Okun (1962) used quarterly data from 1947:Q2 to 1960:Q4 to estimate the following model:

[5] For example, Federal Reserve Chairman Ben Bernanke spoke of Okun's Law at a conference in Arlington, Virginia on March 26, 2012. http://www.federalreserve.gov/newsevents/speech/bernanke20120326a.htm

$$\Delta u_t = \alpha + \beta \Delta y_t + \varepsilon_t \tag{1}$$

where u_t is the aggregate unemployment rate, y_t is the aggregate natural log of output, and ε_t is an idiosyncratic error term. The baseline model for my analysis is a panel version of Okun's:

$$\Delta u_{it} = \alpha + \beta \Delta y_{it} + a_i + v_{it} \tag{2}$$

where i indexes MSAs, a_i is an unobserved time-invariant metropolitan area effect, and v_{it} is an idiosyncratic error term. I also consider Autoregressive Distributive Lag (ADL) models in which I include lags of both the dependent and independent variables as covariates. I control for the dependent variable to allow for that fact that the unemployment rate may not immediately adjust to changes in growth rate of real GDP due to inertia, search frictions, and/or hiring costs which are typical of the canonical search and matching model for unemployment of Mortensen and Pissarides, and its successors (Pissarides, 1985; Mortensen and Pissarides, 1994; Shimer, 2005)[6].

The source of data on metropolitan real gross domestic product is the Bureau of Economic Analysis (BEA).[7] This relatively new data set has been underutilized so far in the academic literature, and, to the best of my knowledge, has not been used for an Okun's Law analysis. The data are available on an annual basis from 2001-2010. The source of metropolitan unemployment rate data is the Bureau of Labor Statistics (BLS).[8] The data are consistently available seasonally-adjusted on a monthly basis from January 2000 to October 2012 for metropolitan areas defined by the most up-to-date definition of MSA given by the Office of Management and Budget (OMB). To remain consistent, I restrict this data to January 2001 – December 2010 and calculate an average annual unemployment rate.

[6] This is by no means an exhaustive list. For a recent review of the search and matching literature, see the IZA Prize in Labor Economics Series book by Mortensen and Pissarides (2011).
[7] http://www.bea.gov/newsreleases/regional/gdp_metro/gdp_metro_newsrelease.htm
[8] http://www.bls.gov/lau/metrossa.htm

Table 1 in the appendix, Section VI, presents the mean, standard deviation, and min/max at the MSA level of real GDP, the growth rate of real GDP, and the unemployment rate for each year in the sample. A few interesting features of the data over the sample period are worth discussing briefly. First, average real GDP for metropolitan areas increased 15.72% from 2001 to 2010, while the standard deviation of real GDP increased by 14.87%. An increase of both of these summary statistics suggests that larger metro areas are diverging from the smaller ones. Second, in any given year, the range of real GDP growth is approximately 30-40 percentage points. Generally though, the minimum and maximum growth metro areas are rather small in size, suggesting that there may be a lot of movement in GDP rank at the tail of the distribution. Lastly, during the recession of 2007-2009 the standard deviation of the unemployment rate increased sharply from an average of approximately 1.5% to an average of 2.75%.

The baseline model is estimated using a simple OLS fixed effects estimator. The dynamic panel-data model is estimated using the Arellano and Bond (1991) estimator. The reason for this is well known: OLS is inconsistent when allowing for both fixed-effects and lags of the dependent variable because the individual effects are correlated with lags of the dependent variable. The Arellano and Bond generalized method of moments (GMM) estimator corrects for this correlation and is consistent for panels with large cross-sectional observations and few time periods, as in our case.

Before estimating these models, I first determine whether or not the data are stationary. In order to test this I consider a number of panel unit roots. Namely, I consider the Harris-Tzavalis (1999) test and Breitung (2000) test of which both assume that the unit root process is homogenous, and the Im-Pesaran-Shin test (2003) test which relaxes the homogeneity assumption by allowing cross-sectional dependence in the unit root process. The advantage of the Harris-Tzavalis test over the Breitung test is that it assumes that the number of time periods, T, is fixed. The disadvantage is that when T is small this test may suffer from severe distortion. As is standard, I allow for the mean and variance of the test statistic under the null to be calculated using T-1 instead of T periods to correct for this distortion. All tests have as the null hypothesis that all panels contain a unit root. The results for the panel unit root tests are provided in Table 2 of the appendix. Encouragingly, all the tests reject the null hypothesis of a unit root process in both the change in the unemployment rate as well as the growth rate of real GDP. Therefore, I assume that the data are stationary.

B. Results and Discussion

The results of the dynamic panel estimation of Okun's Law are given in Table 3. Starting from a contemporaneous Okun's relationship, I find that Okun's coefficient suffers from a possible attenuation bias. Including further lags of both the change in the unemployment rate and the growth rate of output, I find that the fully specified model should include one lag of the dependent variable and two lags of the independent variable. The results from this fully specified model in column (4) suggest that the long-run Okun's coefficient is -0.408. This result suggests that an approximate increase of 2.45-percentage points in the growth rate of output corresponds to a change in the unemployment rate of 1-percentage point at the level of the MSA. Furthermore, the contemporaneous coefficient of -0.280 is exactly the same as the mean estimate of Okun's coefficient found by Owyang and Sekhposyan (2012) in their dynamic specification of Okun's Law. It is worth noting that the long-run Okun's coefficient and the contemporaneous coefficient in specification (4) decrease, respectively, to -0.286 and -0.174 when a time trend is included.

Although these results are consistent with what one might expect, in estimating a dynamic panel one must further consider the possibility of cross-sectional dependence in the errors. If we assume that cross-sectional dependence is caused by unobserved common factors which are uncorrelated with the regressors, then the estimators are consistent, but the standard errors are biased. Whereas if we assume that cross-sectional dependence is caused by unobserved common factors which are correlated with the included regressors, the approaches used in the estimation above will not work because the estimators will be biased and inconsistent. In fact, Phillips and Sul (2003) have shown that if the degree of cross-sectional dependence is severe enough, then dynamic panel estimators may provide little to no gain over single-equation ordinary least squares (De Hoyos and Sarafidis, 2006).

In order to address this possibility, I test for cross-sectional dependence using Pesaran's (2004) cross-sectional dependence (CD) test. Following the estimation of the fixed effects model without lags of the dependent variable (column (1) of Table 3), I estimate the following CD statistic for balanced panels:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{3}$$

I do this in order to test the null hypothesis of no cross-sectional dependence, which can be formally stated as:

$$H_0 = \rho_{ij} = \rho_{ji} = \mathrm{corr}(u_{it,}\, u_{jt}) = 0 \text{ for } i \neq j \tag{4}$$

Pesaran (*ibid.)* showed that under this null hypothesis CD $\rightarrow$N(0,1) for N$\rightarrow\infty$ and T fixed.

I estimate CD to equal 504.506 and strongly reject the null hypothesis of cross-sectional independence with a p-value < 0.0005. I also calculate the average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of residuals to be 0.688, providing further evidence of cross-sectional dependence.

Evidence of cross-sectional dependence suggests that the estimates in Table 3 are most likely inconsistent. Therefore, in modeling Okun's Law, I must consider ways to address this spatial correlation. However, this is not such an obvious task, and how to address this largely depends on the type of cross-sectional dependence that exists, weak or strong (Chudik *et al.*, 2011). A process is cross sectionally weakly dependent if "its weighted average at that time converges to its expectation in quadratic mean, as the cross section dimension is increased without bound," whereas it is said to be strongly dependent if this does not hold and the dependence is pervasive (Holly *et al.*, 2011). Generally, weak cross-sectional dependence is addressed by modeling the dependence as a function of some distance measure, whereas strong dependence is addressed by common factor models. Spatial autoregressive and spatial error models are examples of the former (Cliff and Ord, 1973; Anselin, 1988), whereas Bai (2009) is an example of the latter.

Unfortunately, testing for the degree of cross-sectional dependence in panels with large N and small T is not a straightforward task. Furthermore, the test which is available, developed by Pesaran (2012), is not yet readily applicable in current statistical software. Hence, I move forward by assuming that the cross-sectional dependence is of the weak form, and consider three different spatial panel models of Okun's Law with fixed effects: a spatial autoregressive model (SAR), a spatial Durbin model (SDM), and a spatial autocorrelation model (SAC). I will discuss each of these in turn.

C. Spatial Panel Model

The SAR model with lagged dependent variable can be written in general terms as:

$$y_{it} = \tau y_{it-1} + \rho W y_{it} + \beta X_{it} + a_i + u_{it} \tag{5}$$

where u_{it} is a normally distributed error term, a_i is an individual fixed effect, W is a n x n spatial matrix for the autoregressive component where n is the number of MSAs, and ρ is a scalar parameter that ranges from (-1,1) if the spatial weighting matrix is row standardized. The SAR model assumes that there is substantial autocorrelation in the dependent variable between the regions. In the case of Okun's Law, this would mean that the change in unemployment across regions would be correlated. If this effect is ignored and a simply OLS estimator is used, the estimates will be biased.

The SDM model with lagged dependent variable is:

$$y_{it} = \tau y_{it-1} + \rho W y_{it} + \beta X_{it} + \theta D Z_{it} + a_i + u_{it} \tag{6}$$

where D is an n x n spatial matrix which in general is the same as W, and Z_{it} is a spatially lagged regressor which in general is the same as $X_{it.}$ In this application, significance of the spatially lagged structure would imply that growth rates of GDP are correlated between regions. As discussed in LeSage and Pace (2009), it is quite easy to show that the SDM model is a linear combination of the spatial autoregressive and spatial error models (SEM). Hence, in applied practice when faced with model uncertainty between the SAR and SEM models, one may consider estimating a spatial Durbin model.

The SAC model is similar to the SAR model, except that it also allows for spatial dependence in the disturbances. This model can be written as:

$$y_{it} = \rho W y_{it} + \beta X_{it} + a_i + v_{it} \tag{7}$$

$$v_{it} = \lambda M v_{it} + u_{it} \tag{8}$$

where M is an n x n spatial matrix which again may equal W. Note that the SEM model is a special case of the SAC model, where ρ = τ = 0. Both of these models assume that the shock to one region is transmitted to neighboring regions, but the SEM model is more restrictive in that it does not allow for autocorrelation in the dependent variable. Hence, as I am interested in the coefficient of spatial autocorrelation, I do not consider this model here.

Without yet discriminating between specifications, I present the results for each model in Table 4 of the Appendix. The spatial matrix used for each of these models is a row-standardized rook contiguity matrix (Cliff and Ord, 1973). A rook contiguity matrix is one in which only points that have edge-to-edge contact are considered neighbors, whereas a queen contiguity matrix is one in which points that share both edge-to-edge and vertex-to-vertex contact are considered neighbors. I also considered an inverse-distance matrix, but the results were statistically insignificant. This is most likely due to the fact that the average distance between MSAs in the sample is approximately 550 miles and the range of distances between MSA centroids is approximately 17 - 2,780 miles. On average, one would not expect labor market spillovers to propagate over such large distances when considering purely distance-based dependence. In fact, Hanson (2005) shows that although a 10% fall in personal income reduces employment by 6.0 – 6.4% in counties that are 100 km in distance, this effect declines to zero for counties more than 800 km in distance.

The interpretation of the results is not as straightforward as in a linear regression model due to the fact that a change in the explanatory variable for a given MSA can potentially affect the dependent variable in all other observations. These spatial spillovers arise due to impacts passing through neighboring cities and feeding back to the city itself. The magnitude of the effect depends on the degree of connectivity among cities governed by the weight matrix, the strength of the spatial dependence parameter, ρ, and the coefficient estimate of β. Since the impact of changes in the growth rate of GDP will differ over all cities, it is desirable to have a summary measure of the varying impacts. In light of this, Pace and LeSage (2006) developed the three following scalar summary measures: the Average Direct Impact, which is the average impact of changes in the *i*th observation of x_i on y_i; the Average Total Impact, which is the average total impact on individual observation y_i resulting from changes in the explanatory variable by the same amount across all *n* observations; and the Average Indirect Impact, which is the difference between the two. More specifically, changes in the explanatory variables in city *i* will impact the dependent variable in city *i*, as well as other cities j, leading to an *n x 1* vector of responses. Since we can change each of the cities' explanatory variable value, this will result in an *n x n* matrix of responses in which the average of the main diagonal elements is the Average Direct Impact and the average of the cumulative sum of off-diagonal elements for each row is the Average Indirect Impact. These measures are calculated for each regression specification and reported along with the coefficient estimates.

