Regional Propagation of Shocks - Evidence from Bakken Shale Oil Boom

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Abstract

In this paper, I take advantage of available data at the Metropolitan Statistical Area (MSAs) level to examine spatial propagation of shocks. In particular, I consider the shale oil boom, in the Bakken formation area (Western North Dakota and eastern Montana) using data from 2002 - 2017. I investigate whether MSAs labor market outcomes and housing market, respond to a localized productivity shock from fracking. I employ a Spatial Dynamic Panel and Global Vector Autoregressive models to capture syncronization patterns, and extract persistence profiles for both time and space. I found strong evidence of housing, employment, and earnings spillovers across the region. Migration, commuting, and size of the local economy, determine the response of local labor demand shock. Results also show that MSAs facing lower restrictions in housing supply observe higher employment growth, wages with moderated changes in housing prices. Overall, productivity shock has a large impact on the MSAS where it instigates and the degree it spillovers regionally depends on networks connecting MSAs. These contemporaneous effects are persistent dying after 36 months.

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1 Introduction

The Bakken shale formation, located in western North Dakota and eastern Montana, has been producing oil since 1953, but remained relatively stagnant in the region for the following decades until it was revitalized in the 2000s. With breakthroughs in drilling technology, large part of the untouched oil reserves began to be explored and oil production in the area skyrocketed[1]. Oil production increased rapidly from 2007 to April 2014, from about 123,600 to more than 1 million barrels per day, making North Dakota the second-largest oil-producing state (IHS, 2015)[2]. Moreover, the region witnessed an unprecedented economic boom that appeared to spillover to neighboring regions. Figure (A2) in the appendix, intuitively illustrates changes in the landscape overtime using light intensity. It appears the increasing activity in the Western and Southern area of North Dakota over the last decade from shale gas and oil exploration might have spillover across the region. However, it does not imply any causality, rather it presents an opportunity to study economic and spatial dynamics intrinsically related to the boom.

Empirical analysis of the dynamic interdependencies prevalent in spatial units has gained traction in regional economics (Hausman & Kellogg, 2015). The first law of geography invoked by Tobler (1970) states that "everything is related to everything else, but near things are more related than distant things. Essentially, it defines the concept of spatial correlation in which two or more locations spatially correlated tend to be similar to each other for a given attribute than are spatially distant locations. The presence of dynamic heterogeneities represents a great opportunity to study how shocks propagated across units over time, and characterize cross-sectional differences to disentangle potential sources of these heterogeneities (Canova & Ciccarelli, 2013).

In this paper, I examine the spatial propagation of oil and gas boom, identified as a localized productivity shock, across Metropolitan Statistical Areas (MSAs) using spatial model techniques. I provide some evidence of spatio-temporal transmission of the shock over a span time of 16 years. Specifically, I employ the Generalized Method of Moments (GMM), an augmented autoregressive model with spatially lagged explanatory variables "à la" H. H. Pesaran & Shin (1998). Similar to Black et al. (2005), I take advantage of an economic shock that induced an exogenous shift in the demand for labor as well as features of the model. The long-term relationship of the growth rate of labor outcomes, housing market and

[1]See Figure (A1) in the appendix

[2]IHS (2015). The Effects of North Dakota Oil Production on the Minnesota Economy. Technical report.

population growth are extracted by impulse response functions generated from Global Vector Autoregressive - GVAR. By employing these two techniques I can obtain point estimates as well as show a synchronized pattern of labor market outcomes across the region as evidence of spillover effect. The panel offers extended possibilities not present in cross-sectional data or time series data. Here, I can extract more variation and less collinearity among variables, thus capturing effects not present in cross-sectional or time series data (Elhorst, 2003).

I aim to provide a contribution on empirical estimation of spatial modelling in regional business cycle setting. I take advantage of available regional data and an idiosyncratic sectoral shock that induced an exogenous shift in the demand for labor. For instance, Caliendo et al. (2017), using a general equilibrium model, finds negligible impact to the US economy from North Dakota shale boom. I suspect the short period considered in the model (2002 – 2007) as the main reason considering that 2010 - 2014 was the peak in oil and gas exploration in the Bakken area[3]. Similarly, Feyrer et al. (2017), document the time and space effect of a boom in oil and gas in the US on labor market outcomes using an instrumental variable approach based on geological endowments. The authors find significant increase on employment and income and this effect grows wider with the distance. My analysis differs from previous research in the sense that I employ physical and economic distance weight matrices similar to Vega & Elhorst (2014) to model spatial interaction on top of the traditional concentric ring distance as in Feyrer et al. (2017). A second novelty of the paper is that I employ GVAR model in a regional setting, a non-orthodox technique largely used in time series analysis for the global economy, trade and financial markets. Here, I treat each MSA as a small economy that interacts with others. I defined Bismarck as dominant economy given its proximity to the fields where the exploration is taken place. Moreover, similar empirical work has been done at County level. I define MSA as unit of analysis due its major advantage in capturing labor and housing markets dynamics better than County boundaries and more closer to Commuting Zones in Feyrer et al. (2017).

This paper builds upon several literatures. First, it builds on the literature on geographic and temporal propagation of economic shocks (Feyrer et al., 2017; Caliendo et al., 2017; Bartik et al., 2018). Feyrer et al. (2017), track the propagation across time and space of the oil boom from hydro fracturing across the US using a seven year panel data. The authors construct artificial commuting zones by aggregating counties and drew co-centering rings to capture the effect of the distance. This allows them to address the stylized fact reported in urban economics literature that workers do not necessarily live and shop where

[3] Figure B.1 in the appendix.

they work. Most of the fracking activity takes place in very sparce counties with low if any amenities and therefore, more likely to commute to neighboring counties. In the same vein, Bartik et al. (2018) using a Rosen-Roback style spatial equilibrium model, exploit geological variation and timing of hydraulic fracturing to measure the net welfare consequences of fracking on local communities. Among others, they find that counties with high fracking potential experienced oil and gas boom that translated into sharp increases in total income (4.4 - 6.9%), employment (3.6 - 5.4%), housing prices (5.7%) and housing rental rates (2.7%).

This paper also builds upon the vast empirical work on the economic shocks, labor markets, and housing markets (Blanchard et al., 1992; Saks, 2008; Osei & Winters, 2018). The response of regional labor markets to a localized shock gain much traction after the seminal paper of Blanchard et al. (1992). Using a three-equation vector auto-regressive (VAR) model, they claim that positive shocks to employment increase wages and reduce unemployment; however, the spatial dimension was not clearly defined. More recently, Beenstock & Felsenstein (2007a) extend the model by incorporating a spatial component using different spatial weight matrices to capture the effect of labor mobility as an adjustment mechanism. The authors shown that the region-specific shock has large impact where it originates and impact first and second order neighbours. Osei & Winters (2018) examine whether the effects of labor demand shocks on housing prices vary across time and space. They suggest that labor demand shocks have positive effects on housing prices. However, these effects are heterogeneous across time periods and different types of metropolitan area. Housing market conditions can also influence household mobility since household reallocation depend in part on the relative cost of housing across cities. On the other hand, these housing markets conditions in turn are affected significantly by labor market outcomes - wages affect housing prices. A more vibrant labor market makes a city more desirable to in-migration and increases the willingness to pay for housing in the city.

The paper is also related to the vast literature on migration and labor market outcomes (Blanchard et al., 1992; Cameron & Muellbauer, 2001; Gallin, 2004; Glaeser & Gyourko, 2005; Beenstock & Felsenstein, 2007a; Enrico, 2011; Saks & Wozniak, 2011; Zabel, 2012). Labor mobility, hence population density regulates the relationship among economic shocks, labor and housing markets as the adjustment mechanism. It has been argued in the regional literature [cite here] that most of the regional adjustments to shocks in the labor market happens through movements of workers rather than through job creation or job migration (Blanchard et al., 1992). This is one reason why other authors in regional economics [cite here] focus thei attention to the role of housing market on wages, employment and, unemployment. Cameron & Muellbauer (2001), identify among others four potential market channels of influence on wages and unemployment. The effect of housing tenure on mobility rates which is likely to affect regional labor mismatch. Renters are more likely to migrate than homeowners (Zabel, 2012). Second, the cost of living effect on workers already in the region where the economic shock instigates and also on potential migrants from house, and indirectly land prices. This can give rise to temporarily high regional mismatch associated with temporarily high house price differentials relative to earnings differentials, which constrain net migration to booming regions. Third, the cost of location effect from land prices on firms in the region and potential movers into the region. Finally, expectations effect in that future movements of earnings may be capitalized in house and land prices. Glaeser & Gyourko (2005) presents a simple model of urban decline and durable housing and tests its implications. The model predicts, among other things, that positive shocks increase population more than increase housing prices; negative shocks decrease housing prices more than they decrease population. This relationship between variations in housing prices and population is strongly concave[4].

This paper also explores the literature on regional business cycle, propagation of shocks and spatial dynamic modeling. Economic shocks affect regions unequally and the degree through which it affects depends on networks connecting regions, cities or industries. Changes in unemployment across neighboring cities during the oil boom or in the Great Recession is illustrative of it. Blanchard et al. (1992) show that net migration respond positively to increased labor demand. When a region experiences an increase in labor demand, it will attract additional migrants, amplifying the boom[5].

Empirical work on spatial dynamic panels is limited, albeit techniques for estimating spatial auto-regressive model using cross-sectional or panel data are well grounded in the literature. However, application of spatial econometrics techniques to investigate spatial effects to hydraulic fracking boom in more disagregated geographical units is limited. On the other hand, there exists considerable body of empirical application on housing markets. For instance, Cohen et al. (2016) examine spatial diffusion patterns in the growth of urban housing prices in the USA. They find that lagged price changes in a submarket affect the current house price of a contiguous submarket positively and more pronounced than the lagged house price changes on non-contiguous submarket, but not in the same MSA. Sim-

[4] The kinked housing supply curve implies asymetric response to positive and negative demand shocks.

[5] Greg Howard (2017), refers to this as "migration accelerator - the additional increase in employment due to endogenous response of migration"

ilarly, Pollakowski & Ray (1997) find that shocks in housing prices in one MSA are likely to Granger-cause subsequent shocks in housing prices in other MSAs. Brady (2011) using spatial impulse response function, finds that the propagation of regional housing prices across space lasts up to two and a half years. He employs the local projection method proposed by Jordà (2005) showing how the shock is transmitted through spatial correlation over time. More recently, Brady (2014) estimates the diffusion of housing prices across US states over 1975 - 2011. He finds that spatial diffusion is persistent and more pronounced after 1999.

I find evidence of significant spatial spillovers across MSAs in response to the massive exploration of shale oil and gas. The effect is reflected in increased employment, wages and higher demand for housing, and overall synchronized economic growth. Migration flows across MSAs, the size of the local economy, distance between MSAs and the driving time, were the mechanisms at work in explaining the spatial propagation. I also find that the effect is persistent and go beyond 3 years specially for housing prices and unemployment. The paper proceeds as follows: section 2 provides a brief background of the the boom, section 3 outlines the conceptual framework based covered extensively in the appendix section. In section 4, I outline the econometric model, the Bartik instrument and define the spatial weight matrices employed in the paper. Section 5 describe the data and empirical relationship in key variables. Section 6 present the results and discussion. Section 7 present concludes.

2 Background - Bakken Oil Boom

The unprecedented shale extraction in the late 2000s, accelerated in 2010 traduced in massive economic boom affecting the region. Higher growth rates in Gross Domestic Product have driven a rapid job growth and increasing wages not only in the oil sector but in other sectors. Yet, since 2007, North Dakota has become the fastest growing state in the nation since 2011 in terms of population (U.S. Census Bureau, 2012a)[6]. The statewide unemployment was the lowest at 3 percent in 2012 (Bureau of Labor Statistics, 2012)[7], and industry estimates indicate that approximately 65,000 new jobs were created (Council, 2012). Similarly, jobs and wages grew in the region, from fast food workers to government jobs, transport and construction crews[8].

[6]Press release retrieved from https://www.census.gov/newsroom/releases/archives/population/cb12-250.html.

[7]Press release # USDL-13-0340, REGIONAL AND STATE UNEMPLOYMENT — 2012 ANNUAL AVERAGES; Bureau of Labor Statistics

[8]retrieved from http://www.ci.billings.mt.us/DocumentCenter/View/26270.

Most of shale exploration occurred in rural counties with very sparse population, lacking infrastructure, and limited housing units to sustain an increasing demand for housing. Thus, the "new oil rush" accompanied by higher wages, brought a new wave of workers/residents pressuring local communities in terms of urban amenities. The IHS (2015) referencing American Community Survey, reports that between 2008 and 2012 a total of 3,101 residents of the five counties in Minnesota with common border with North Dakota migrated to the latter; most went to Fargo[9] and only 55 moved to the Bakken counties. Moreover, unemployment rates were slightly impacted in areas lying between 200 and 300 miles from the extraction areas.

3 Conceptual Framework

This section, outlines a simple conceptual framework to derive key implications of the model and motivate the empirical analysis. It is based on a simple spatial equilibrium model with homogeneous labor proposed by Moretti (2011) well documented in Appendix (A). It is based on standard assumptions of most Rosen-Roback spatial equilibrium models. The model serves two purposes: first, it explains how a sector-specific shock have impact on employment, nominal wages and housing costs in the affected region; and second, it allows to capture the spillover effect of the shock over space and time in the neighboring of affected region. Essentially, the model is concerned with the joint determination of regional wages, employment, population and house prices (Roback, 1982).

The pass-through from a productivity shock in one region to equilibrium wages, housing prices, and employment in a specific MSA and its neighbors can be summarized as follows. First, let us assume two identical $MSAs$[10] and that the Total factor Productivity (TFP) increases in MSA_2 in a exogenous fashion. Thus, an increase in productivity in MSA_2 will shift the local labor demand curve to the right, resulting in higher employment and higher nominal wages. Consequently, housing costs increase due to higher local employment and wages. Essentially, workers are more productive in MSA_2 than MSA_1 and some of them move to MSA_2 attracted by this higher productivity. As employment declines in MSA_1, the cost of housing declines and real wages increase. The shock affecting labor market condi-

[9]Fargo MSA is located in the border between North Dakota State and Minnesota.

[10]Clearly this is a strong assumption because we are ignoring industry mix and employment patterns. But say this is not a big deal or defend the assumption.

tions in one region have regional implications and labor mobility across regions models that relationship. The size of these effects depend on the elasticities of labor supply and housing supply.

Labor mobility is the mechanism through which shocks propagate from one MSA to another. The increase in MSA_2 TFP forces workers to move out from MSA_1 to MSA_2. In turn, for a given labor demand elasticity and housing supply elasticity, there are changes in the nominal wages and rents in MSA_1. Secondly, the effect of a productivity shock is generally more pronounced in MSA_2 directly hit by the shock. This effect is present under the assumption of less than perfect mobility otherwise, real wages will only be completely equalized if there is perfect mobility[11]. Only marginal worker is indifferent between the two MSA_s in equilibrium and only with no idiosyncratic location preferences would all workers be indifferent between two MSA_s. Overall, the simplified model with two MSA_s prescribes a more concentrated and large indirect effect on MSA_1. In reality; however, there are many possible MSA_s of origin for workers who move to MSA_2. Thus, the indirect effects in each of these MSA_s are diffused and relatively small. The size of the indirect effects on wages and rents in each origin MSA are not the same for all MSA_s, as they depend on local elasticities of housing supply.

4 Empirical Strategy

In this section, I presents two complement estimation strategy that mimic the dynamic interactions of the labor demand shock across MSAs. I start off by estimating a baseline spatial dynamic model to illustrate the overall effect of the shock on labor market outcomes and housing across the region. However, the estimations from baseline model are the same across different locations. The second strategy is the estimation of the Global Vector Autoregression (GVAR) view as an unrestricted Spatial Vector Autoregressive model (SpVAR). It captures heterogeneous effects not presented in the baseline model and allow for global interdependence across geographic units through key variable. More importantly, we can evaluate spillovers effects from one geographic-specific shock to any other endogenous variables within

[11] The Rosen-Roback model assumes complete mobility of labor so that, the local labor supply is infinitely elastic and therefore the costs of changing from one location to another are zero. On the other hand, Moretti's model relaxes this assumption by assuming incomplete labor mobility due to worker's idiosyncratic preferences for locations.

the system and generate the respective persistence profiles[12].

4.1 Spatial Dynamic Panel Model

The full spatial dynamic panel model[13] considered in this paper is

$$Y_{jit} = \tau Y_{jit-1} + \rho W Y^{*}_{jit} + \beta X_{jit} + \theta W X^{*}_{jit} + a_i + u_t + \epsilon_{it} \tag{1}$$

where $Y_{jit} = (Y_{1t}, ...Y_{Nt})$ is NT x 1 vector of the dependent variable j for region i, Y_{jit-1} is the vector of time lagged regressor; WY^{*}_{jit} is the spatial lag regressor (endogenous interaction effect); X_{jit} is an NT x r matrix of explanatory exogenous regressors; θWX is exogenous spatially lagged regressor (exogenous interaction effect); a_i is an individual fixed effects; u_i is time fixed effects; ϵ_{jit} is a normally distributed error term which, we assume $E(\epsilon) = 0$ for the error vector ϵ of dimension (N x 1); W is a nxn spatial matrix for the autoregressive component where n is the number of MSAs; and ρ is a scalar parameter of the normalized spatial weighting matrix.

Rewriting equation (1) yields[14]

$$Y_{jit} = (I - \rho W)^{-1}(\tau I + \rho W) Y_{jit-1} + (I - \rho W)^{-1}(\beta X_{jit} + \theta W X_{jit}) + R \tag{2}$$

$$\Delta y_{jit} = \tau \Delta Y_{jit-1} + \rho_1 \sum_{j=1}^{N} W_{ij} \Delta Y^{*}_{jit} + \beta \Delta x_{jit} + \Delta \epsilon_{it} \tag{3}$$

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[12] This is of great deal since the standard Panel VAR does not distinguish heterogeneous effects of the shock across different regions.

[13] In the spatial literature, this model is knows as Dynamic Spatial Durbin model (Debarsy et al., 2012). One might include in the specification of baseline model the time lags of spatial endogenous and exogenous regressors $\psi W Y_{jit-1}$ and $\omega W X^{*}_{jit-1}$, respectively; include spatial lag in the error term. However, the proliferation of excessive parameters in such model will not be identified (Anselin & Bera, 1998; Elhorst, 2003)

[14] Since both spatial and temporal dynamics are present, equation (15) can be seen as a Structural SpSVAR. When $\rho = \theta = 0$ the equation represent an unrestricted Panel Vector Autoregressive model (PVAR). It is worthwhile to mention that a SpVAR differ from typical VARs in that they incorporate spatial as well as temporal dynamics, and they differ from spatial models because they incorporate temporal dynamics. In SpVARs we have variables at time t that may depend upon contemporaneous spatial lags as in spatial models for cross-section data. In addition, variables at time t may depend upon spatial lags at time $t - \lambda(\lambda > 0)$ (Beenstock & Felsenstein, 2007b)

By including θWX, we assume that exogenous variables are spatially correlated. Estimates of the $\tau's$ describe the temporal lag structure within regions and estimates of ρ describe the temporal lag structure between regions. We assume that shocks are correlated across regions by variable, but shocks between variables are uncorrelated, i.e $E(\epsilon_j, \epsilon_h) \neq 0$. There is spatial autocorrelation in variable j, but no spatial autocorrelation across variables. Alike autocorrelation in time series, here spatial correlation can be thought as an omitted variable problem. For the sake of clarity, henceforward I refer to spatial correlation as the correlation between regions and $\rho W y_{it}$ as the spatial regressor in a dynamic panel.

Among several methods, I estimate the full model using the General Method of Moments (GMM) proposed by Arellano and Bond (1991) and Mutl (2006). This method overcomes deficiencies of the OLS estimator by purging the fixed effects and as well as addressing the incidental parameter problem by adding region-specific temporal lag coefficients[15] (Dewachter et al., 2012). More specifically, it eliminates the individual effect a_i which is correlated with covariates and the lagged dependent variable, by differencing for individual i at time t - equation (3). The GMM estimator is based on instrumental variable where sufficiently lagged values of the endogenous variables can be used as instrument for Y_{jit-1}; WY_{jit}; and WX_{jit} (Abrigo et al., 2016; Beenstock & Felsenstein, 2007a). I differentiate equation (3) and obtain equation (4).