With this now in mind, it is easily seen from the results that a 3.25 – 4.25 percentage point change in the growth rate of real GDP across all MSAs correlates with an average 1-percentage point contemporaneous reduction in the unemployment rate. This is in line with the contemporaneous estimates from the dynamic panel model. This is interesting to note because given that the spatial autocorrelation coefficient, ρ, is moderately large and statistically significant across all the specifications, one would presume that the coefficient of interest would be substantially biased in the original dynamic panel model. Another feature of the results is that the Average Indirect Effect accounts for between 35-45% of the Average Total Effect. I interpret this as growth spillovers' accounting for approximately a third of the impact of changes in the unemployment rate. Lastly, in the SAC model, the estimate of λ is negative and significant. Two possible interpretations of this negative dependence come to mind. First, it may be the case that cities that share a common border may compete with each other for both financial resources and employees, and the negative dependence is an indication of competitive forces outweighing cooperative ones. This may be particularly true if there is colocation of industries between neighboring cities that differ in terms of cyclical characteristics. The second possible interpretation of this result is that neighboring cities may tend to produce substitute goods. It would be interesting to pursue these ideas further in future research by interacting distance-based and similarity-based weight matrices.

In order to further deconstruct the aggregate spatial relationships across MSAs, I also estimate the three models for each of the four major Census Regions. The results are provided in Tables 5-8 in the Appendix. Comparing results across Census Regions, one can see that the spatial autocorrelation coefficient, ρ, is, on average, largest for the Northeast and smallest for the Midwest. This is expected given the degree of isolation of MSAs in the Midwest and the close proximity of them in the Northeast, but it also possibly an outcome of the spatial weights matrices being distance-based measures. Also, the range of the Average Total Effect for the Northeast implies that a 2.4 – 3.4 percentage point change in the growth rate of real GDP across all MSAs is associated with an average 1-percentage point contemporaneous reduction in the unemployment rate, whereas the South requires an approximate 5 percentage point change, and the West and Midwest Regions an approximate 3.4 – 4.3 percentage point change. Furthermore, the proportion of the Average Total Effect which is derived from the Average Indirect Effect is largest for the Northeast and the West and smallest for the South and Midwest. Lastly, the spatial error coefficient, λ, is only statistically significant in the Northeast and South regressions and largest for the Northeast. Again, this may be an outcome of the spatial weights matrices being distance-based. Otherwise, one would interpret this as exogenous shocks spilling over across cities in the Northeast and South Census Regions, but not necessarily in the West and Midwest.

The analysis up to this point comes with two important caveats. First, I have thus far only considered distance-based measures of the spatial weights matrix, which of course is an arbitrary assessment of spatial relationships. Although it is common in the spatial econometrics literature to take this approach, it lacks structural economic interpretation (Corrado and Fingleton, 2010). This approach is essentially based on Tobler's first law of geography that, "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This may in fact be true to some extent, but it is also important to consider how cities are related through both economic and social distance measures. In discussing the difficulty of measuring spatial spillovers, Krugman (1991) remarked that knowledge flows "leave no paper trail by which they can be measured or tracked, and there is nothing to prevent the theorist from assuming anything about them that she likes." The second caveat is that the model suffers from obvious omitted variable bias. Unfortunately, for the time period and frequency over which this analysis takes place, available data for MSAs are limited.

In order to address both of these concerns, I follow Owyang *et. al*. (2010) in constructing the following measure of industrial similarity between cities i and j:

$$IS_{ij} = 1 - \frac{1}{n}\sum_{k=1}^{n} |x_{ik} - x_{jk}| \tag{9}$$

where x_{ik} is the employment share of sector k in city $i,$ and n is the number of sectors. IS_{ij} equals 1 if cities have identical employment shares for all n sectors and the range is (0,1].[9] I construct this measure using annual data from 2001-2010, and take the average for each city pair in order to construct a spatial weight matrix of industrial similarity. This measure can be thought of as a measure of economic distance, as first discussed in a spatial econometrics context by Conley

[9] The annual data is from the BLS and is seasonally unadjusted from 2001-2010. The sectors are mining logging, and construction; manufacturing; trade, transportation, and utilities; information; financial activities; professional and business services; education and health services; leisure and hospitality; other services; and government.

(1999). Given this measure, it is important to note that only a fairly small part of employment share changes cause the variation in industrial similarity across cities. As discussed in Chapter 7 of Ioannides (2013), this is because "even the largest relative employment shares for industrial sectors in U.S. cities are rather small in absolute terms." One may consider this a consequence of the hierarchy principle which asserts that industries found in small cities must also be found in large cities. That is to say, all cities must host certain necessary industries in order to function, such as gas stations and hospitals, but not all cities will be host to an opera house.

The mean industrial similarity is 0.953, while the maximum and minimum are .9994 and 0.8732, respectively. The most similar pair of MSAs is Evansville, IN-KY and Gainesville, GA and the least similar pair is Ames, IA and Elkhart-Goshen, IN. Encouragingly, the correlation coefficient for unemployment rates between Evansville and Gainesville is 0.9909, and is only 0.9213 between Ames and Elkhart-Goshen. Furthermore, the correlation coefficient for changes in the unemployment rate is 0.9540 between Evansville and Gainesville, and only 0.7640 between Ames and Elkhart-Goshen. The average annual unemployment rates for these cities are reported in Table 9 of the appendix.

The results of the four aforementioned spatial panel models with the industrial similarity weight matrix are provided in Table 10. The results suggest that when taking into account industrial proximity, rather than geographical, a 1-percentage point decrease in the unemployment rate is associated with an approximate 1.25 to 1.67 percentage point increase in the growth rate of GDP. Furthermore, the spatial correlation coefficient, ρ, is approximately 0.90, which is both statistically and economically significant. Lastly, the indirect effect now dominates the direct effect in determining this relationship. These results together imply that changes in the unemployment rate in city *i* are largely determined by the growth rate changes and unemployment rate changes in cities with similar industrial structure.

The strong spatial correlation leads me to wonder whether or not there is a near unit root in the spatial structure, and if so, what would its impact be on my results? Fortunately, contrary to the near unit root model of an autoregressive time series process, the asymptotic distributions of the coefficient estimates remain normal (Lee and Yu, 2008). These authors attribute this to differences in structures of the SAR model from the autoregressive time series process. Mainly, it is due to the fact that there is no initial value problem in the SAR model since the spatial units lie in a circular world which has neither a beginning nor an end. Hence, while the conditional variance of the dependent variable in an autoregressive time series process grows large over time in the presence of a near unit root, variances of all outcomes of spatial units in the presence of a near unit root have the same orders of magnitude.

In order to test the robustness of these results, I also consider a weight matrix of educational attainment similarity, ES_{ij}, defined in the same fashion as the industrial similarity matrix. The educational attainment data is from the 2007-2011 American Community Survey 5-Year Estimates and is for the population age 25 years and over.[10] The assumption behind the use of this index is that cities with similar educational attainment have a similar supply of labor in terms of skill level, and thus are subject to similar shocks originating in the industries that use those skills intensively. One might further expect that labor force participation is similar in cities with similar educational attainment, and that it is through this channel that there would be a similarity in the effect on the unemployment rate across cities.

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[10] The educational attainment categories are: Less than 9th grade; 9th to 12th grade (no diploma); High school graduate; Some college (no degree); Associate's degree; Bachelor's degree; and Graduate or professional degree.

Remarkably, the results do not change when replacing the industrial similarity index with the educational attainment similarity index. This may not be surprising though given the similarity in summary statistics between the two matrices.

Summary of Spatial-weighting Matrices

	ISij	ESij
min > 0	0.873	0.866
Mean	0.952	0.956
Max	0.999	0.997

In fact, the average correlation between matrix columns is 0.919 and the standard deviation is 0.022. This suggests that the results are robust to the choice of the spatial weights matrix because the industrial similarity and educational attainment similarity matrices are highly correlated. That is, cities with similar industrial structure also have similar levels of educational attainment, whereas cities with dissimilar industrial structure also have dissimilar levels of educational attainment. As can be seen in the table below, this relationship holds across Census Regions.

Correlation of IS_{ij} and ES_{ij} by Census Region

	Northeast	South	Midwest	West
Mean	0.919	0.917	0.914	0.930
Std. Dev.	0.017	0.023	0.023	0.016
Minimum	0.887	0.821	0.801	0.860
Maximum	0.950	0.950	0.955	0.957
Observations	30	148	93	77

Given the strong correlation between the two economic similarity measures, I introduce a third measure of similarity between cities that is not as highly correlated with IS_{ij} and $ES_{ij.}$ I do this in order to test further the robustness of my results. In the same fashion as earlier, I now construct a race similarity index, RS_{ij}.[11] The race composition data are again from the 2007-2011

[11] The categories for race are: White; Black or African American; American Indian and Alaska Native; Asian; Native Hawaiian and Other Pacific Islander; Some other race;

American Community Survey 5-Year Estimates. The average correlation between columns of the educational attainment similarity and race similarity matrices is 0.846 with a standard deviation of 0.048. Similar results hold between the industrial similarity and race similarity matrices. Again, this average correlation between indices is consistent across Census Regions.

Correlation of RS_{ij} and ES_{ij} by Census Region

	Northeast	South	Midwest	West
Mean	0.845	0.856	0.840	0.835
Std. Dev.	0.041	0.047	0.044	0.053
Minimum	0.768	0.735	0.745	0.747
Maximum	0.916	0.929	0.923	0.942
Observations	30	148	93	77

The results of the spatial panel models with a race similarity weighting matrix are presented in Table 12. Once again, the results do not change, further supporting the robustness of my results.

Overall, three main results have been derived from the spatial investigation of Okun's Law. First, there exists a moderate to high level of cross-sectional dependence between MSAs, with the spatial correlation coefficient, ρ, ranging from 0.40 to 0.94. In fact, more importantly, the dependence increases substantially when I consider spatial proximity measures that have economic structure. Second, estimates of Okun's coefficient for cities range from approximately -0.60 to -0.80 when taking into account structural measures of similarity between MSAs (here, industry, education, and race). This suggests that a 1.25 to 1.67 percentage point increase in the growth rate of Real GDP across all cities correlates with a 1-percentage point decrease in the unemployment rate. Since the aggregate estimates for Okun's Coefficient generally range from 0.25 to 0.50, this may suggest that growth in cities is more effective in reducing unemployment (Owyang and Sekhposyan, 2012). Third, nearly 90% of the effect of the growth rate of GDP on the unemployment rate is an indirect effect. That is, growth spill overs impact the local unemployment rate more than growth in own-city GDP. This last point suggests that, given the high level of dependence between cities, place-based policies may not offer an advantage over policy implemented at the federal level.

IV. GVAR model

Before the introduction of the global vector autoregressive model, cointegrating VAR systems only allowed for an analysis of a single country covering a few key macroeconomic variables. While it was in theory possible to allow for inter-relationships across different economies in these models, dimensionality issues made them infeasible to estimate. In fact, in an unrestricted VAR model with N regions, the number of unknown parameters that would need to be estimated per equation is $p(kN - 1)$, where p is the lag order of the VAR and k is the number of endogenous variables per region (PSW, 2004). Hence, considering our example at hand, for say 50 cities, a lag order of 2, and 5 endogenous variables per city, the number of unknown coefficients per equation would be 498.

In light of this difficulty, PSW developed a global VAR model that avoids this data limitation, and at the same time provided a consistent framework that allows for cross-sectional dependencies. To bypass the data limitations, the authors start with the construction of separate 'foreign' variables for use in each of the separate national models. They then treat these country-specific foreign variables as weakly exogenous when estimating each of the country models. Specifically, individual VEC models are estimated using domestic and foreign macroeconomic variables, where the foreign variables are constructed from other economies' data using weights that are chosen based on *a priori* assumptions. The individual country models are then combined in a consistent manner to generate forecasts for all variables in the world economy simultaneously.