However, even after differentiating (equation 3), there is still correlation between the differenced lagged dependent variable and the idiosyncratic error (a first order moving average process, or MA(1)): the former contains y_{jit-1} and the latter contains ϵ_{jit}. Given that, the GMM estimator is still biased and inconsistent and so it requires further assumptions. Arellano and Bond (1991) offer the system GMM, which estimate simultaneously equation (1) and (3). The strict exogeneity of the covariates is the underlying assumption alongside with instrumenting different endogenous variables including the spatially lag. The valid moment conditions for the system GMM involves the forthcoming restrictions:

[15] A pooled Ordinary Least Squares of equation (15) will clearly be biased due the presence of lag dependent variable which is correlated with the fixed effects - "dynamic panel bias" (Nickell, 1981)[16]. Moreover, the consistency assumption of OLS estimation will be violated when allowing for both fixed-effects and lags of the dependent variable (Anselin & Bera, 1998; LeSage et al., 1998).

$$
\begin{aligned}
E(\Delta Y_{i,t-l}\epsilon_{it}) &= 0; \textit{for t= 3, ..., T} \\
E(\Delta X_{i,t}\epsilon_{it}) &= 0; \textit{for t= 3, ..., T} \\
E(\Delta X_{i,t-l}\epsilon_{it}) &= 0; \textit{for t= 3, ..., T} \\
E(\Delta[W_{t-1}Y_{t-1}]\epsilon_{it}) &= 0; \textit{for t= 3, ..., T}
\end{aligned} \tag{4}
$$

It is important to note that the number of instruments grows as the sample size T rises and can lead to fail to correct endogeneity and produce inaccurate estimation of the weight matrix; biased two-step standard errors; and generate wrong inference in the Hansen test of instruments validity (Kukenova & Monteiro, 2008). Kukenova & Monteiro (2008) suggest to restrict the number of instruments by defining the maximum number of lags and/or collapsing the instruments.

4.2 Global Vector Autoregressive - GVAR

Originally proposed by M. H. Pesaran et al. (2004), and Dees et al. (2007) the GVAR provides a relaltively simple and effective way of modelling interactions in a complex high-dimensional system such as the global economy. The model is an unrestricted Spatial Panel Vector Auto-regressive (SpVAR) with the advantage of allowing for heterogeneous effects of the shocks across different locations. Although the model in particular was designed to analyze credit risk, the effect of adverse global and regional shocks on major banks during the Asian Financial crises its application expanded rapidly to numerous areas. Rather than countries as the unit of analysis, one can have small units such as regions within the same country, industries, goods categories, cities, banks or sectors[17](Chudik & Pesaran, 2016).

GVAR modelling is a two-step procedure approach. First, I estimate a small-scale MSAs specific models conditional on the rest of the other MSAs. These models are represented as augmented Vector Autoregressive (VAR) denoted as VAR* and represent domestic variables and weighted cross-section averages of foreign variables (other MSAs), which are also commonly referred as "star variables" treated as weakly exogenous. In the second step, individual MSAs VARX* models are stacked and solved simultaneously as one large global VAR model. The solution can be used for shock analysis and forecasting similar with what is done using traditional VAR model.

[17]It was developed essentially in the aftermath of 1997 Asian Financial Crisis when the main concern was the contagious effect of macroeconomic developments on the losses of major financial institutions (Chudik & Pesaran, 2016).

4.2.1 Modelling using GVAR

Consider a panel of N cross-section units (MSAs), indexed by $i = 0, 1, 2, ..., N$ each featuring k_i variables observed during the time periods $t = 1, 2, ..., T$. Let x_{it} denote k_i x 1 vector of variables specific to a cross-section unit i in time period t, and let $x_t = (x'_{1t}, x'_{2t}, ..., x'_{Nt})$ denote a $kx1$ vector of all variables in the panel, where $k = \sum_{i=1}^{N} k_i$. Within the GVAR, the small-scale MSA specific conditional models can be estimated separately. These individual MSAs models explain the domestic variables for a given MSA economy, x_{it}, conditional on MSA-specific cross-section averages of foreign variables from $k^\star$ x 1 vector for $i = 1, 2, ..., N$ where $\tilde{W}_i$ is k x $k^\star$ matrix of MSA-specific weights, typically constructed using data on bilateral foreign trade, capital flows, or geographic interconnections between MSAs[18]. x_{it} is modelled as a VARX* model, namely a VAR model augmented by the vector of the foreign variables - star variables $x^\star_{it}$ and their lagged values,

$$x_{it} = \sum_{l=1}^{pi} \mathbf{\Phi}_{il} X_{i,t-l} + \mathbf{\Lambda}_{i0} X^\star_{i,t} + \sum_{l=1}^{qi} \mathbf{\Lambda}_{il} X^\star_{i,t-l} + \varepsilon_{it} \tag{5}$$

for $i = 1, 2, ..., N$, where $\mathbf{\Phi}_{il}$, for $l = 1, 2, ..., p_i$, $\mathbf{\Lambda}_{il}$, for $l = 0, 1, 2, ...q_i$, are k_i x k_i and k_i x $k*$ matrices of unknown parameters, respectively, and ε_{it} are k_i x 1 error vector of idiosyncratic country-specific shocks, and

$$x_{it} : k_i \text{ x } 1 \text{ vector of domestic variables}$$
$$x^\star_{it} : k^\star_i \text{ x } 1 \text{ vector of foreign variables}$$

where

$$\mathbf{x}^\star_{it} = \sum_{j=1}^{N} w_{ij} x_{jt}, \tag{6}$$

with $w_{ii} = 0$, $w_{ij}, j = 0, 1, 2, ..., N$ a set of weights such that $\sum_{j=1}^{N} w_{ij} = 1$ and ε_{it} are cross sectionally weak correlated such that $\bar{\varepsilon}_{it} = \sum_{j=0}^{N} w_{ij}\varepsilon_{jt} \xrightarrow{p} \mathbf{0}$, as $N \longrightarrow \infty$. Essentially, the region-specifc errors are assumed to be serially uncorrelated with mean zero and a non-singular covariance matrix. Although the model is estimated for each region individually, the shocks are allowed to be weakly correlated across regions.

The first step estimating GVAR models is the the estimation of individual MSA models in (5) which allows for cointegration within and across countries. We can treat x^*_{it} as weakly exogenous I(1) with respect to the parameters of the model. This implies no long-run feedbacks from x_{it} to x^*_{it}, without ruling out short-run feedbacks. Thus, x_{it} is long run forcing

[18] Both k_i and $k^\star$ are treated as small (between 4 to 6)

x_{it}^*, and implies that the error correction mechanisms in individual region equation do not enter in the marginal model of x_{it}^* (Vansteenkiste, 2007). Essentially,equation (5) resembles typical small open economy macroeconomic models in the literature where domestic variables are modeled conditional on the rest of the world.

The second step consists of stacking estimated MSAs models to obtain one large global VAR model. Essentially, we solve simultaneously for all endogenous variables estimated in the first step. Using $(k + k_i^*)$ x k vector dimensional link matrices $W_j = (E_i', \tilde{W}_i')$, where E_i is k x k_i - dimensional selection matrix that select x_it, namely $x_{it} = E_i' x_i$, and $\tilde{W}_i'$ is the weight matrix given in (16) to define region-specific foreign star variables. Let's define

$$z_it = \begin{pmatrix} x_{it} \\ x_{it}^\star \end{pmatrix} = W_i \mathbf{x}_t \tag{7}$$

and rewriting (21) as:

$$A_{i0} Z_{it} = \textstyle\sum_{l=1}^{p} A_{il} Z_{i,t-l} + \varepsilon_{it}$$

where $A_{i0} = (I_{ki} - \Lambda_{i0})$, $A_{il} = (\Phi_{il}, \Lambda_{il})$ for $l = 1, 2, ..., p$.

and stacking these models for each region from $i = 1, 2, ..., N$, we obtain the following Global VAR model:

$$G_0 \mathbf{x}_t = \sum_{l=1}^{p} \mathbf{x}_{t-l} + \varepsilon_{it} \tag{8}$$

where $\varepsilon_t = \varepsilon_{1t}^{'}, \varepsilon_{2t}^{'}, ..., \varepsilon_{Nt}^{'}$, and

$$G_l = \begin{pmatrix} A_{1,l} W_1 \\ A_{2,l} W_2 \\ \vdots \\ A_{N,l} W_N \end{pmatrix}$$

The solution to the GVAR is obtained by multiplying both sides of (24) by $\mathbf{G}_0^{-1}$ as long matrix G_0 is invertible[19].

$$\mathbf{x}_t = \sum_{l-1}^{p} \mathbf{F}_l \mathbf{x}_{t-l} + \mathbf{G}_0^{-1} \varepsilon_t \tag{9}$$

[19]Chudik et al. (2004) show that the system in (24) is undetermined when G_0 is singular and suggest the additional equations required for X_t to be uniquely determined.

where $\mathbf{F}_l = \mathbf{G}_0^{-1}\mathbf{G}_l$ for $l = 1, 2, ..., p$[20]. Equation (25) can be solved recursively. There no restrictions placed on the covariance matrix, unless one specifically decides to impose (Di Mauro & Pesaran, 2013).

Overall, the GVAR model allows for interactions among different MSAs through three distinct but interrelated channels:

- contemporaneous dependence of MSA specific variables (x_{it}) on their counterpart foreign variables (x^*_{it}) defined here as the other MSAs and on its lagged values;
- dependence of MSA-specific variables on common global exogenous variables, and
- contemporaneous dependence of shocks in MSA i on the shocks in MSA j, measured through the cross-region covariances (Garratt et al., 2012).

Differently from (3) data limitation and dimensionality issues are the main challenges in estimating (9). To accomplish this goal, I use a different set of higher frequency data covering the period under analysis (2007M1 to 2017M12). By doing this I circumvent some of the limitations presented in the baseline model with regard to heterogeneous effects by presenting a more robust and unrestricted approach. I seek to generate persistence profiles that will help me answer questions such as, how a MSA's labor outcomes and housing prices react to regional shocks associated to the shale boom; and whether the heterogeneous effects across MSA's explained by distance or other measure of economic relation.

4.3 Mechanism

I borrowed the state variables from the extensive empirical work on housing markets to infer how a shock in the oil sector in Bakken area spillovers across different MSAs. Economic theory shows that housing prices vary directly with demand for houses, reflecting income and demographic factors. It varies inversely with the housing stock and land use regulations on the supply side. One of the characteristics of the North Dakota shale boom was the shortage of housing. From Moretti's model it is conceivable to think that in the medium and long-term, higher wages will pressure housing market as people change from temporary to permanent residence. However, and for a given housing supply elasticity, workers and their families may choose to live in neighborhoods with better amenities such as better schools,

[20]PSW estabilished that the overall number of cointegrating relationships in the GVAR model cannot exceed the total number of long-run relations that exist in the underlying region-specific models

larger shopping areas, and thus willing to commute to maximize their utility. Hence, commuting workers will ease the pressure in the local housing demand and place in nearby areas with minimal or no drilling activity.

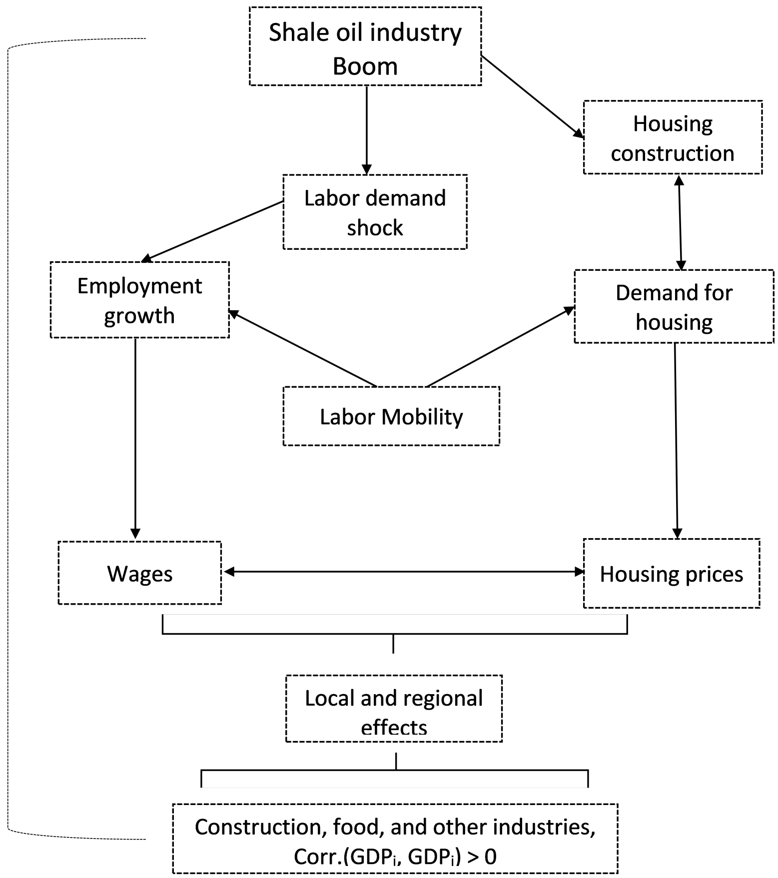


Figure 1: Mechanism

Figure 1 shows the shows that a regional labor demand shock on oil and gas industry will affect the local employment and overall earnings which in turns out to affect demand for housing. Housing market conditions can also affect workers mobility since workers reallocation decisions depend on in part on the relative cost of housing across MSAs. Therefore, labor mobility measured by migration flows is the mechanism at work with implications on local labor and housing markets. Clearly, the housing supply response to increasing housing demand hinges on the pace and scale of drilling activity; characteristics of the MSA; and its housing stock. Stringency and zoning regulations will affect the response. One can think that regions with fewer barriers to construction will observe an increase of new construction permits and higher economic growth. Overall the drilling activity regulates the relationship between labor market outcomes, housing prices, and housing stock across the MSAs. We expect a dynamic relationship among all endogenous variables across MSAs.

4.4 Shock Variable

The labor demand or productivity shock is based on Bartik (1991). It is based on the industrial composition of each metropolitan area and national industrial growth. The underlying idea here is to break any contemporaneous link between changes in MSA average productivity and changes in MSA-level industrial composition by using cross-MSA differences in initial industrial composition combined with national-level growth by industry. Following Bartik (1991), I take the national employment-level growth in employment for each industry and construct a location specific shock based on a baseline industry composition for each area. For each MSA, the predicted growth in labor demand is a weighted average of national industry growth rates, where the weights are equal to the share of an industry's employment relative to total metropolitan area employment. To be more precise, I compute the employment growth at the national level for each of the 12 selected industries[21] between over the years and then assign a predicted employment shock to MSA i, based on the baseline composition (year 2002) in MSA i. I constructed two Bartik instruments using two major labor market variables that mimic the labor market dynamics. The first is the average annual average employment variable to predict the employment shock - equation (26). The Wage Salary Employment is used to create the predicted wage shock - equation (27). Essentially, the Bartik instrument is the inner product of the industry location shares and industry component of the growth rates (Goldsmith-Pinkham et al., 2018). The exclusion restriction rest on the assumption that the 2002 industrial composition of each MSA is pre-determined at the time of later nationwide shocks, and that nationwide labor demand shocks are exogenous to each individual location[22].

[21] I compiled two and three digit NAICS industry classification: Oil and Gas Extraction (211); Mining, except oil and gas (212); Support Activities for mining (213); Utilities (221); Construction of Buildings (236); Manufacturing (31-33); Wholesale trade (42); Retail Trade (44-45); Transportation and Warehousing (48-49); Real State and Rental and Leasing (53); Accommodation and Food Services (72); and Other Services, except public administration (81).

[22] Bartik instrument relies on the assertion that neither industry composition not unobserved variables correlated with it directly predicted the outcomes of interest conditional on controls (Baum-Snow & Ferreira, 2015)

$$\triangle \ Empl \ shock_{it} = \sum_{I}^{12} \underbrace{\frac{empl^{I}_{i,2002}}{\sum_I empl_{[i,2002]}}}_{\text{term 1}} \cdot \underbrace{\triangle \ log \left(\sum_{j \in msa \neq i} empl^{I}_{j,t-k \ to \ t} \right)}_{\text{term 2}} \tag{10}$$

$$\triangle \ Wage \ shock_{it} = \sum_{I}^{12} \underbrace{\frac{wage^{I}_{i,2002}}{\sum_I wage_{[i,2002]}}}_{\text{term 1}} \cdot \underbrace{\triangle \ log \left(\sum_{j \in msa \neq i} wage^{I}_{j,t-k \ to \ t} \right)}_{\text{term 2}} \tag{11}$$

where, for instance for employment, $log \ empl_{[I-i,t]}$ is the average employment growth in industry I in MSA i at year t, and and $\triangle_{t-k \ to \ t}$ is the difference between years $t-k$ and t. The first term gives the share on employment(wage) in MSA i that is employed (wage bill) in industry I in the base year (2002). The second term express the change in employment (wage) in industry I, for all other regions. It gives for example, a measure of how employment in oil and gas industry has changes in the U.S. outside a particular MSA like Bismarck in North Dakota. Equations (26) and (27) above shows that the industry employment (wage) growth rates are adjusted to exclude local employment (wage) growth when calculating industry employment (wage) growth rates and express industry employment (wage) relative to national employment (wage) growth. The shock accounts for variation across space in the location of industry[23]. The intuition is that in MSAs with an initial concentration in industries that grow fast at national level, workers in all industries will experience better outside options and will be able to observe better wages. One can think these two shocks as instruments for employment and wage growth variables. Both variables are available on the Quarterly Census of Employment and Wages (QCEW). However, I also use the same variables reported on Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS).

4.5 Aggregation weight matrix

In this paper I employ three alternative spatial weight matrices[24]. The first is the spatial weighting matrix based on the geographical distance (latitude and longitude)[25]. The rational

[23]Table C.1 in the appendix reports the OLS reduced form. Both employment and wage shock instruments have the right sign and significant.

[24]The choice of proper weight matrix has significant impact on the estimatiom (Anselin et al., 2013).

[25]ArcGIS provides centroids (reference points at the center of each polygon) for all MSAs. The physical distances, measured in miles, between any pair of centroids define the entries in the matrix. One limitation

is that from Tobler's first law of geography - the closest a region is to the epicenter of the shock the large will be the impact. The inverse distance captures this notion that the effect declines with the distance[26]. Similar to Vega & Elhorst (2014), I use travel times and distance to capture the notion of costs of commuting and physical barriers such as rivers, mountains, type of roads and transportation from one MSA to another as well as the speed limits across urban versus non urban areas[27]. A typical simplified set of row normalized spatial weights matrix can be written as follow,

$$W = \begin{bmatrix} 0 & w_{12} & \dots & w_{1n} \\ w_{21} & 0 & \dots & w_{2n} \\ \vdots & \vdots & 0 & \vdots \\ w_{n1} & \dots & \dots & 0 \end{bmatrix} \tag{12}$$

where W mirror the spatial connectivity structure between locations necessary to build the region-specific-lagged endogenous variables. For each region, a vector of spatial regressor is built as ($Y^*_{it} = \sum_{i=1}^{N} w_{it} Y_{it}$). The regions specific weights w_{it} form a NxN spatial connectivity matrix W with $w_{11} + w_{21} + ... + w_{n1} = 1$. For instance, in a model with three variables, we are essentially estimating three system of equations for each region i. Then, the spatially lagged vector Y^*_{it} represents the state of the economy in the neighboring regions.

Figure (2) depicts employment decaying with the distance from Bismarck, the closest MSA to the Bakken Shale exploration as evidence of the presence of some spatial diffusion. The OLS coefficient of the fit line in panel (a) is negative and significant indicating that in average employment growth reduces by 0.3% for an extra 1 mile from Bismarck during during the period 2002 - 2007. Interestingly, the pattern still present after 2009 (panel (b)), though less pronounced. This trend seems to reflect a combination of economic downturn and subsequent recovery at the time when the production in the Bakken area reached the peak.

of this method of calculation is that these centroids are forced by ArcGIS to be in the center of each MSA's polygon. Residential areas may be located at the periphery of the polygon, and thus measuring distances in this fashion introduces measurement errors (cite here).

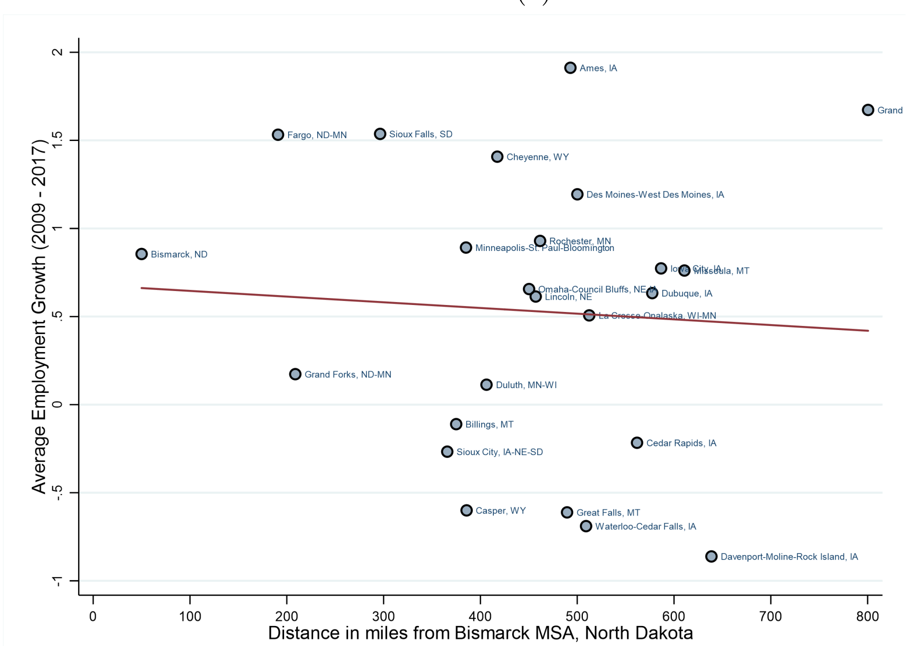
[26] I ruled out the contiguity weight matrix since most of MSAs across the country do not share common boundaries.