To illustrate this idea, suppose there are $N + 1$ cities in a regional economy, indexed by $i = 0, 1,\ldots, N$, and denote country-specific variables by the k x 1 vector $\mathbf{x}_{it}$ and the associated city-specific foreign variables by the k x 1 vector $\mathbf{x}_{it}^{*}$. A first-order city-specific model that controls for time fixed-effects and an s x 1 vector of common global weakly exogenous variables, $\mathbf{d}_t$, can be written as follows:

$$\boldsymbol{x}_{it} = \boldsymbol{a}_{i0} + \boldsymbol{a}_1 t + \boldsymbol{\Phi}_i \boldsymbol{x}_{i,t-1} + \boldsymbol{\Lambda}_{i0} \boldsymbol{x}_{it}^{*} + \boldsymbol{\Lambda}_{i1} \boldsymbol{x}_{i,t-1}^{*} + \boldsymbol{\Psi}_{i0} \boldsymbol{d}_t + \boldsymbol{\Psi}_{i1} \boldsymbol{d}_{t-1} + \boldsymbol{u}_{it} \tag{10}$$

$$\boldsymbol{x}_{it}^{*} = \sum_{j=0}^{N} w_{ij} \boldsymbol{x}_{jt} \tag{11}$$

where $w_{ij} \geq 0$ are the weights that are assigned to the foreign variables. The city-specific errors $\mathbf{u}_{it}$ are assumed to be serially uncorrelated with mean zero and a non-singular covariance matrix $[\boldsymbol{\Omega}_{ij}]$. Although the model is estimated for each city individually, the shocks are allowed to be weakly correlated across cities.

Each individual model is estimated allowing for unit roots and cointegration with the identification assumption that region-specific foreign variables are weakly exogenous. To obtain the global VAR model, define the $(k_i + k_i^*)$ x 1 vector

$$\boldsymbol{z}_{it} = \begin{pmatrix} \boldsymbol{x}_{it} \\ \boldsymbol{x}_{it}^{*} \end{pmatrix} \tag{12}$$

and rewrite equation (10) as:

$$\boldsymbol{A}_i \boldsymbol{z}_{it} = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1} t + \boldsymbol{B}_i \boldsymbol{z}_{i,t-1} + \boldsymbol{\Psi}_{i0} \boldsymbol{d}_t + \boldsymbol{\Psi}_{i1} \boldsymbol{d}_{t-1} + \boldsymbol{u}_{it} \tag{13}$$

where

$$\boldsymbol{A}_i = \left(\boldsymbol{I}_{ki,} - \boldsymbol{\Lambda}_{i0}\right), \quad \boldsymbol{B}_i = (\boldsymbol{\Phi}_i, \boldsymbol{\Lambda}_{i1}) \tag{14}$$

The dimensions of each are k_i x $(k_i + k_i^*)$, and $Rank(\boldsymbol{A}_i) = k_i$. It is easily seen that, after collecting all of the endogenous variables to create a global vector, $\boldsymbol{x}_t$, with dimensions k x 1,

$$\boldsymbol{x}_t = \begin{pmatrix} \boldsymbol{x}_{0t} \\ \boldsymbol{x}_{1t} \\ \vdots \\ \boldsymbol{x}_{Nt} \end{pmatrix} \tag{15}$$

where $k = \sum_{i=0}^{N} k_i$, equation (12) can be written as follows:

$$\boldsymbol{z}_{it} = \boldsymbol{W}_i \boldsymbol{x}_t, \forall i = 0,1, \dots, N \tag{16}$$

and $\mathbf{W}_i$ is a matrix of fixed-weights with dimensions ($k_i + k_i$*) x k. Substituting equation (16) into equation (13) we obtain:

$$\boldsymbol{A}_i \boldsymbol{W}_i \boldsymbol{x}_t = \boldsymbol{a}_{i0} + \boldsymbol{a}_{i1} t + \boldsymbol{B}_i \boldsymbol{W}_i \boldsymbol{x}_{t-1} + \boldsymbol{\Psi}_{i0} \boldsymbol{d}_t + \boldsymbol{\Psi}_{i1} \boldsymbol{d}_{t-1} + \boldsymbol{u}_{it} \tag{17}$$

By stacking each city-specific model in (17), we obtain the following Global VAR model:

$$\boldsymbol{G} \boldsymbol{x}_t = \boldsymbol{a}_0 + \boldsymbol{a}_1 t + \boldsymbol{H} \boldsymbol{x}_{t-1} + \boldsymbol{\Psi}_0 \boldsymbol{d}_t + \boldsymbol{\Psi}_1 \boldsymbol{d}_{t-1} + \boldsymbol{u}_t \tag{18}$$

Where $\boldsymbol{a}_0 = \begin{pmatrix} \boldsymbol{a}_{00} \\ \boldsymbol{a}_{10} \\ \vdots \\ \boldsymbol{a}_{N0} \end{pmatrix}, \boldsymbol{u}_t = \begin{pmatrix} \boldsymbol{u}_{0t} \\ \boldsymbol{u}_{1t} \\ \vdots \\ \boldsymbol{u}_{Nt} \end{pmatrix}, \boldsymbol{G} = \begin{pmatrix} \boldsymbol{A}_0 \boldsymbol{W}_0 \\ \boldsymbol{A}_1 \boldsymbol{W}_1 \\ \vdots \\ \boldsymbol{A}_N \boldsymbol{W}_N \end{pmatrix}, H = \begin{pmatrix} \boldsymbol{B}_0 \boldsymbol{W}_0 \\ \boldsymbol{B}_1 \boldsymbol{W}_1 \\ \vdots \\ \boldsymbol{B}_N \boldsymbol{W}_N \end{pmatrix}, \dots$

$$\boldsymbol{\Psi}_0 = \begin{pmatrix} \boldsymbol{\Psi}_{00} \\ \boldsymbol{\Psi}_{10} \\ \vdots \\ \boldsymbol{\Psi}_{N0} \end{pmatrix}, \text{and } \boldsymbol{\Psi}_1 = \begin{pmatrix} \boldsymbol{\Psi}_{01} \\ \boldsymbol{\Psi}_{11} \\ \vdots \\ \boldsymbol{\Psi}_{N1} \end{pmatrix}. \tag{19}$$

Hence, after estimating each city model in equation (17) separately, the global model above can be solved for recursively forward to obtain future values of all endogenous variables in the model.

Overall, the GVAR methodology allows for city interactions through three distinct, but interrelated channels: the direct dependence of city-specific variables on their foreign counterparts, the dependence of city-specific variables on common global exogenous variables, and the contemporaneous dependence of shocks in city *i* on shocks in city *j* (Garratt *et al*., 2006). These distinct features of the model allow me to investigate the employment dynamics for each city following exogenous shocks to global and city variables, and allow me to assess the role of spillovers in transmitting selected city-specific idiosyncratic shocks. Some questions that I seek to answer are: How does each city react to global shocks to US equity prices and the regional vacancy rate? Are certain cities more insulated than others from these aggregate shocks? Is it possible to identify dominant cities in each region? And, if so, how do shocks to these dominant cities propagate to other cities?

A. Data and Aggregation Weights

Due to computational limitations of the GVAR toolbox, the model I estimate is restricted to the 34 largest MSAs in the Northeast Census Region. A full list of the cities is available in below in Table 13. The set $\mathbf{x}_{it}$ of city-specific labor market variables included in the model are: the unemployment rate (*ur*), average hourly earnings (*w*), and average weekly hours (*hr*). The set of global variables $\mathbf{d}_t$ include the regional vacancy rate (*v*) and equity prices (*eq*). The source of all of the city-specific data is the Bureau of Labor Statistics (BLS).[12] The source of the vacancy rates data is the BLS Job Openings and Labor Turnover Survey (JOLTS). All data are monthly from January 2007 – October 2012. I do not construct aggregation weights using trade flows data as is common in GVAR models since such data does not exist for MSAs. Instead, I follow the approach laid out earlier in the Okun's Law investigation by constructing an industrial similarity index for the Northeast Census Region.

B. Unit Root Tests

An advantage of the GVAR methodology is that it can be applied to stationary and/or integrated variables so that one can distinguish between short-run and long-run relations, where the long-run relationships are interpreted as cointegrating. Therefore, I begin by reporting

[12] The source of unemployment data is the Local Area Unemployment Statistics (LAUS), whereas the average hourly earnings and average weekly hours are from the Current Employment Statistics (CES). See Table 14 for descriptive statistics.

Augment Dickey-Fuller (ADF) unit root test statistics in Table 15 for both domestic and foreign variables in levels, first differences, and second differences. The ADF statistics are based on univariate AR (*p*) models in levels with *p* chosen according to the AIC, with a maximum lag order of 12. The 95% critical value of the ADF statistics for regressions with trend is -3.45, and for regressions without trend is -2.89. The results suggest that all variables are *I*(1).

C. Specification and Estimation of City-Specific Models

Having established that the variables are I(1), I begin by estimating the cointegrating city-specific models which include three endogenous variables, their starred counterparts, along with the regional vacancy rate and equity prices as global, weakly exogenous variables. The important assumption needed to estimate these single-city models is that all city-specific foreign variables are weakly exogenous *I*(1) variables, and that the parameters of the individual models are stable over time (DdPS). The weak exogeneity assumption in the context of cointegrating models is that there is no long-run feedback from $\mathbf{x}_{it}$ to $\mathbf{x}_{it}^*$ without ruling out short-run feedback (Johansen, 1992).

Initially, as is standard, the order of the individual city VARX*(p_i, q_i) models are selected according to the AIC. Due to data limitations, I follow DdPS and set the maximum lag order to two, and restrict the lag order of the foreign variables, q_i, to one for all cities. I then continue with the cointegration analysis, where the city-specific models are estimated subject to reduced rank restrictions. The rank of the cointegrating space for each city is then computed using Johansen's trace statistic as set out in Pesaran *et al*. (2000) for models with weakly exogenous *I*(1) regressions. This approach is atheoretical, so the cointegrating relationships that are found are purely statistical in nature. The orders of the VARX* models and the number of cointegrating relationships for each city is provided in Table 16. Exactly half of the 34 cities have one cointegrating relationship, and two of the cities, Lancaster, PA and Pittsburgh, PA have two.

D. Weak Exogeneity Tests

As mentioned previously, the assumption underlying estimation is the weak exogeneity of the city-specific foreign variables with respect to the long-run parameters of the error correction form of the VARX* model. This can be tested following the procedure of Johansen (1992). It involves a joint significance test of the estimated error correction terms for the foreign-specific and global variables for each city-specific model. More specifically, grouping foreign-specific and global variables in $\tilde{\boldsymbol{x}}_{\boldsymbol{it}}^{*}$, for each l^{th} element of $\tilde{\boldsymbol{x}}_{\boldsymbol{it}}^{*}$, the following regression is estimated:

$$\Delta\tilde{x}_{it,l}^{*} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ij,l} ECM_{i,t-1}^{j} + \sum_{k=1}^{p_i} \phi_{ik,l} \Delta\boldsymbol{x}_{i,t-k} + \sum_{m=1}^{q_i} \theta_{im,l} \Delta\tilde{\boldsymbol{x}}_{i,t-m}^{*} + \varepsilon_{it,l}$$

where $ECM^{j}_{i,t-1}$ is the estimated error correction terms, and r_i is the number of cointegration relation found for the i^{th} city model; The test is an F test of the joint hypothesis that $\gamma_{ij,l} = 0$ for each j = 1, …, r_i. The results in Table 17 suggest that most of the weak exogeneity assumptions cannot be rejected. In fact, only 7 of the 93 exogeneity tests indicated a rejection. Therefore, I move forward with the assumption of weak exogeneity, and begin to present results in the following section.