[27] The results using using time travel and travel distance driving weight matrices are qualitatively similar. I obtained this values using the distance calculator available on `https://distancecalculator.globefeed.com/US_Distance_Calculator.asp`

In light with the conceptual framework, I made the case that labor mobility regulates the relationship employment; wages; and housing market. So, the second approach is a socio-demographic weight matrix. Here I built a spatial weight matrix based on the net average migration flows across MSAs. For example, I record the net migration from MSA_i to MSA_j which corresponds to the symmetric flow from MSA_j to MSA_i. At the end I built a symmetric 24 x 24 normalized weight matrix. The intuition is straightforward. MSAs with higher rate of net in-migration should observe for instance, higher housing prices assuming other factors regulating housing supply remain unchanged. Data for metro to metro area migration flows is an average migration flows from 2010 - 2014 from the American Community Survey in the Census Bureau[28].

[28]Figure B.6 in the appendix outline Moran's spatial correlation plots.

(a)



(b)

Figure 2: Employment Growth and Distance

Finally, I employ a spatial weighting matrix based on economic distance. Evidence has shown spatial correlation across regions and markets through key economic variables and less by distance. In absence of on bilateral trade flows between MSAs, I built a gravity-type weight matrix which has long tradition in the field of international economics. The key feature is that the size of the trade or economic relation between any two locations is proportional to the economic mass of the two locations, typically measures by GDP and population, and inversely related to the distance between them. The economic mass of MSA_i and MSA_j is the product of the GDP of both MSAs weighted by travel time t between i and j: $w_{i,j} = [(GDP_i * GDP_j)/t_{i,j}]$. The rationality is that, the impact of the shock will depend not only in the economic mass but also proportional to the level of flows (migration, commuting) between two locations[29].

5 Empirical Analysis

5.1 Data and Methodology

I combine data from multiple sources and frequencies over the period 2002 - 2017, covering 24 MSAs[30], defined as my geographical unit of analysis. The bulk of data used in this paper is from the Quarterly Census of Employment and Wages (QCEW) program from the Bureau of Labor Statistics[31]. It covers more than 95 percent of U.S. jobs available at the County, Metropolitan Statistical Area (MSA), State, and national level, by detailed industry. I compiled annual data on employment levels, total annual wage and salary income, total payroll by industry and metropolitan statistical area. I supplement the QCEW data with data on employment and unemployment from the Bureau of Labor Statistics (BLS). From the Bureau Of Economic Analysis (BEA), I obtain data on yearly time series for Real Gross Domestic Product in chained dollars (y); employment rate ($empl$), wage salary ($wsal$), personal income ($pinc$) and population (pop).

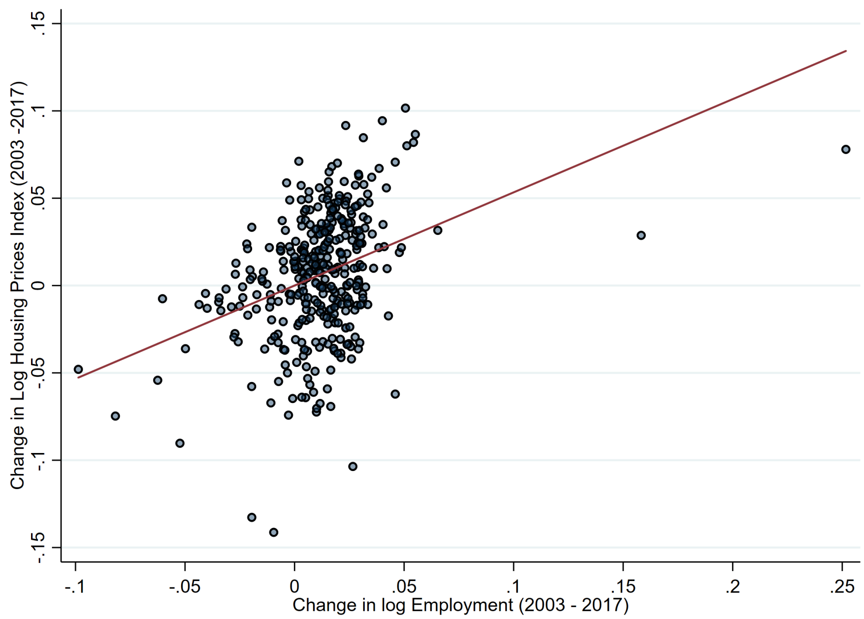
Data on Housing Price Index (hpi) is from Freedie Mac in a monthly frequency deflated using Consumer Price Index - all urban consumers seasonally adjusted (cpi). Figure (3) shows the empirical relationship overtime between employment, wages and housing prices for the selected MSAs. Panel (a) shows a positive relationship between changes in housing prices and annual growth in employment. One can observe the employment growth range

[29]Figure B.7 in the appendix displays Moran's spatial correlation plots.

[30]See Table (A1) in the Appendix display all variables used in the estimation, their measurement, frequency, transformation, and sources

[31]The QCEW provides an employment benchmark and sample frames for other Bureau of Labor Statistics (BLS) programs, as well as a basis of estimation of the wage and salary component for the Bureau of Economic Analysis Personal Income statistic.

from negative to positive 5% with log housing prices changes between -7% to 10%. Similarly, most of MSAs growth wages (-3% and 5%) are positively correlated with changes in housing prices. Overall, figure (3) is illustrative of a positive correlation between labor market outcomes and housing prices. We also observe considerable heterogeneity across MSAs.



(a)

(b)

Figure 3: Annual Employment, Wage and Housing Prices Growth

Measures of oil production *oilprod*; wells production *wprod*; oil permits *wperm*; rig counts; and North Dakota Crude Oil First Purchase Price *oilp* are from North Dakota State Government and Energy Information Department (EIA). These variables are highly correlated with employment in the oil and gas industry and therefore mimic perfectly the productivity shock in the sector.

I use the MSA classification from BEA/Census as my unit of analysis. I want to take advantage of more recent data on GDP not widely used as well as an economic division that fits better regional labor markets dynamics. One alternative would be using Commuting Zones (CZ) that are better aggregation of labor markets. However, this option is off the table since there are few defined CZ in the neighboring of Bakken shale[32]. Moreover, since I want to estimate regional spillover from exploration of Bakken shale, I restricted my analysis to the neighborhood of North Dakota and Montana states. First, using GIS I mapped all MSAs in the USA and defined a 400 mile radius from the center of Bismarck MSA in North Dakota, the nearest MSA to Bakken Shale field. Most of the counties in the Bakken area are rural with high degree of sprawl and not part of any MSA in both North Dakota (William; Mountrail; Mackenzie; Dunn and, Stark) and Montana (Prairie and Richland). This distance is based on anecdotal evidence from testimonials from commuting workers in the field[33] as well as personal discretion - I assume 400 miles a decent maximum average distance an individual is willing to commute weekly. The average distance across the sample is 447 miles.

Second, to maximize the geographic information and alluding Tobler (1970)'s first law of geography, I defined a 50, 150, 300 and 400 mile radius from the centroid in Bismack (Figure (4) below). However, very few MSAs have data available in key variables such as GDP, I circumvent this by relaxing the mile radius criteria by including all MSAs with available data on key variables such as GDP[34]. I end up with a balance panel data comprising 24 MSAs across 7 states, namely, North Dakota (ND), South Dakota (SD), Montana (MT), Wyoming (WY), Nebraska (NE), Minnesota (MN), and Iowa (IA) - MSAs in green color in figure (4).

[32]Daron et. all use commuting zones to evaluate the impact of fracking across the US

[33]From internet/CNN documentary

[34]Figure (A.3) in the appendix.

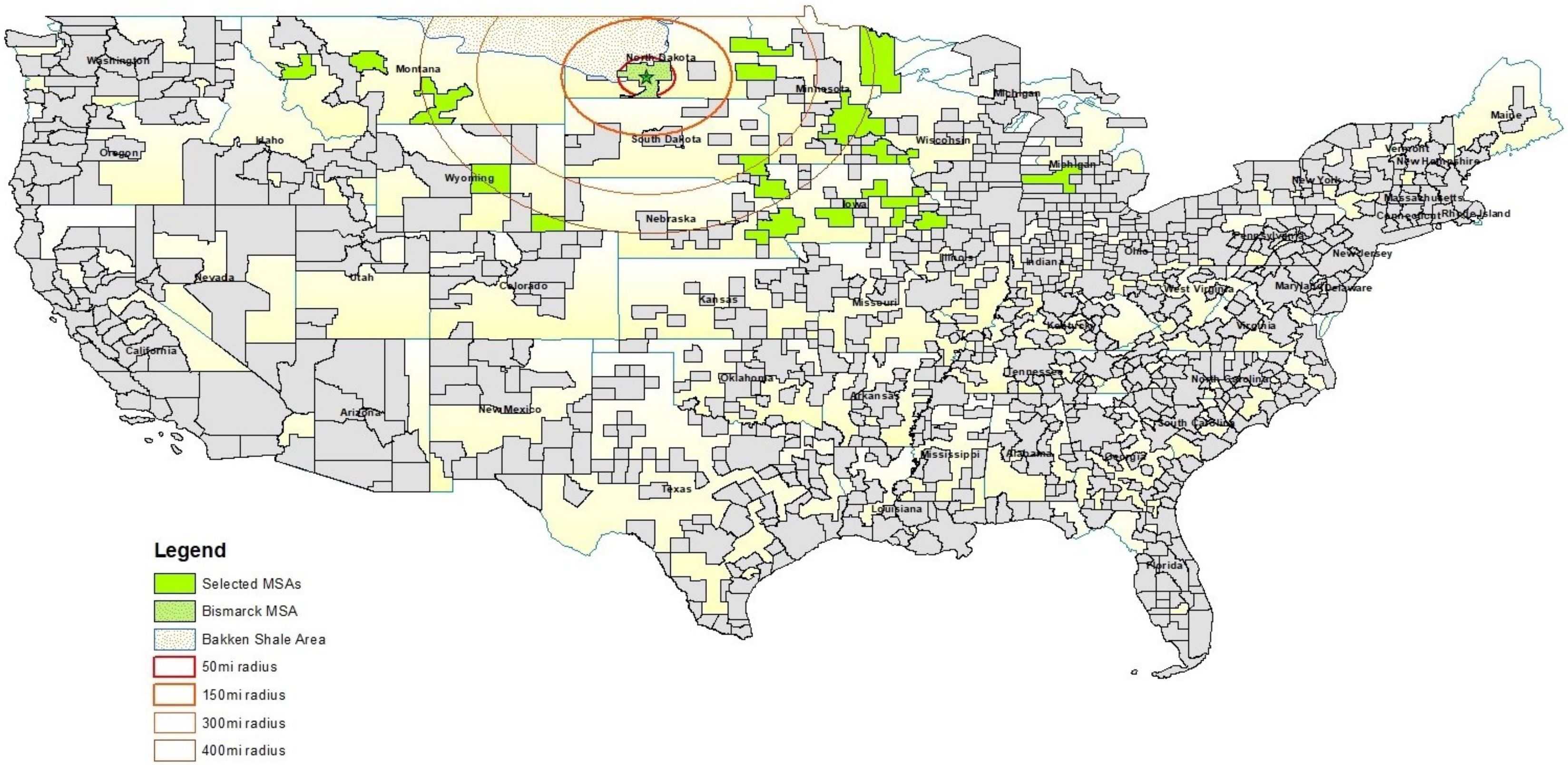


Figure 4: Metropolitan Statistical Areas in the USA

The average employment rate was 1.14 percent however with great variability across MSAs (see Figure A.4 in Appendix). Not surprisingly, Bismarck and Fargo, still showing higher average employment growth rate both with 2.10%; higher labor force participation growth - Fargo (1.84%), Bismarck (1.35%); and lower average unemployment rate - both with 3.10%. Overall, wage growth exhibit less variability averaging 4.1 percent across the sample. Notably, both Bismarck and Fargo still ranked first and second in wage growth (6.2% and 5.5%, respectively). In similar fashion, changes in the housing price index was also dominated by the three MSAs located in North Dakota (see Figure A.5 in the Appendix) - Bismarck (2.95%), Grand Forks (2.35%) and Fargo (1.76%). Furthermore, nearby MSAs such as Casper in Wyoming, and Billings in Montana noticed higher housing price changes (1.84% and 1.61%, respectively).

Table 1: Summary Statistics table:

	Mean	SD	Min	Max
GDP growth rate	2.29	4.298	-13.7	22
Unemployment rate	4.327	1.343	2.0	12
Annual Average Employment Growth	0.011	0.025	-0.1	0
Annual Average Employment	167,473	299,840	26,114	1,666,133
Labor Force Participation	210,407	370,758	37441.2	1,991,127
National Employment	135,898.25	4921.9	130345.0	146,611
Employment in Oil ad Gas Extraction (NAICS 211)	89.416	229,74	0.0	890
Population Growth	0.923	0.736	-1.7	3
Housing Prices Index (log changes)	0.006	0.036	-0.1	0
Personal Income Growth	0.043	0.036	-0.1	0
Personal Income (millions)	16,662.09	32,520.251	2,152.8	215,087
Total Annual Wages (millions)	7,402.7	15,702.04	644	102,3311
Total Wages Growth	0.0410	0.0373	-0.2	0
Annual Aver. Weekly Wage in Oil and Gas Extraction (NAICS 211)	505.60	874.0063	0.0	3,341
Annual Average Weekly Wage	730.46	137.89	456.1	1,182
Wage salary Growth	0.0086	0.0161	-0.1	0
Wage Salary Employment	212,792	371,244	35,774	2,038,811
Housing Permits (units)	1,838.719	3,292.16	120	27,714
Annual labor productivity Oil and Gas Extraction (NAICS 211)	4.703	0.148	4.4	5
Distance (in miles)	447.09	155.376	50	800
Wharton Regulation Index - WRLURI	-0.484	0.553	-1.3	1
Housing Supply Elasticity	3.653	1.1624	1.45	5.98
Observations	384			

6 Results and Discussion

6.1 Spatial Regression - Dynamic Panel Data using "GMM"

Tables 2 to 4 report estimation results for the effect of labor demand shock and housing regulations on housing prices, employment and wages by instrumenting the endogenous variables system GMM. Additionally, I present the non spatial GMM estimates alongside with alternative unit row-normalized spatial weight matrices. I want to test to evaluate the sensibility of the estimates to the specification of the weight matrix. The interpretation of the coefficients is not straightforward as in liner regression models due to the composed effect of spatial interaction and time dynamics as expressed in equation 2. Thus, we report the marginal effects that can be interpreted as elasticities in the spatial models (column 2 to 9).

Table 2: Housing price changes, shock and regulation

	△ Log Housing Prices								
	Non-Spatial	Inv. Distance		Migration		Gravity		Drive Time	
	Coeff.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Lag depend Var.	0.605***	0.646***	0.648***	0.618***	0.620***	0.627**	0.629***	0.652***	0.654***
	[0.046]	[0.038]		[0.038]		[0.038]		[0.038]	
Shock1	0.349**	0.602**	0.159**	1.308**	0.346**	1.347**	0.357**	0.905	0.239
	[0.159]	[0.272]		[0.541]		[0.560]		[0.581]	
Shock1*WRLURI	0.176	0.216	-0.018	0.517*	-0.044*	0.387	-0.033	0.251	-0.02
	[0.240]	[0.289]		[0.273]		[0.264]		[0.268]	
W1.Shock1		0.0001	0.014	0.988	0.322	0.383	0.109	-0.842	-0.114
		[0.003]		[1.049]		[0.748]		[0.529]	
W1 Shock1*WRLURI		0.003	-0.119	6.154	-0.544	4.238**	-0.379**	-1.202	0.062
		[0.007]		[2.415]		[1.544]		[1.091]	
Observations	285	360		360		360		360	

Notes: [1] * Denotes 1% significance level, ** denotes 5% significance level, *** denotes 10% significance level. [2] Standard errors in brackets. [3] Shock 1 - BartiK employment shock

Overall, coefficient estimates for the serially lagged dependent variable are significantly different from zero at 1 per cent level and large, especially for housing prices. The effect of the shock is positive and significant for all three variables; however, we find mix results when changing the spatial weight matrix. A careful look into Table 3, one can observe the effect of the shock is larger when using gravity (column 7) and migration (column 5) weight matrices and insignificant at 5 per cent level using inverse distance and drive time weigh matrices. This suggest the size of the MSA and migration flows are in part the driving forces behind housing prices. One percent increase in the shock variable increased housing prices growth by 0.36 and 0.35 percent. The magnitude is almost similar to that found in the non-spatial in column (1); however, strongly significant in column in the spatial setting. The effect of zoning and land regulation within the MSA is insignificant and with wrong signal. No significant spatial effect of the shock and land use restrictions are present.

Table 3 display the effect of the shock on employment growth. The coefficient of the spatially lagged value of employment growth is positive across different weigh matrices specifications ranging from 1.48 pp to 1.74 pp. Whereas the effect of the shock is significant across the four weigh matrices, the size is larger when using drive time (0.309) and migration (0.226) weight matrices. The impact of the shock on employment growth drops with zoning and land restriction for housing construction. This sizable effect is present using migration and gravity weight matrices. Therefore, zoning restrictions reduce the initial employment growth response to 10% increase in the labor demand shock by 0.2 pp. Labor demand shock in other MSAs reduce employment at local MSA irrespective of the weight matrix. The estimated coefficients in column 5 and column 3, suggest that workers respond to external labor demand shocks mostly by migrating (0.53) and this response is inversely proportional to the distance (0.47 pp). The size of the MSA and commuting still relevant mechanisms in play. Zoning restrictions in the neighbor MSAs have positive and significant effects on local employment growth.

Table 3: Employment growth, labor demand shock and regulation

	△ Log Employment								
	Non-Spatial	Inv. Distance		Migration		Gravity		Drive Time	
	Coeff.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Lag depend Var.	0.148***	0.162***	0.162***	0.173***	0.174***	0.165**	0.165***	0.168***	0.168***
	[0.039]	[0.035]		[0.035]		[0.035]		[0.035]	
Shock1	1.005***	1.289**	0.182**	1.884***	0.226***	1.496**	0.211**	2.190***	0.309***
	[0.137]	[0.224]		[0.424]		[0.445]		[0.439]	
Shock1*WRLURI	0.038	-0.586***	0.027***	-0.424*	-0.019*	-0.370*	-0.016*	-0.287	0.013
	[0.214]	[0.236]		[0.227]		[0.222]		[0.219]	
W1.Shock1		-0.009***	-0.470***	-3.028***	-0.526***	-1.823**	-0.276**	-1.340***	-0.097***
		[0.002]		[0.834]		[0.617]		[0.401]	
W1 Shock1*WRLURI		0.022***	0.444***	-6.831**	0.322***	-3.868**	0.185**	-2.50**	0.056**
		[0.005]		[2.144]		[1.310]		[0.8747]	
Observations	285	360		360		360		360	

Notes: [1] * Denotes 1% significance level, ** denotes 5% significance level, *** denotes 10%significance level. [2] Standard errors in brackets. [3] Shock 1 - BartiK employment shock

Table 4 reports the effect of the shock on wages. We find that one percent point increase of the shock in a particular MSA increases wages between 0.34 pp to 1.29 pp in the spatial model (columns 2 - 9). The estimated coefficient from non-spatial model lies between the spatial model coefficients. This effect is significant and more pronounced using inverse distance (1.39) and drive time (0.39 pp) weight matrices. I identified the presence of significant and meaningful spatial spillovers. Shocks in other MSAs reduce wages in a particular MSA and this effect is larger the closest the other MSAs are located (3.35 pp in column 3) and greater out migration takes place (0.67 pp in column 5). This result suggests workers move out to more productive regions and therefore depressing wages in the areas they left. Looking into stringency in housing regulation, we confirm wages are higher in MSAs with higher zoning and land restriction for construction of housing. It further increases wages by 0.18 pp and 0.02 pp more in MSAs, a result that is supported in the literature (authors that find similar result).