E. Contemporaneous Effects of Foreign Variables on Domestic Counterparts

Table 18 presents the contemporaneous effects of foreign variables on their domestic counterparts, which can be interpreted as impact elasticities. Most of the results are positive and significant, as expected. The average contemporaneous effect of the foreign unemployment rate on the domestic unemployment rate is 1.02, with a minimum of 0.04 and a maximum of 1.85, notably positive. The most sensitive city to changes in the foreign unemployment rate is Barnstable Town, MA with an elasticity of 1.85. This result is interesting since Barnstable Town, MA is the largest community in Cape Cod, a popular tourist destination. One could therefore speculate that as unemployment rises in other Northeast Census Region cities, this would have an impact on the unemployment rate in Barnstable Town through a drop in tourist activity. The least sensitive city to changes in the foreign unemployment rate is Boston-Cambridge-Quincy, MA. In fact, one cannot reject the null hypothesis of the coefficient being equal to zero. This may imply that Boston-Cambridge-Quincy, MA is insulated and is not affected by unemployment spillovers. This is an especially significant result given that Boston is of course very diversified, and arguably more interdependent with distant MSAs. Furthermore, the average contemporaneous effect of foreign average weekly hours on the domestic weekly hours worked is 0.81, with a minimum of 0.00 for New Haven-Milford, CT and a maximum of 1.81 for York-Hanover, PA. Lastly, the average contemporaneous effect of foreign average weekly earnings on domestic weekly earnings is 0.70 with a minimum of -0.24 for State College, PA and a maximum of 1.61 for Binghamton, NY. Overall, the results suggest strong contemporaneous linkages between cities for all three labor market variables. This raises the question of how relevant and useful local policy is, and encourages further exploration of how a city's own diversification impacts employment.

F. Average Pair-Wise Cross-Section Correlations

Another key assumption of the GVAR modeling is that the idiosyncratic shocks of the individual cities models should be cross-sectionally weakly correlated. More specifically, as the number of cities approaches infinity, the covariance between the weakly exogenous foreign specific variables and the idiosyncratic error term should converge to zero. In order to assess how well the GVAR model does in reducing cross-section correlation of the variables, average pair-wise cross-section correlations for the levels and first differences of the endogenous variables, as well for the residuals from the city-specific models, are presented in Table 19.

Generally, the average cross-section correlations are high for the unemployment rate, moderately high for average weekly earnings, and fairly weak for the average weekly hours. The results tend to vary widely across the variables, but not so much across the cities. The effect of first differencing tends to reduce the average cross-section correlations, but it remains moderately high for the change in the unemployment rate. The only exception is for Boston-Cambridge-Quincy, MA, which helps to explain the low impact elasticity of foreign unemployment rates on the domestic unemployment rate discussed earlier. On average, evidence suggests significant cross-city correlations for the variables in the GVAR model, with the largest for unemployment rates, as expected.

Lastly, the cross-section correlation of the residuals is near zero for all of the VARX* models, illustrating the success of the model in capturing the common effects on the unemployment rate, average weekly earnings, and average weekly hours. Although this is not a formal test, it is strong evidence that only a modest degree of correlation exists across shocks once the foreign variables have been controlled for. With this key assumption now supported by the results above, I am able to move forward with an investigation of the dynamic properties of the GVAR model by means of Generalized Impulse Response Functions (GIRFs).

G. Generalized Impulse Response Analysis

In what follows, I use GIRFs developed by Koop, Pesaran, and Potter (1996) in order to assess the impact of three alternative shocks: (1) a one standard error positive shock to US equity prices; (2) a one standard error positive shock to the regional vacancy rate; and (3) a one standard error negative idiosyncratic shock to the unemployment rate of the largest MSAs in the model, namely, New York-Northern New Jersey-Long Island, Boston-Cambridge-Quincy, and Philadelphia. In this global framework, GIRFs are more appealing than the traditional Sims' (1980) Orthogonalized Impulse Response (OIR) because they are invariant to the ordering of the variables and of the cities. This is advantageous since it is unclear how economic theory could guide the selection of ordering the cities, and because, unlike the OIR obtained using a Cholesky factorization, the GI responses are unique. Another important difference between the two functions is that, while the OIR requires impulse responses be computed with respect to a set of Orthogonalized shocks, the GIR approach considers shocks to individual errors and integrates out the effects of other shocks. That is, the traditional impulse response function provides a solution to the state of the system at time $t + n$ after a shock of size δ at time t, assuming no other shocks hit the system, while the generalized impulse response function is constructed as the average of what might happen conditioned on only the history and/or shock (Koop *et al*., 1996). Lastly, if we were to introduce nonlinearities in the underlying GVAR model, the OIR has a symmetry property which implies that shocks in recessions are as persistent as shocks in an expansion, while the GIR allows for asymmetric profiles.[13]

Before presenting and discussing the results of the GIRFs, the stability properties of the GVAR can be assessed by analyzing the eigenvalues of the system. The model contains 104 endogenous variables with a maximum lag order of 2, which gives rise to 208 eigenvalues. From theorems developed in PSW, the rank of the cointegrating matrix should not exceed the number of cointegrating relations in all the individual city models. Hence, the global system should have

[13] It may be that the absence of nonlinearities in the model is too restrictive because it does adequately capture asymmetries that exist in business cycle fluctuations. These asymmetries are particularly important because, as Pesaran and Potter (1994) argue, recessionary shocks are less persistent than are expansionary ones. As this is a first attempt at solving the GVAR model for interlinked cities, I leave the consideration of nonlinearities for future research.

at least 104 – 21 = 83 eigenvalues that fall on the unit circle. Encouragingly, exactly 83 of the eigenvalues fall on the unit circle, and the remainders have moduli less than unity. This suggests that the model is stable and that some shocks will have permanent effects on the endogenous variables. Furthermore, the largest modulus within the unit circle is 0.7964, which suggests a reasonably fast rate of convergence for the GIRFs. Lastly, 74 of the eigenvalues are complex, which introduces cyclical features in the impulse responses.

I now present the results from each of three aforementioned simulations in turn. In order to condense the results, I aggregate the cities by states using real GDP weights, and present only state GIRFs. No loss of information is suffered in doing so as the cities tend to react similarly to the global shocks. Furthermore, I only present median long-run point estimates for the idiosyncratic shock simulations, thus leaving out bootstrap error bounds. Once again, the reason for doing so is to condense the results as I would have to present 33 separate GIRFs for each idiosyncratic shock.

1. **Positive Shock to US Equity Prices**

The state GIRFs for a one standard error positive shock to US equity prices are presented in Figure 2 of the Appendix for an impact on unemployment rates over a 40 month horizon. All of the states' dynamics are similar, but Massachusetts stands out as benefiting the most from a positive shock to US equity prices with an impact of reducing the unemployment rate by approximately 0.29%. This is driven by Boston-Cambridge-Quincy, the largest MSA in Massachusetts, whose impact from a positive shock to US equity prices is approximately a 0.30 percentage-point long-run reduction in the unemployment rate. The smallest city-specific impact is for Kingston, NY, whose impact is approximately a 0.15 percentage-point long-run reduction in the unemployment rate. Of course, these impacts above are only median point estimates, and it is important to note that when 90% bootstrap error bounds are generated, I cannot reject the null hypothesis that the long-run impacts are statistically different from zero.

2. Positive Shock to the Regional Job Openings Rate

The state GIRFs following a one standard error positive shock to the regional jobs openings rate are presented in Figure 3. Again, the impact on the unemployment rate is assessed and the horizon is 40 months. As expected, the response to a positive shock to the jobs opening rate is a decrease in the unemployment rate. As this rate is a regional measure, and each city labor market would of course have its own job openings rate, the heterogeneity in the results is not surprising. On average, the results suggest that a one standard error positive shock to the regional job openings rate is associated with a long-run 0.55 to 0.82 percentage-point decrease in the unemployment rate. Again though, 90% bootstrap error bounds suggest that this long-run impact is not statistically different from zero. Only for the first six months following the shock does the impact have a statistically significant negative impact on the unemployment rate, with error bounds ranging from -0.20 to -4.40 percentage-points.

3. Negative Shock to Specific City Unemployment Rates

Given its large share of metropolitan economic activity, accounting for nearly 10% the metropolitan portion of U.S. real GDP, it is interesting to first assess how a negative shock to the unemployment rate in the New York-Northern New Jersey-Long Island MSA impacts other city labor markets. Keep in mind a negative shock here means a decrease in the unemployment rate. In order to condense the results, I instead present in Table 20 the long-run median point estimates for the impact on unemployment rates rather than each city-specific GIRF. The dynamics are similar to the above GIRFs for the shock to the regional job openings rate. As expected, a negative shock to the unemployment rate in the New York MSA generates a decrease in the unemployment rate in all other cities. The magnitude of the impact is quite surprising though as it ranges from a 0.39-0.97 percentage-point decrease in the unemployment rate. This impact is larger than the effects of positive shocks to US equity prices and the regional vacancy rate.

The impact from negative shocks to the unemployment rate of Boston-Cambridge-Quincy, MA and Philadelphia, PA both produce starkly different results from those found above. In fact, the results suggest that a negative shock to the unemployment rates of Boston-Cambridge-Quincy and Philadelphia correlate with long-run increases in the unemployment rates of other cities in the Northeast Census Region. This magnitude of the impact is equal or larger for all cities when there is a shock to the Philadelphia unemployment rate.

Once again, all of the results above must be viewed with caution because up to this point I have only analyzed median point estimates of the impact from the idiosyncratic shocks without considering the upper and lower bounds of these estimates. In fact, in generating 90% bootstrap error bounds with 100 replications, I am unable to reject the null hypothesis that the impacts are statistically different from zero. Therefore, using this particular model, I am unable to find evidence of labor market spillovers occurring from local unemployment rate shocks.

In light of the notably positive average contemporaneous effects of the foreign labor market variables on the domestic variables, the absence of labor market spillovers is a bit surprising. A possible explanation is that there was a clear regime change from expansionary to recessionary during the time period of analysis, and so not taking this into account in the model may have dampened the contribution of city-specific shocks. That is, as the shocks are generated based on the empirical distribution of innovations in the time series up to time t, they may be drastically understated. Along with the introduction of nonlinearities into the GVAR framework, a regime switch should also be considered in future research.

V. Conclusion

The first conclusion that should be drawn from this research is that at least a moderate degree of cross-sectional dependence exists amongst metropolitan labor markets. This result is robust to a number of different ways to measure spatial proximity that relate changes in unemployment rates between cities. In fact, in considering measures of economic distance, rather than spatial distance, the degree of cross-sectional dependence increases dramatically. This result supports the use of spatial autoregressive models in correcting for omitted variable bias, as well as bias from spatial correlation.

Furthermore, the result that unemployment rate changes are largely affected by *indirect* increases in metropolitan growth rates, rather than *direct*, is relevant for place-based *investment* policies as a solution to the large variation in unemployment rates across cities. This does not mean that other long-term place-based policies aimed at changing structural components of the metropolitan economy should be ignored. Given the substantial correlation in unemployment rate changes between cities due to educational and industrial similarity, it would be more important for local policy-makers to focus on these issues. Lastly, the results here suggest that Okun's coefficient is possibly higher for cities than it is for the aggregate economy. Since the aggregate economy data for GDP and unemployment rates are an average of the metropolitan and non-metropolitan area data, this may suggest that the impact on unemployment rates due to growth rate changes is stronger for metropolitan areas than non-metropolitan ones. Of course, this last result must be further researched as Okun's Law is merely an empirical relationship.

From the vantage point of Global VAR modeling, the result of spatial dependence in metropolitan labor markets is supported by notably positive contemporaneous relationships between "domestic" variables and their "foreign" counterparts. Yet, in analyzing how idiosyncratic shocks propagate across cities, I do not find evidence of statistically significant spillovers from shocks to the unemployment rate of cities in the northeast, such as New York, Boston, and Philadelphia. Of course, this result must be viewed cautiously since not enough data currently exist to properly model the complex interactions between cities. It would be ideal to pursue this idea further by relating cities through a trade-based weighting matrix.