Table 4: Wage growth, labor demand shock and regulation

	△ Log Wages								
	Non-Spatial	Inv. Distance		Migration		Gravity		Drive Time	
	Coeff.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Lag depend Var.	0.219***	0.228***	0.229***	0.233***	0.233***	0.224***	0.224***	0.220***	0.220***
	[0.320]	[0.030]		[0.029]		[0.029]		[0.029]	
Shock1	0.767***	0.884***	1.387***	1.830***	0.345***	1.839***	0.349***	2.084***	0.392***
	[0.069]	[0.086]		[0.209]		[0.218]		[0.218]	
Shock1*WRLURI	0.066	-0.331**	0.182**	-0.270**	0.016**	-0.131	0.008	-0.108	0.007
	[0.105]	[0.100]		[0.109]		[0.105]		[0.104]	
W1.Shock1		-0.005***	-3.346***	-2.903***	-0.673***	-1.220***	-0.246***	-1.204***	-0.116***
		[0.001]		[0.421]		[0.288]		[0.195]	
W1 Shock1*WRLURI		-0.012***	2.698***	-5.741***	0.361***	-0.574	0.037	0.027	-0.001
		[0.001]		[1.086]		[0.627]		[0.430]	
Observations	266	360		360		360		360	

Notes: [1] * Denotes 1% significance level, ** denotes 5% significance level, *** denotes 10%significance level. [2] Standard errors in brackets. [3] Shock 1 - BartiK employment shock

Until now, I have estimated the impact of the labor demand shock on housing price, employment, and employment by system GMM to address endogeneity on the lag dependent variable and the spatial component. However, the theoretical model and empirical work has shown that housing supply impacts labor market outcomes through housing prices and migration responses. With this in mind, I run an augmented model where employment and housing prices changes are endogenous. Table 5 reports the estimates of the impact of the shock on housing prices through employment controlling for land use and regulations on the housing supply side. I found evidence of significant effect of employment and wages on housing prices. One percent increase in employment increases the housing price index by about 0.43 to 0.45 pp on average within the MSA across all spatial weight matrices. This result suggests employment increases more in MSAs with lower housing supply elasticity and lower stringency in housing construction. Similarly, the effect of local wages on housing prices is significant and more pronounced through migration and gravity spatial weight matrices. We also observe negative wage spillover from other MSAs to local housing prices. One percent increase in wages outside MSAs drops local wages growth by 85 pp (column 4). These results matches the prediction of the theoretical model. As workers migrate into these cities to take advantage of the increased wages, they drive up the housing prices by increasing the local demand for housing. It is also consistent with that from Saks (2008), Glaeser et al (2006). Land regulation and housing supply elasticities affect the employment response to the shock with significant implications on housing price changes. The effect of the local labor demand shock translates into higher employment growth and moderated increases in housing prices. Places with higher wages observe higher growth in housing prices. Additionally, proximity, size of the economy and migration flow are key determinants of these effects.

Table 5: Housing wages and employment (IV)

	△ Log Housing Prices							
	Inv. Distance		Migration		Gravity		Drive Time	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Lag depend Var.	0.614***	0.615***	0.622***	0.623***	0.627***	0.623***	0.648***	0.650***
	[0.042]		[0.041]		[0.042]		[0.043]	
Log change Employment	0.234**	0.439***	0.231**	0.433**	0.239**	0.448**	0.220**	0.412**
	[0.100]		[0.099]		[0.100]		[0.099]	
Log change Wages	0.283*	0.398*	0.377**	0.530**	0.370**	0.520**	0.294*	0.413**
	[0.151]		[0.168]		[0.172]		[0.167]	
W1.Wages	-0.001**	-0.648**	-0.608***	-0.850***	-0.603***	-0.851***	-0.402**	-0.555**
	[0.000]		[0.154]		[0.168]		[0.136]	
Observations	360		360		360		360	
R-squared	0.492		0.502		0.496		0.495	

Notes: [1] * Denotes 1% significance level, ** denotes 5% significance level, *** denotes 10% significance level. [2] Standard errors in brackets. [3] Endogenous variable: employment. [3] Endogenous variable: employment. [4] Instruments: Bartik employment shock, housing supply elasticity (from Saiz), land use regulation (WRLURI).

Furthermore, investigate the effect of housing prices, a measure of demand, on housing construction measured my building permits, I run a model where I instrument housing prices using bartik employment and wages shocks, housing supply elasticity and zoning regulations. Table 6 depicts the impact of housing price and wages on building permits. The estimated effects are significant, positive and of the same size irrespective of the spatial weight matrix employed. Building permits are more sensitive to past values of itself than housing price changes and no reaction to local and other places. One percent point increase in housing price index increase building permits by 0.4%. These results indicate housing permits are function of a more complex set of determinants beyond housing supply elasticity and regulation. The urban literature provide large evidence that small increases in housing prices do not translate into large supply responses in cities because the increasing housing stock will be followed by a rise in land prices(Fujita, 1989; DiPasquale & Wheaton, 1994).

Table 6: Housing Permits and Hosuing Prices

	Log Building Permits							
	Inv. Distance		Migration		Gravity		Drive Time	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Lag depend Var.	0.501***	0.50***	0.484***	0.483***	0.500***	0.499***	0.499***	0.498***
	[0.041]		[0.041]		[0.041]		[0.041]	
Housing Prices	4.932***	0.004***	5.025***	0.004***	4.864***	0.004***	4.783***	0.004***
	[0.501]		[0.501]		[0.449]		[0.495]	
Wage	0.156	0.000	- 0.017	-0.000	0.251	0.001	0.186	0.001
	[0.525]		[0.552]		[0.578]		[0.540]	
W1.Wage	0.003**	0.008	1.814**	0.010	1.119	0.006	1.305	0.007
	[0.002]		[0.793]		[0.836]		[0.720]	
Observations	360		360		360		360	
R-squared	0.594		0.555		0.548		0.550	

Notes: [1] * Denotes 1% significance level, ** denotes 5% significance level, *** denotes 10% significance level. [2] Standard errors in brackets. [3] Endogenous variable: housing price. [4] Instruments - bartik employment and wage shock, housing supply elasticity (from Saiz), and land use regulation (WRLURI)

The model predicts that housing market conditions can influence workers mobility since their reallocation decision depend among others in part on the relative cost of housing across MSAs. The mechanism at work here is straightforward. Labor demand shock and housing regulations affect labor participation through employment growth. Table 7 provides estimates on the response of labor force participation to an increase in labor demand. The effect is significant ranging from 0.26 pp to 0.28 pp for all spatial weights matrices. I identified spatial spillovers related to proximity (-0.14 pp) in column 2, and commute (-0.06 pp) in column 8. Labor demand shocks in other MSAs with less restrictive policies in housing construction will reduce local labor force participation. Workers move to the closest neighbor MSAs or those with lower driving time commuting. Productivity shock translates into higher employment growth in MSAs the more elastic housing supply is and less restrictive construction policies are in place. This result is also consistent with Glaeser & Gyourko (2005).

Table 7: Labor Force Participation

	Labor Force Participation Growth							
	Inv. Distance		Migration		Gravity		Drive Time	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Lag depend Var.	0.244***	0.246***	0.249***	0.250***	0.245***	0.274***	0.248***	0.251***
	[0.054]		[0.055]		[0.054]		[0.054]	
Employment	0.158***	0.275***	0.154***	0.270***	0.157***	0.274***	0.150***	0.263***
	[0.037]		[0.037]		[0.037]		[0.037]	
Employment shock	0.486*	0.120*	0.323	0.080	0.510*	0.126*	0.420	0.104
	[0.272]		[0.259]		[0.274]		[0.273]	
W1.Employment.Shock	-0.604**	-0.141**	-0.431	-0.131	-0.631	-0.167	-0.503*	-0.064*
	[0.277]		[0.262]		[0.280]		[0.262]	
Observations	360		360		360		360	
R-squared	0.120		0.115		0.121		0.117	

Notes: [1] * Denotes 1% significance level, ** denotes 5% significance level, *** denotes 10% significance level. [2] Standard errors in brackets. [3] Endogenous variable: employment. [4] Instruments - Bartik employment and wage shock, housing supply elasticity (from Saiz), and land use regulation (WRLURI).

6.2 Global Vector Auto Regressive - Estimation and Testing

GVAR methodology can be applied to both stationary and integrated variables so that one can distinguish between short-run and long-run relations. I investigate the order of integration of each variable by performing the Augmented Dickey-Fuller (ADF) test and Weighted-Symmetric augmented Dickey-Fuller (WS) tests for all domestic, foreign-specific and global variables included in the GVAR statistics. The results reported in Table D.1 and D.2 in the appendix Akaike indicate that most of the variables in levels contain a unit root. However, all variables are stationary after first difference. The 95% critical value of ADF statistics for regressions with trend is -3.45 and -2.89 without trend.

I search for the optimal lag length as well as the optimal lag for the global variables for each MSA-specific model by using the AIC criteria. However, due to data limitation, I follow DdPS and set the maximum lag order of three for domestic variables "p" and two for foreign variables "q". Table D.4 in the appendix reports the lag order of individual VARX*. It should be noted that "p" and "q" need not to be the same for each model. The lag order of th GVAR "p" is computed as the maximum of the maximum lag order of "p" and "q" across all individual MSA models.

Table D.4 also reports the cointegrating relationships. It is computed using the Johansen's trace and maximum eigenvalue statistics defined in Pesaran, Shin and Smith (2000) for models with weakly exogenous I(1) regressors. I kept the intercepts and restricted the trend coefficients in the Vector Error Correction Model (VECM). With exception of Lincoln, all MSA show at least one cointegrating relationship. Interestingly, the three MSAs in North Dakota have at least 2 cointegrating relationship - Bismarck (2), Fargo (3) and Great Forks (2). However, the computed cointegrated relationships are purely statistical in nature. They are not grounded in any economic theory.