For future research, it would be interesting to consider other possible weight matrices that interact spatial and economic distance in order to develop a better understanding of the relationships that exist between city labor markets. Also, in the context of the GVAR model in particular, it would be a great addition to include data on metropolitan vacancy rates, which is provided as part of the Conference Board Help Wanted OnLine (HWOL) index. This may be particularly fruitful in testing theoretical results derived from a search and matching model embedded in a systems-of-cities framework, as is currently being considered in a paper by Ioannides (2013). As this is the first such consideration of modeling city interlinkages using the GVAR methodology, I believe the ideas tested here can be expanded upon greatly, and with many likely advances that could provide further interesting results.

VI. Appendix – Figures and Tables

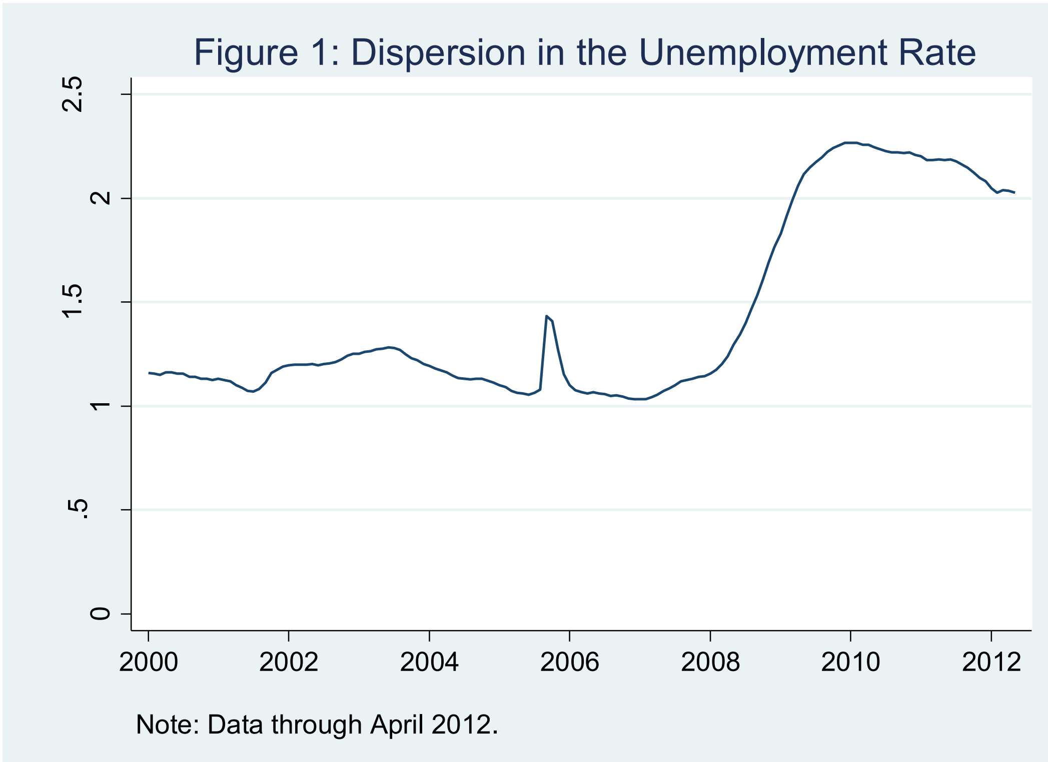

Figure 2: Positive Shock to US Equity Prices

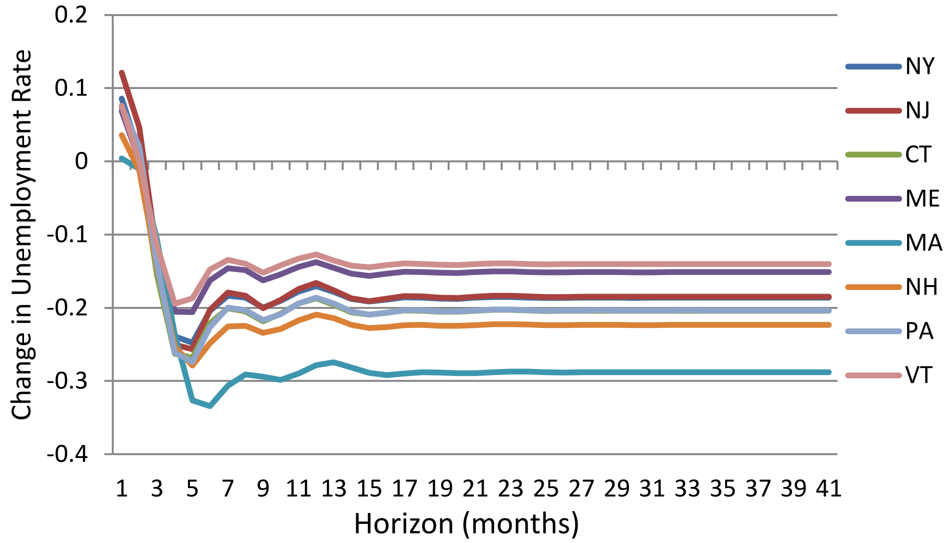

Figure 3: Positive Shock to Regional Job Openings Rate

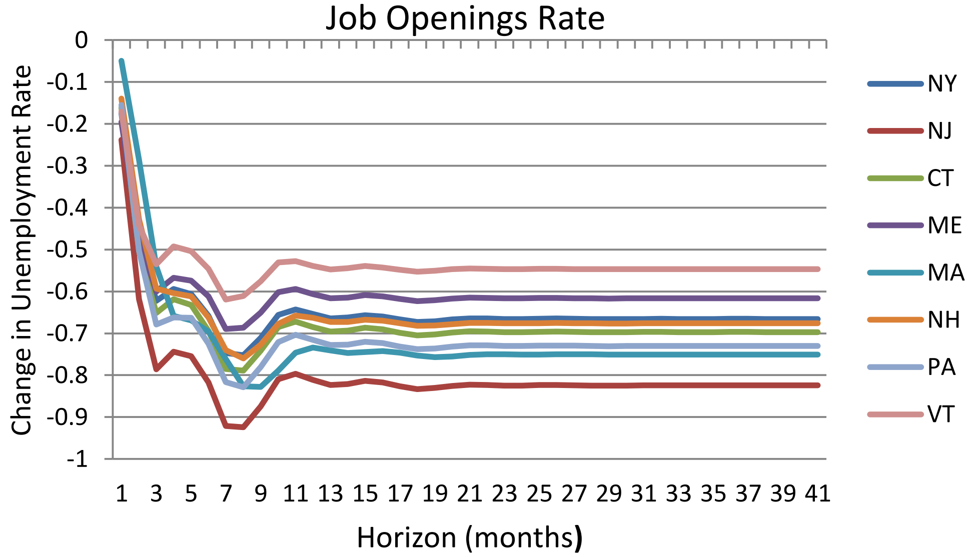

TABLE 1: SUMMARY STATISTICS FOR METROPOLITAN STATISTICAL AREAS

	Real GDP ($)	Real GDP Growth (%)	Unemployment Rate (%)
Year			
2001	27,404	-	4.84
	(78,238)	-	(1.61)
	842	-	2.06
	1,010,235	-	16.4
2002	27,907	2.61	5.72
	(78,745)	(3.87)	(1.68)
	1,014	-10.61	2.50
	1,003,589	20.01	16.54
2003	28,492	2.77	5.89
	(79,672)	(3.32)	(1.73)
	1,416	-9.65	2.77
	1,004,947	33.39	16.77
2004	29,502	2.97	5.52
	(82,493)	(3.35)	(1.62)
	1,305	-8.16	2.98
	1,032,796	22.70	17.05
2005	30,403	2.52	5.18
	(85,254)	(3.61)	(1.57)
	1,370	-8.02	2.77
	1,074,737	27.70	16.07
2006	31,283	2.31	4.72
	(88,346)	(3.55)	(1.53)
	1,370	-18.85	2.29
	1,120,164	18.09	15.35
2007	31,931	1.59	4.65
	(90,150)	(3.33)	(1.54)
	1,294	-22.09	2.08
	1,141,534	15.51	17.98
2008	31,798	-0.57	5.81
	(89,936)	(3.50)	(1.97)
	1,199	-15.35	2.75
	1,138,364	21.23	22.36
2009	30,993	-2.25	9.20
	(87,074)	(3.74)	(2.80)
	1,181	-16.64	3.73
	1,096,869	12.46	27.92
2010	31,765	2.09	9.55
	(89,910)	(2.40)	(2.91)
	1,200	-3.85	3.77
	1,147,917	13.41	29.93
Observations	348	348	348

Notes: 1. Column format - mean, (standard deviation), min, max
2. Real GDP is in millions of chained 2005 dollars

TABLE 2: PANEL UNIT ROOT TESTS

	Δln(real GDP)		ΔUnemployment Rate	
	Statistic	P-value	Statistic	P-Value
Harris-Tzavalis	0.1261	0.0000	0.2380	0.0000
Breitung	-16.14	0.0000	-24.63	0.0000
Im-Pesaran-Shin	-15.72	0.0000	-13.69	0.0000

TABLE 3: DYNAMIC PANEL MODEL OF OKUN'S LAW

Dependent Variable: First Difference in Unemployment Rate

	(1)	(2)	(3)	(4)	(5)
VARIABLES					
L.depvar		0.228***	0.101***	0.052**	0.043
		(0.019)	(0.020)	(0.024)	(0.027)
Growth of Real GDP	**-0.181*** **	**-0.238**	**-0.241**	**-0.267*** **	**-0.280*** **
	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)
L.indepvar			-0.099***	-0.115***	-0.113***
			(0.008)	(0.009)	(0.010)
L2.indepvar				-0.026***	-0.022*
				(0.009)	(0.011)
L3.indepvar					0.001
					(0.010)
Constant	0.807***	0.696***	0.918***	1.034***	1.067***
	(0.023)	(0.028)	(0.032)	(0.044)	(0.057)
Observations	3,132	2,436	2,436	2,088	1,740
Number of MSAs	348	348	348	348	348

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE 4: SPATIAL PANEL MODEL OF OKUN'S LAW

Dependent Variable: First Difference in Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.126		0.132	
		(0.014)		(0.014)	
Growth of Real GDP	-0.133	-0.51	-0.131	-0.148	-0.128
	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)
W*Growth of Real GDP			-0.034	-0.052	
			(0.008)	(0.011)	
Spatial - ρ	0.493	0.473	0.466	0.426	0.572
	(0.018)	(0.019)	(0.019)	(0.020)	(0.037)
Spatial - λ					-0.159
					(0.063)
Direct Effect	-0.151	-0.168	-0.154	-0.171	-0.153
	(0.012)	(0.018)	(0.012)	(0.017)	(0.013)
Indirect Effect	-0.079	-0.083	-0.109	-0.124	-0.104
	(0.007)	(0.008)	(0.009)	(0.010)	(0.014)
Total Effect	-0.230	-0.251	-0.262	-0.295	-0.257
	(0.019)	(0.025)	(0.017)	(0.022)	(0.024)
R-squared	0.2880	0.3844	0.2885	0.3872	0.2907
Observations	3,132	2,784	3,132	2,784	3,132
Number of MSAs	348	348	348	348	348

Robust Standard errors in parentheses

All coefficients are statistically significant

TABLE 5: SPATIAL PANEL MODEL OF OKUN'S LAW

NORTHEAST CENSUS REGION

Dependent Variable: First Difference in Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.197		0.223	
		(0.032)		(0.031)	
Growth of Real GDP	-0.117	-0.167	-0.111	-0.157	-0.103
	(0.018)	(0.021)	(0.018)	(0.020)	(0.025)
W*Growth of Real GDP			-0.031	-0.074	
			(0.021)	(0.025)	
Spatial - ρ	0.643	0.589	0.619	0.512	0.731
	(0.031)	(0.039)	(0.033)	(0.043)	(0.071)
Spatial - λ					-0.278
					(0.180)
Direct Effect	-0.147	-0.197	-0.147	-0.194	-0.147
	(0.018)	(0.023)	(0.017)	(0.021)	(0.021)
Indirect Effect	-0.151	-0.17	-0.184	-0.226	-0.202
	(0.025)	(0.023)	(0.038)	(0.035)	(0.045)
Total Effect	-0.298	-0.367	-0.331	-0.419	-0.348
	(0.040)	(0.041)	(0.049)	(0.047)	(0.056)
R-squared	0.3805	0.6225	0.3822	0.6315	0.3830
Observations	396	352	396	352	352
Number of MSAs	44	44	44	44	44

Robust Standard errors in parentheses

All coefficients are statistically significant

TABLE 6: SPATIAL PANEL MODEL OF OKUN'S LAW
SOUTH CENSUS REGION
Dependent Variable: First Difference in Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.150		0.154	
		(0.017)		(0.017)	
Growth of Real GDP	-0.136	-0.146	-0.136	-0.145	-0.135
	(0.024)	(0.026)	(0.023)	(0.026)	(0.023)
W*Growth of Real GDP			-0.070	-0.084	
			(0.018)	(0.020)	
Spatial - ρ	0.427	0.411	0.37	0.337	0.506
	(0.026)	(0.027)	(0.028)	(0.030)	(0.051)
Spatial - λ					-0.151
					(0.073)
Direct Effect	-0.147	-0.155	-0.155	-0.161	-0.154
	(0.021)	(0.029)	(0.019)	(0.027)	(0.022)
Indirect Effect	-0.051	-0.051	-0.097	-0.102	-0.070
	(0.008)	(0.008)	(0.013)	(0.013)	(0.015)
Total Effect	-0.198	-0.206	-0.251	-0.264	-0.222
	(0.028)	(0.037)	(0.024)	(0.031)	(0.034)
R-squared	0.2564	0.3286	0.2612	0.3353	0.2619
Observations	1,332	1,183	1,332	1,183	1,332
Number of MSAs	148	148	148	148	148

Robust Standard errors in parentheses
All coefficients are statistically significant

TABLE 7: SPATIAL PANEL MODEL OF OKUN'S LAW

WEST CENSUS REGION

Dependent Variable: First Difference in Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.177		0.165	
		(0.033)		(0.032)	
Growth of Real GDP	-0.109	-0.112	-0.106	-0.111	-0.105
	(0.024)	(0.025)	(0.024)	(0.025)	(0.024)
W*Growth of Real GDP			-0.040	-0.059	
			(0.019)	(0.025)	
Spatial - ρ	0.574	0.552	0.539	0.490	0.635
	(0.048)	(0.042)	(0.042)	(0.051)	(0.072)
Spatial - λ					-0.154
					(0.137)
Direct Effect	-0.133	-0.130	-0.137	-0.139	-0.138
	(0.022)	(0.029)	(0.021)	(0.027)	(0.024)
Indirect Effect	-0.100	-0.092	-0.142	-0.151	-0.128
	(0.017)	(0.016)	(0.025)	(0.027)	(0.034)
Total Effect	-0.233	-0.222	-0.279	-0.290	-0.266
	(0.037)	(0.043)	(0.037)	(0.045)	(0.051)
R-squared	0.3318	0.4553	0.3326	0.4731	0.3335
Observations	693	616	693	616	693
Number of MSAs	77	77	77	77	77

Robust Standard errors in parentheses

All estimates except for that of λ are statistically significant

TABLE 8: SPATIAL PANEL MODEL OF OKUN'S LAW

MIDWEST CENSUS REGION

Dependent Variable: First Difference in Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.098		0.098	
		(0.022)		(0.022)	
Growth of Real GDP	-0.182	-0.231	-0.182	-0.230	-0.185
	(0.019)	(0.022)	(0.195)	(0.023)	(0.020)
W*Growth of Real GDP			0.001	-0.006	
			(0.025)	(0.026)	
Spatial - ρ	0.41	0.390	0.411	0.384	0.347
	(0.045)	(0.044)	(0.035)	(0.034)	(0.097)
Spatial - λ					0.104
					(0.096)
Direct Effect	-0.195	-0.242	-0.195	-0.242	-0.196
	(0.017)	(0.025)	(0.017)	(0.025)	(0.020)
Indirect Effect	-0.042	-0.048	-0.039	-0.050	-0.036
	(0.008)	(0.008)	(0.017)	(0.017	(0.017)
Total Effect	-0.237	-0.291	-0.235	-0.292	-0.232
	(0.023)	(0.029)	(0.027)	(0.034)	(0.034)
R-squared	0.2873	0.3559	0.2875	0.3553	0.2893
Observations	837	745	837	745	837
Number of MSAs	92	92	92	92	92

Robust Standard errors in parentheses

All coefficients except W* and λ are statistically significant

TABLE 9: UNEMPLOYMENT RATES

Year	Gainesville, GA	Evansville, IN-KY	Ames, IA	Elkhart-Goshen, IN
2002	4.11	4.53	2.5	4.76
2003	3.98	4.83	2.77	4.65
2004	3.94	4.73	3.05	4.23
2005	4.38	5.03	3.05	4.53
2006	3.81	4.68	2.66	4.68
2007	3.68	4.63	2.82	4.60
2008	5.45	5.25	3.06	8.61
2009	9.28	8.58	4.60	18.01
2010	9.12	8.55	4.76	13.5

TABLE 10: SPATIAL PANEL MODEL OF OKUN'S LAW

Industrial Similarity Weight Matrix

Dependent Variable: First Difference in Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.018		0.017	
		(0.013)		(0.015)	
Growth of Real GDP	-0.061	-0.068	-0.063	-0.068	-0.064
	(0.009)	(0.011)	(0.009)	(0.011)	(0.010)
W*Growth of Real GDP			0.027	0.007	
			(0.012)	(0.018)	
Spatial - ρ	0.911	0.896	0.939	0.905	0.889
	(0.016)	(0.019)	(0.010)	(0.021)	(0.071)
Spatial - λ					0.498
					(0.149)
Direct Effect	-0.063	-0.068	-0.065	-0.069	-0.066
	(0.008)	(0.012)	(0.008)	(0.012)	(0.009)
Indirect Effect	-0.659	-0.599	-0.541	-0.568	-0.733
	(0.155)	(0.115)	(0.198)	(0.131)	(1.152)
Total Effect	-0.723	-0.668	-0.606	-0.637	-0.800
	(0.158)	(0.118)	(0.199)	(0.133)	(1.16)
R-squared	0.6041	0.7207	0.6044	0.7209	0.6043
Observations	3,132	2,784	3,132	2,784	3,132
Number of MSAs	348	348	348	348	348

Robust Standard errors in parentheses

L.depvar/Indirect and Total Effects for SAC model are not significant

TABLE 11: SPATIAL PANEL MODEL OF OKUN'S LAW

Educational Attainment Similarity Weight Matrix

Dependent Variable: First Difference in Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.044		0.018	
		(0.016)		(0.014)	
Growth of Real GDP	-0.061	-0.066	-0.063	-0.068	-0.063
	(0.009)	(0.007)	(0.010)	(0.011)	(0.010)
W*Growth of Real GDP			0.028	0.009	
			(0.012)	(0.018)	
Spatial - ρ	0.912	0.891	0.941	0.907	0.864
	(0.016)	(0.015)	(0.010)	(0.021)	(0.050)
Spatial - λ					0.696
					(0.086)
Direct Effect	-0.063	-0.066	-0.065	-0.068	-0.066
	(0.008)	(0.012)	(0.008)	(0.012)	(0.011)
Indirect Effect	-0.660	-0.540	-0.532	-0.561	-0.700
	(0.156)	(0.070)	(0.203)	(0.133)	(1.962)
Total Effect	-0.723	-0.607	-0.597	-0.630	-0.765
	(0.159)	(0.072)	(0.204)	(0.136)	(1.197)
R-squared	0.6020	0.6973	0.6024	0.7204	0.6000
Observations	3,132	2,784	3,132	2,784	3,132
Number of MSAs	348	348	348	348	348

Robust Standard errors in parentheses

L.depvar/Indirect and Total Effects for SAC model are not significant

TABLE 12: SPATIAL PANEL MODEL OF OKUN'S LAW

Race Similarity Weight Matrix

Dependent Variable: First Difference Unemployment Rate

	SAR (1)	SAR (2)	SDM (1)	SDM (2)	SAC
VARIABLES					
L.depvar		0.019		0.018	
		(0.012)		(0.015)	
Growth of Real GDP	-0.061	-0.068	-0.063	-0.068	-0.064
	(0.009)	(0.011)	(0.012)	(0.011)	(0.010)
W*Growth of Real GDP			0.027	0.007	
			(0.012)	(0.018)	
Spatial - ρ	0.912	0.896	0.940	0.905	0.892
	(0.016)	(0.019)	(0.010)	(0.021)	(0.034)
Spatial - λ					0.473
					(0.154)
Direct Effect	-0.063	-0.069	-0.065	-0.069	-0.066
	(0.008)	(0.012)	(0.008)	(0.012)	(0.009)
Indirect Effect	-0.663	-0.600	-0.544	-0.567	-0.694
	(0.156)	(0.116)	(0.200)	(0.131)	(0.744)
Total Effect	-0.726	-0.669	-0.609	-0.639	-0.760
	(0.160)	(0.119)	(0.201)	(0.133)	(0.747)
R-squared	0.6042	0.7213	0.6046	0.7215	0.6045
Observations	3,132	2,784	3,132	2,784	3,132
Number of MSAs	348	348	348	348	348

Robust Standard errors in parentheses

L.depvar/Indirect and Total Effects for SAC model are not significant

TABLE 13: CITIES OF THE NORTHEAST CENSUS REGION

Connecticut

Bridgeport-Stamford-Norwalk
Hartford-West Hartford-East Hartford
New Haven-Milford
Norwich-New London

Maine

Bangor
Portland-South Portland-Biddeford

Massachusetts

Barnstable Town
Boston-Cambridge-Quincy
Springfield
Worcester

New Hampshire

Manchester-Nashua

New Jersey

Atlantic City-Hammonton
Trenton-Ewing
Vineland-Millville-Bridgeton

New York

Albany-Schenectady-Troy
Binghamton
Buffalo-Niagara Falls
Kingston
New York-Northern New Jersey-Long Island
Poughkeepsie-Newburgh-Middletown
Rochester
Syracuse
Utica-Rome

Pennsylvania

Allentown-Bethlehem-Easton
Erie
Harrisburg-Carlisle
Lancaster
Philadelphia-Camden-Wilmington
Pittsburgh
Reading
Scranton-Wilkes-Barre
State College
York-Hanover

Vermont

Burlington-South Burlington

TABLE 14: SUMMARY STATISTICS FOR METROPOLITAN STATISTICAL AREAS

Variable		Mean	Std. Dev.	Min	Max	Observations
Unemployment Rate	overall	7.03	2.14	2.92	15.33	N = 2380
	between		1.25	4.57	11.22	n = 34
	within		1.75	1.50	11.92	T = 70
Weekly Hours	overall	33.65	1.33	28.80	39.20	N = 2380
	between		1.05	30.81	35.31	n = 34
	within		0.84	29.55	38.23	T = 70
Hourly Earnings	overall	22.82	4.17	15.21	36.59	N = 2380
	between		4.10	16.37	34.31	n = 34
	within		1.03	18.16	27.03	T = 70

TABLE 15: ADF UNIT ROOT TEST STATISTICS FOR DOMESTIC AND FOREIGN VARIABLES

Variables	ALB	ALL	ATL	BAN	BAR	BIN	BOS	BRI	BUF	BUR	ERIE	HAR	HART	KIN	LAN	MAN	NEWH
ur (trend)	-1.46	-0.67	-1.91	-1.71	-3.07	-1.53	-0.32	-0.72	-1.80	-1.50	-0.74	-0.61	-0.78	-1.38	-0.72	-0.88	-0.76
Ur	-1.61	-1.70	-1.55	-1.67	-2.95	-1.56	-1.39	-1.78	-1.67	-1.69	-1.60	-1.77	-1.48	-1.72	-1.72	-1.22	-1.48
Dur	-8.03	-7.17	-4.26	-4.06	-5.31	-7.31	-7.31	-7.39	-4.49	-5.49	-3.18	-7.38	-8.36	-5.48	-6.92	-2.84	-8.10
DDur	-7.45	-7.50	-5.84	-6.53	-7.14	-7.07	-8.75	-8.71	-7.29	-7.21	-10.55	-9.70	-8.56	-10.17	-7.24	-10.85	-9.61
hr (trend)	-3.27	-2.36	-4.55	-2.30	-3.64	-2.18	-1.87	-0.85	-1.85	-5.43	-1.40	-1.90	-2.69	-3.40	-5.06	-2.81	-2.28
hr	-3.05	-2.30	-1.44	-2.25	-2.36	-1.89	-1.95	-1.33	-2.09	-4.65	-1.57	-2.06	-2.64	-3.47	-1.34	-2.86	-2.30
Dhr	-4.35	-6.41	-4.84	-4.93	-8.33	-6.34	-5.78	-5.06	-4.88	-5.02	-7.69	-5.59	-6.47	-5.43	-6.86	-5.95	-10.63
DDhr	-7.38	-7.52	-10.71	-6.02	-11.31	-7.68	-7.69	-7.35	-7.26	-8.78	-7.29	-7.07	-7.48	-8.35	-8.83	-7.57	-10.31
w (trend)	-2.54	-4.11	-3.81	-3.22	-5.04	-2.85	-3.38	-1.74	-2.76	-5.43	-2.93	-2.46	-1.45	-1.95	-3.24	1.18	-1.90
w	-0.50	-0.96	-0.78	-1.19	-5.07	-3.83	-0.09	-2.34	0.11	-4.65	-1.51	-0.58	-2.22	-1.68	0.90	-0.40	-2.08
Dw	-4.55	-6.26	-6.77	-7.95	-5.34	-3.44	-5.85	-9.40	-6.78	-5.02	-7.35	-3.30	-7.34	-6.79	-5.85	-3.55	-7.02
DDw	-7.94	-9.16	-8.49	-8.73	-6.95	-8.64	-7.62	-8.87	-6.81	-8.78	-7.31	-11.39	-7.48	-7.05	-8.50	-7.85	-6.49
ur* (trend)	-1.02	-0.89	-0.92	-1.10	-0.95	-0.99	-1.09	-0.91	-1.00	-1.09	-1.04	-0.60	-0.92	-0.98	-0.58	-1.00	-0.93
ur*	-1.68	-1.68	-1.64	-1.71	-1.67	-1.68	-1.68	-1.65	-1.70	-1.69	-1.68	-1.64	-1.66	-1.69	-1.65	-1.72	-1.67
Dur*	-4.35	-8.20	-4.50	-4.15	-4.20	-4.48	-4.26	-4.54	-4.43	-4.19	-4.47	-8.03	-4.49	-4.37	-7.84	-4.08	-4.47
Ddur*	-7.59	-7.67	-8.22	-7.14	-8.09	-7.45	-7.00	-8.15	-7.22	-7.44	-7.34	-7.35	-7.96	-7.80	-7.49	-7.86	-7.99
hr* (trend)	-2.14	-1.66	-2.10	-2.15	-2.36	-2.07	-2.46	-2.27	-1.99	-2.36	-2.24	-3.09	-1.69	-2.20	-2.08	-3.06	-1.74
hr*	-2.04	-1.66	-1.78	-2.08	-2.33	-1.99	-2.36	-1.75	-1.90	-2.23	-2.04	-1.55	-1.91	-1.91	-1.64	-2.34	-1.92
Dhr*	-4.80	-5.24	-6.59	-4.70	-4.92	-4.89	-4.85	-5.52	-4.72	-4.55	-4.89	-5.72	-5.07	-7.06	-5.52	-4.85	-4.97
DDhr*	-7.03	-7.64	-8.33	-8.60	-8.68	-7.30	-9.37	-9.83	-7.27	-8.24	-7.25	-8.03	-9.28	-8.70	-7.56	-7.13	-7.26
w* (trend)	-2.95	-1.80	-2.39	-2.83	-2.92	-2.37	-2.86	-3.25	-2.48	-2.75	-2.14	-1.96	-2.90	-2.09	-2.07	-4.22	-2.99
w*	-0.83	0.55	-0.70	-0.42	-0.22	0.11	-0.77	-0.71	-0.28	-0.36	0.34	0.24	-0.30	-0.04	0.01	-0.74	-0.77
Dw*	-4.92	-4.12	-4.45	-5.04	-4.79	-6.72	-5.19	-6.41	-4.71	-4.99	-4.63	-4.00	-5.07	-7.01	-3.82	-5.01	-4.45
DDw*	-6.53	-13.01	-7.14	-6.69	-6.74	-6.72	-6.43	-12.06	-6.66	-6.65	-6.50	-13.50	-6.29	-13.01	-13.74	-6.42	-13.54

Variables	NEWY	NOR	PHI	PIT	POR	POU	READ	ROCH	SCRA	SPR	SCOL	SYR	TREN	UROM	VINE	WORC	YORK
ur (trend)	-0.92	-0.95	-0.50	-0.63	-2.09	-1.17	-0.71	-1.40	-0.96	-0.32	-0.71	-1.55	-1.07	-2.82	-1.22	-0.57	-0.70
ur	-1.70	-1.49	-1.76	-1.54	-2.18	-1.90	-1.83	-1.73	-1.57	-1.40	-1.36	-1.69	-1.53	-1.87	-1.36	-1.54	-1.69
Dur	-4.04	-7.32	-7.79	-3.97	-4.45	-4.04	-6.39	-4.26	-3.92	-9.46	-5.03	-4.51	-8.90	-4.57	-7.89	-8.02	-3.19
DDur	-9.81	-8.03	-8.46	-7.40	-4.70	-7.64	-7.07	-7.80	-10.11	-9.09	-16.27	-7.06	-9.29	-9.00	-9.13	-9.37	-9.86
hr (trend)	-3.09	-1.38	-3.40	-1.48	-1.56	-1.99	-1.80	-2.83	-4.10	-2.79	-3.07	-2.75	-1.64	-3.57	-4.06	-3.58	-3.67
hr	-2.34	-2.18	-3.10	-1.56	-1.70	-1.14	-1.48	-3.08	-4.07	-2.29	-3.03	-2.64	-2.35	-1.60	-2.51	-3.48	-0.10
Dhr	-6.14	-6.86	-8.31	-10.29	-5.33	-5.87	-6.83	-6.68	-6.55	-5.59	-5.20	-4.29	-7.07	-5.69	-5.11	-5.70	-5.50
DDhr	-8.80	-7.43	-9.04	-8.12	-7.33	-6.81	-7.63	-7.33	-8.43	-9.32	-6.04	-8.60	-8.41	-6.89	-8.97	-7.01	-8.51
w (trend)	-3.27	-0.47	-2.25	-0.70	-3.37	-1.46	-0.99	-3.28	-1.13	-1.54	0.54	-2.69	-0.97	-3.26	-2.11	-1.71	-3.90
w	-1.26	1.04	0.57	2.69	-0.79	-0.05	0.23	-2.36	1.43	-1.81	1.99	-2.76	0.13	-3.25	-2.06	-1.16	-1.26
Dw	-5.21	-6.93	-4.51	-4.90	-5.88	-5.33	-5.41	-6.31	-5.95	-4.85	-3.01	-7.93	-2.86	-7.17	-3.01	-6.78	-5.48
DDw	-7.29	-7.05	-7.30	-8.11	-6.68	-6.63	-7.38	-6.37	-7.58	-7.63	-11.59	-8.62	-9.09	-8.20	-6.82	-8.15	-7.33
ur* (trend)	-0.94	-0.91	-0.97	-0.93	-1.05	-0.94	-0.84	-1.10	-0.95	-0.98	-0.91	-1.14	-0.90	-1.06	-0.97	-1.00	-0.59
ur*	-1.67	-1.65	-1.66	-1.68	-1.67	-1.67	-1.66	-1.68	-1.69	-1.67	-1.68	-1.69	-1.67	-1.69	-1.67	-1.65	-1.64
Dur*	-4.48	-4.45	-4.35	-8.18	-4.17	-4.56	-8.07	-4.36	-4.45	-4.31	-7.97	-4.32	-4.45	-4.33	-4.25	-4.27	-8.01
Ddur*	-7.94	-7.88	-7.72	-7.27	-7.33	-8.07	-7.61	-7.22	-7.56	-7.74	-7.35	-7.24	-7.69	-7.47	-7.45	-7.53	-7.44
hr* (trend)	-1.58	-2.63	-1.91	-1.90	-3.25	-1.89	-2.85	-2.33	-1.85	-2.07	-2.01	-2.28	-2.89	-2.40	-2.41	-2.27	-1.46
hr*	-1.76	-1.94	-1.54	-1.78	-2.59	-1.89	-1.67	-2.14	-1.79	-2.12	-1.78	-1.99	-1.83	-2.36	-1.53	-2.29	-1.58
Dhr*	-5.11	-5.29	-6.76	-5.15	-4.82	-4.93	-5.81	-4.53	-5.22	-5.12	-5.25	-4.67	-5.30	-4.41	-7.53	-4.95	-5.85
DDhr*	-7.24	-9.34	-8.88	-7.46	-8.70	-7.47	-8.12	-13.43	-7.49	-9.24	-7.63	-7.04	-9.39	-13.14	-7.66	-9.05	-8.37
w* (trend)	-2.54	-3.47	-2.26	-2.54	-3.33	-3.51	-2.68	-2.43	-2.89	-2.55	-2.63	-2.45	-3.09	-2.70	-2.39	-3.39	-2.35
w*	-0.13	-1.28	0.19	0.32	-0.55	-0.80	-0.09	-0.19	-0.59	-0.66	0.27	-0.50	-0.52	-0.51	0.54	-0.59	-0.12
Dw*	-7.33	-4.79	-6.51	-3.97	-4.98	-4.76	-4.26	-6.73	-4.03	-4.88	-3.91	-7.15	-4.21	-4.84	-4.54	-5.02	-3.67
DDw	-13.28	-11.95	-12.28	-12.96	-6.35	-6.69	-12.94	-12.49	-13.41	-6.42	-13.10	-6.81	-13.50	-6.29	-13.03	-6.48	-12.72

TABLE 16: VARX* ORDER AND NUMBER OF COINTEGRATING RELATIONSHIPS					
City	p	# Cointegrating Relationships	City	p	# Cointegrating Relationships
ALBANY	2	0	NEW YORK	1	1
ALLENTOWN	1	1	NORWICH	2	0
ATLANTIC CITY	2	1	PHILADELPHIA	1	1
BANGOR	1	1	PITTSBURGH	2	2
BARNSTABLE	2	1	PORTLAND	2	0
BINGHAMTON	1	1	POUGHKEEPSIE	1	1
BOSTON	2	1	READING	2	1
BRIDGEPORT	2	1	ROCHESTER	1	0
BUFFALO	2	0	SCRANTON	2	0
BURLINGTON	2	0	SPRINGFIELD	2	0
ERIE	1	0	STATE COLLEGE	2	1
HARRISBURG	2	1	SYRACUSE	2	0
HARTFORD	2	0	TRENTON	1	0
KINGSTON	1	1	UTICA ROME	1	1
LANCASTER	1	2	VINELAND	1	0
MANCHESTER	2	0	WORCESTER	2	0
NEW HAVEN	2	1	YORK HANOVER	1	1

TABLE 17: TEST FOR WEAK EXOGENEITY AT THE 5% SIGNIFICANCE LEVEL							
City		95% F-stat Critical Value	ur*	hr*	w*	eq	v
ALLENTOWN	F(1,57)	4.01	0.67	0.00	2.26	0.48	0.65
ATLANTIC CITY	F(1,54)	4.02	**7.15**	2.02	2.24	0.88	**5.21**
BANGOR	F(1,57)	4.01	0.07	0.11	0.02	0.74	2.07
BARNSTABLE	F(1,54)	4.02	0.41	1.22	0.33	3.17	0.04
BINGHAMTON	F(1,57)	4.01	3.97	0.13	1.03	1.41	1.56
BOSTON	F(1,54)	4.02	0.21	0.34	0.00	0.37	1.74
BRIDGEPORT	F(1,54)	4.02	1.37	0.41	0.32	0.31	3.18
HARRISBURG	F(1,54)	4.02	0.28	0.00	1.21	0.30	2.91
KINGSTON	F(1,57)	4.01	0.02	0.02	2.17	0.16	1.44
LANCASTER	F(2,56)	3.16	0.47	0.49	0.96	1.37	0.32
NEW HAVEN	F(1,54)	4.02	**6.94**	0.97	0.46	0.06	**4.78**
NEW YORK	F(1,57)	4.01	**4.02**	**6.08**	**4.23**	-	-
PHILADELPHIA	F(1,57)	4.01	2.76	0.06	1.01	0.11	0.14
PITTSBURGH	F(2,53)	3.17	0.56	1.03	0.19	2.42	2.14
POUGHKEEPSIE	F(1,57)	4.01	1.01	0.13	0.01	0.28	0.10
READING	F(1,54)	4.02	1.18	0.24	0.59	0.30	0.14
STATE COLLEGE	F(1,54)	4.02	0.60	1.76	0.72	1.39	1.92
UTICA ROME	F(1,57)	4.01	0.15	1.38	1.57	0.44	2.98
YORK HANOVER	F(1,57)	4.01	1.41	1.71	0.00	0.41	2.92

TABLE 18: CONTEMPORANEOUS EFFECTS
OF FOREIGN VARIABLES ON DOMESTIC COUNTERPARTS

	Variables				Variables		
City	ur	hr	w	City	ur	hr	w
ALBANY	0.91	0.69	0.85	NEW YORK	0.85	0.76	0.99
	[32.46]	[4.09]	[3.06]		[0.22]	[14.82]	[7.12]
ALLENTOWN	1.08	0.74	0.56	NORWICH	0.87	0.29	0.57
	[41.35]	[6.39]	[2.62]		[14.54]	[1.10]	[2.13]
ATLANTIC CITY	1.15	0.91	0.61	PHILADELPHIA	0.82	0.88	0.60
	[13.29]	[5.69]	[2.60]		[26.65]	[10.49]	[8.75]
BANGOR	0.93	0.88	0.57	PITTSBURGH	1.07	0.97	1.02
	[12.44]	[2.88]	[3.13]		[27.63]	[10.02]	[8.74]
BARNSTABLE	1.85	0.09	0.68	PORTLAND	0.82	0.45	1.01
	[9.80]	[0.27]	[1.72]		[8.46]	[1.80]	[4.71]
BINGHAMTON	1.15	0.56	1.61	POUGHKEEPSIE	0.84	0.68	0.37
	[29.07]	[1.89]	[4.48]		[16.35]	[4.34]	[1.64]
BOSTON	0.04	0.87	1.44	READING	1.16	1.45	0.36
	[0.60]	[3.72]	[6.26]		[27.49]	[5.51]	[2.12]
BRIDGEPORT	0.83	1.27	0.93	ROCHESTER	0.92	0.75	0.80
	[16.69]	[6.19]	[1.61]		[27.02]	[6.06]	[2.57]
BUFFALO	1.03	0.80	0.83	SCRANTON	1.21	0.69	0.64
	[14.59]	[5.03]	[6.19]		[26.01]	[5.00]	[3.04]
BURLINGTON	0.87	0.56	0.16	SPRINGFIELD	1.42	0.69	0.37
	[9.64]	[2.84]	[0.70]		[29.70]	[3.34]	[1.95]
ERIE	1.21	0.72	0.38	STATE COLLEGE	0.94	0.89	-0.24
	[20.42]	[3.02]	[2.23]		[13.76]	[3.34]	[-1.53]
HARRISBURG	0.89	0.84	0.76	SYRACUSE	1.09	0.80	0.47
	[39.15]	[4.47]	[4.43]		[29.54]	[2.75]	[2.16]
HARTFORD	1.06	0.84	1.54	TRENTON	0.89	1.22	1.06
	[19.20]	[4.64]	[4.48]		[12.22]	[4.86]	[2.12]
KINGSTON	1.15	0.28	1.16	UTICA ROME	1.04	0.60	0.89
	[36.79]	[1.02]	[3.11]		[18.88]	[3.23]	[3.21]
LANCASTER	0.98	0.95	0.54	VINELAND	1.57	1.37	0.62
	[29.98]	[5.25]	[2.97]		[17.85]	[2.96]	[1.30]
MANCHESTER	0.75	1.03	0.72	WORCESTER	1.16	1.14	0.16
	[13.95]	[3.53]	[3.09]		[17.00]	[5.27]	[0.85]
NEW HAVEN	1.11	0.00	0.23	YORK HANOVER	1.03	1.81	0.44
	[23.45]	[0.00]	[0.87]		[23.96]	[8.14]	[2.62]

Note: White's heteroskedastic robust *t*-ratios are in brackets.

TABLE 19: AVERAGE PAIR-WISE CROSS-SECTION DEPENDENCE: VARIABLES AND RESIDUALS

City	ur	Dur	Residuals	City	ur	Dur	Residuals
ALBANY	0.94	0.84	-0.01	NEW YORK	0.94	0.80	-0.02
ALLENTOWN	0.96	0.84	-0.02	NORWICH	0.93	0.79	-0.05
ATLANTIC CITY	0.93	0.73	-0.07	PHILADELPHIA	0.94	0.82	0.01
BANGOR	0.93	0.73	-0.02	PITTSBURGH	0.95	0.80	0.01
BARNSTABLE	0.75	0.64	-0.05	PORTLAND	0.93	0.69	-0.03
BINGHAMTON	0.94	0.81	-0.04	POUGHKEEPSIE	0.94	0.80	-0.01
BOSTON	0.87	0.26	-0.02	READING	0.95	0.81	0.02
BRIDGEPORT	0.94	0.78	-0.04	ROCHESTER	0.95	0.82	0.00
BUFFALO	0.93	0.80	-0.02	SCRANTON	0.94	0.82	-0.03
BURLINGTON	0.73	0.68	-0.02	SPRINGFIELD	0.93	0.83	-0.02
ERIE	0.92	0.80	-0.02	STATE COLLEGE	0.91	0.72	0.00
HARRISBURG	0.95	0.81	-0.01	SYRACUSE	0.95	0.81	-0.01
HARTFORD	0.94	0.80	-0.03	TRENTON	0.94	0.75	-0.03
KINGSTON	0.92	0.82	-0.02	UTICA ROME	0.91	0.76	-0.03
LANCASTER	0.95	0.81	-0.01	VINELAND	0.94	0.79	-0.06
MANCHESTER	0.91	0.78	0.00	WORCESTER	0.91	0.78	-0.02
NEW HAVEN	0.92	0.78	-0.03	YORK-HANOVER	0.95	0.77	0.00
	hr	Dhr	Residuals		hr	Dhr	Residuals
ALBANY	0.02	0.22	0.00	NEW YORK	0.40	0.36	-0.01
ALLENTOWN	0.28	0.26	-0.03	NORWICH	0.28	0.05	-0.05
ATLANTIC CITY	0.29	0.19	-0.01	PHILADELPHIA	0.42	0.37	0.00
BANGOR	0.17	0.15	0.00	PITTSBURGH	0.40	0.32	-0.02
BARNSTABLE	0.28	0.08	-0.02	PORTLAND	0.40	0.12	0.00
BINGHAMTON	0.19	0.07	-0.02	POUGHKEEPSIE	0.09	0.23	0.02
BOSTON	-0.22	0.24	0.02	READING	0.43	0.26	-0.03
BRIDGEPORT	0.44	0.34	-0.01	ROCHESTER	0.20	0.22	-0.01
BUFFALO	0.14	0.28	0.02	SCRANTON	0.39	0.23	-0.01
BURLINGTON	0.11	0.20	0.02	SPRINGFIELD	0.29	0.19	0.01
ERIE	0.40	0.21	-0.02	STATE COLLEGE	0.27	0.13	-0.02
HARRISBURG	0.38	0.28	0.00	SYRACUSE	0.16	0.17	0.00
HARTFORD	0.35	0.22	-0.01	TRENTON	0.37	0.29	-0.04
KINGSTON	0.22	0.08	-0.01	UTICA ROME	0.23	0.16	-0.03
LANCASTER	0.27	0.25	-0.03	VINELAND	0.28	0.13	-0.06
MANCHESTER	0.24	0.20	0.00	WORCESTER	0.08	0.31	0.01
NEW HAVEN	0.15	-0.04	-0.03	YORK-HANOVER	0.22	0.33	-0.04
	w	Dw	Residuals		w	Dw	Residuals
ALBANY	0.50	0.16	-0.02	NEW YORK	0.54	0.26	0.02
ALLENTOWN	0.54	0.15	-0.02	NORWICH	0.48	0.13	0.00
ATLANTIC CITY	0.53	0.14	0.00	PHILADELPHIA	0.57	0.27	0.01
BANGOR	0.54	0.13	-0.02	PITTSBURGH	0.55	0.31	0.02
BARNSTABLE	0.01	0.13	0.00	PORTLAND	0.51	0.12	0.00
BINGHAMTON	0.47	0.17	-0.04	POUGHKEEPSIE	0.55	0.13	0.02
BOSTON	0.55	0.26	0.02	READING	0.51	0.10	-0.01
BRIDGEPORT	-0.41	0.12	-0.02	ROCHESTER	-0.44	0.10	-0.04
BUFFALO	0.52	0.21	0.00	SCRANTON	0.54	0.22	0.00
BURLINGTON	-0.11	0.05	-0.04	SPRINGFIELD	0.46	0.11	-0.03
ERIE	0.47	0.12	-0.02	STATE COLLEGE	0.50	-0.05	0.00
HARRISBURG	0.55	0.19	0.00	SYRACUSE	0.04	0.11	-0.02
HARTFORD	0.34	0.18	-0.02	TRENTON	0.42	0.17	-0.01
KINGSTON	0.39	0.18	-0.03	UTICA ROME	0.36	0.18	0.00
LANCASTER	0.56	0.18	0.01	VINELAND	0.19	0.07	-0.04
MANCHESTER	-0.10	0.16	-0.02	WORCESTER	-0.20	0.05	-0.03
NEW HAVEN	0.42	0.08	-0.04	YORK-HANOVER	0.48	0.14	-0.01

TABLE 20: LONG-RUN IMPACT OF NEGATIVE SHOCK TO NEW YORK, NY, BOSTON, MA AND PHILADELPHIA, PA UNEMPLOYMENT RATES

City	New York	Boston	Philadelphia	City	New York	Boston	Philadelphia
ALBANY	-0.50	0.09	0.19	NEW YORK	-0.37	0.13	0.25
ALLENTOWN	-0.67	0.13	0.30	NORWICH	-0.51	0.08	0.20
ATLANTIC CITY	-0.65	0.16	0.17	PHILADELPHIA	-0.48	0.11	0.30
BANGOR	-0.48	0.10	0.16	PITTSBURGH	-0.55	0.11	0.23
BARNSTABLE	-0.97	0.14	0.14	PORTLAND	-0.44	0.12	0.12
BINGHAMTON	-0.63	0.10	0.22	POUGHKEEPSIE	-0.46	0.08	0.22
BOSTON	-0.55	0.12	0.24	READING	-0.76	0.15	0.33
BRIDGEPORT	-0.51	0.09	0.25	ROCHESTER	-0.52	0.09	0.20
BUFFALO	-0.59	0.10	0.18	SCRANTON	-0.69	0.13	0.30
BURLINGTON	-0.43	0.01	0.11	SPRINGFIELD	-0.70	0.10	0.28
ERIE	-0.68	0.15	0.27	STATE COLLEGE	-0.53	0.10	0.24
HARRISBURG	-0.51	0.11	0.24	SYRACUSE	-0.60	0.11	0.20
HARTFORD	-0.59	0.11	0.28	TRENTON	-0.39	0.09	0.22
KINGSTON	-0.43	0.09	0.19	UTICA ROME	-0.70	0.12	0.15
LANCASTER	-0.63	0.13	0.28	VINELAND	-0.85	0.22	0.27
MANCHESTER	-0.53	0.10	0.24	WORCESTER	-0.52	0.07	0.25
NEW HAVEN	-0.62	0.13	0.30	YORK-HANOVER	-0.57	0.14	0.29

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