Table 8: Set of varibles used for MSA-specific VARX* models

	non-Bismarck model (i$\neq$ *Bism.*)			Bismarck Model (i = Bism.)		
	Domestic	foreign	global	domestic	foreign	glogal
	$\boldsymbol{x_{it}}$	$\boldsymbol{x^{\star}_{it}}$	$\boldsymbol{d_{it}}$	$\boldsymbol{x_{it}}$	$\boldsymbol{x^{\star}_{it}}$	$\boldsymbol{d_{it}}$
Unemployment rate	urt_{it}	$urt^{\star}_{it}$		urt_{it}		
Employment	emp_{it}	$emp^{\star}_{it}$		emp_{it}		
Total Private Payroll	tpp_{it}	$tpp^{\star}_{it}$		tpp_{it}	tpp_{it}	
Housing Price Index	hp_{it}	$hpi^{\star}_{it}$		hpi_{it}		
Average Hours Earnings	ahe_{it}				$ahe^{\star}_{it}$	
Average Week Earnings		$awe^{\star}_{it}$		awe_{it}		
Bakken Oil Production			oil_t	oil_t		
Bakken Wells Producing			wel_t	$well_t$		
Shale Oil Permits			$perm_t$	$perm_t$		
Well Spud			spd_t	spd_t		
Average Rig Count			rig_t	rig_t		

The weak exogeneity assumption is the key feature of the GVAR modeling. By assuming all MSA-specific foreign variables are weak exogenous with respect to the long-run parameters of the error correction form of the VARX* model. This assumption allows to each MSA model to be estimated individually and only at later stage combined together. In the context of cointegrating models, this assumption implies no feedback from domestic variables to foreign variables[35]. The F-test for the joint significance of the estimates error correction terms for the MSA foreign-specific and global variables. Table D.5 in appendix reports these estimates. Results at 5% significance level suggest that most of the weak exogeneity assumptions cannot be rejected. Only 21 out of 157 exogeneity test were rejected.

Table D.6 in the appendix presents the contemporaneous effects of foreign variables on their domestic variables on their domestic counterparts together with t-ratios computed using the Newey-West heteroskedasticity and autocorrelation consistent variance estimator. Because all variables are log-differenced, we can interpret the estimates as impact elasticities. The average contemporaneous effect of foreign housing price on domestic housing price changes is 0.88 with a minimum of 0.44 and a maximum of 1.02. Billings (1.02) Sioux City (0.96) and Fargo (0.86) are the top three most sensitive MSAs to changes in foreign housing price changes. This observation is consistent with proximity of these MSAs with Bismarck suggesting spillover effect through distance. Similar pattern is present by looking into average week wages and unemployment rate with Fargo positioning among the top three. Overall results are suggestive of high elasticity between housing prices, total payroll, and earnings. In contrast, we find rather low average elasticities for unemployment rate (0.15), however, with higher variability across the MSAs (a maximum of 2.62 and minimum of -1.83).

Furthermore I examine the weak dependence of the idiosyncratic shocks of the individual MSAs models. More precisely, this key assumption in GVAR modelling requires that individual MSAs models be cross-sectionally weakly correlated as the number of MSAs approaches to infinity as I pointed out in the previous section 4.2. Table D.7 in the appendix reports the average pairwise cross-section correlations for the levels and differences of the endogenous variables as well as the associated the associated residuals of the MSA-specific VECMX* models. The housing price show the highest cross-section correlation among the variables in first differences ranging between 66% and 85%, followed by average week wages (5% - 45%). Unemployment rate shows a lower cross-section correlation (-1% - 23%). Despite overall cross-section correlations were reduced after first difference the same is not true for housing prices which remains moderately high in first differences (from an average of 75% in levels to 82%).

Finally, a closer look to cross-correlation of the residuals from the VECMX* models revels that the model has been successful in capturing the common effects on all variables. The

[35] $x_{it}^{\star}$ is said to be "long run" forcing for x_{it}

cross-correlations of the residuals are lower, ranging from -15% to 17%[36]. Total payroll and average week earnings are the two variables high higher average cross-section correlation of the residuals ranging from -3% to 8%. It is worth nothing that the cross-section correlation of the VECMX* is not a formal statistical test of the importance of the foreign variables in the model; still they provide guidance about the usefulness in modelling global interdependencies (Di Mauro & Pesaran, 2013). Overall, the results provide strong evidence of lower degree of correlation exists across shocks after conditional on foreign variables. More specifically, once country-specific models are defined conditional of foreign variables, the remains only a modest degree of correlations across the shocks from different MSAs.

[36]The minimum and higher values of the cross-section correlation of the residuals are from housing prices The housing prices although with higher variability.

6.2.1 Persistence

In this section, I estimated the Generalized Impulse Response Functions (GIRFs) from the estimated GVAR[37]. It is an alternative to the orthogonalized impulse response (OIR) proposed by Sims (1980) for not being constrained by the order of the variables. Indeed, the GIRFs here generate shock response profiles that do not vary for different orders of variables. This feature is also relevant since it is unclear how economic theory could guide the ordering hierarchy. Most of the eigenvalues fall on the unit circle suggesting the model is stable and that shocks will have permanent effects on endogenous variables.

I started off by examine the impact of Bismarck one standard error positive shock on Bakken oil Production, Well Spud, and "Rig Count"[38] using migration weight matrix. However, the GVAR model using "Average Rig Count" as a global variable stands out. Therefore, I simulate the impact of the positive shock on "Rig Count" on the following: (a) average week wages; (b) average hours earnings; (c) unemployment; and (d) housing price. Secondly, I consider the effect of Bismarck one standard error (s.e.) positive shock on average week earnings. I assumed Bismarck as the dominant model from which global shocks are generated. Figures 5 to 9 present the bootstrap median estimates and the associated 90% bootstrap confidence intervals for the GIRFs.

Average week earnings. Figure 5 below traces out the evolution of average week wages across after one s.e. positive shock to rig count in North Dakota over a 40 month horizon. I report the 8 MSAs closer (8 graphs on top of the panel), and 8 MSAs more distant from Bismark (8 graphs in bottom of the panel)[39]. I assume being in the vicinity of the region, migration flows and the size of the MSA are important mechanisms in the spillover effect. This shock is equivalent to an increase of around 15%[40] in the average week earnings in Bismarck per month which is quite large. The response of the shock across the MSAS takes place quickly with exception of Cedar, Dubuque and Casper which react with some delay of

[37]It was introduced by (Koop et al., 1996) and further developed H. H. Pesaran & Shin (1998) for vector error-correcting models.

[38]An oil rig is a large machine that's used for drilling deep holes in the earth so that oil can be extracted. There are both on-shore and off-shore oil rigs. An oil rig is almost always an enormous, complex structure that can drill miles into the ground to access oil. Interestingly, this variable capture better the first stage of oil and gas exploration - investment stage, and latter production. Once the rig is open in the first stage, and the gas and oil capacities are determined, the production takes place which defines the production stage. Generally speaking, this variable resembles a combination of well spud and oil and gas production.

[39]Seee table xx in the appendix

[40]The standard deviation of weak wages in Bismarck over the sample is 0.148.

approximately 4 months. A one percent increase in "rig count" in North Dakota results in 0.47% increase in average week wages in Bismark after one year and a half. This effect is the largest across the MSAs reflecting the feedback effect. For those MSAs in the vicinity of Bismark, the impact of the shock is positive. On impact, average week earnings increased by 0.05% after 32 months in Billings, the largest impact across the MSAs. Great Forks shows a quick positive impact (0.003%) which declines after 3 months and bounces back to an average 0.002% after 2 years. Similarly, Fargo shows a modest impact in earnings growth (0.02%) after 3 months, however moving to a negative territory after one year and dissipating after 40 months. However, a different picture is illustrated for Sioux City, Sioux Falls, and Davenport - the first two are closer to Bismarck and the later farther. They experienced a more persistent declining in average week earnings growth over the period. Not surprisingly, similar pattern in the response of the average hours earnings for the four closest and four further MSAs to a shock in the "rig counts" (Figure 6).

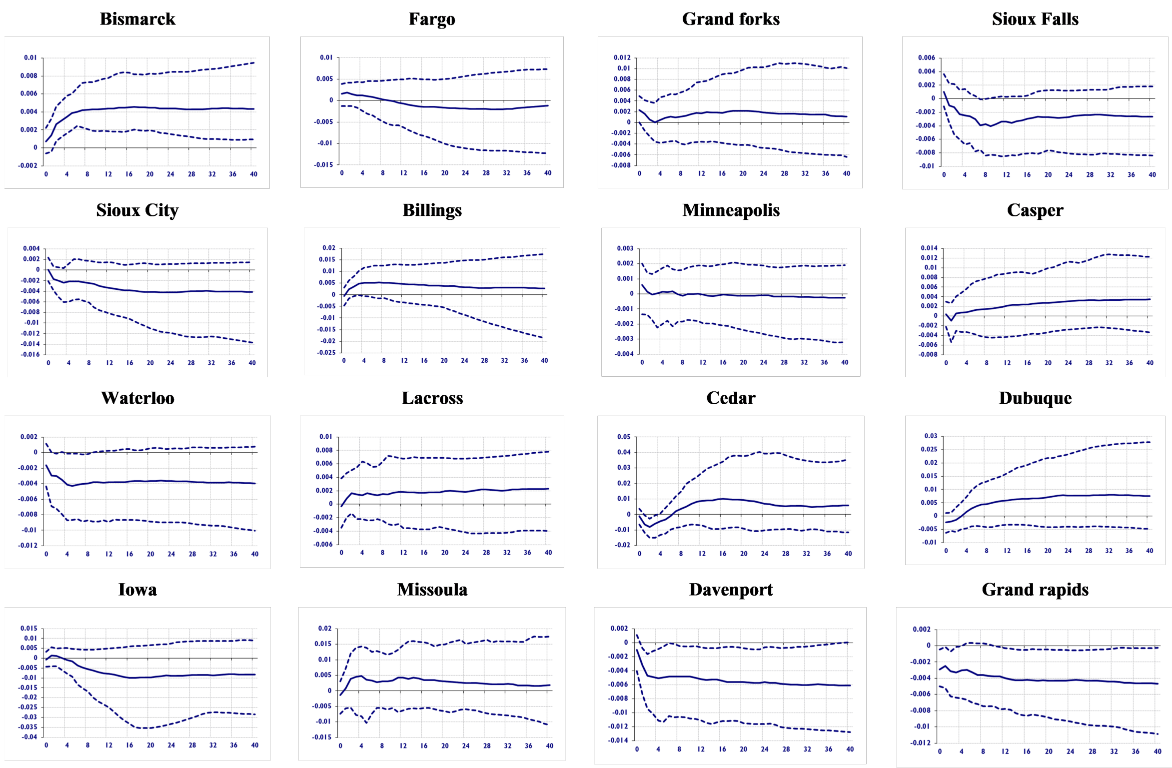


Figure 5: Bootstrapped GIRFs from one SE positive shock on Rig Count in Bismarck on regional Average Week Earnings

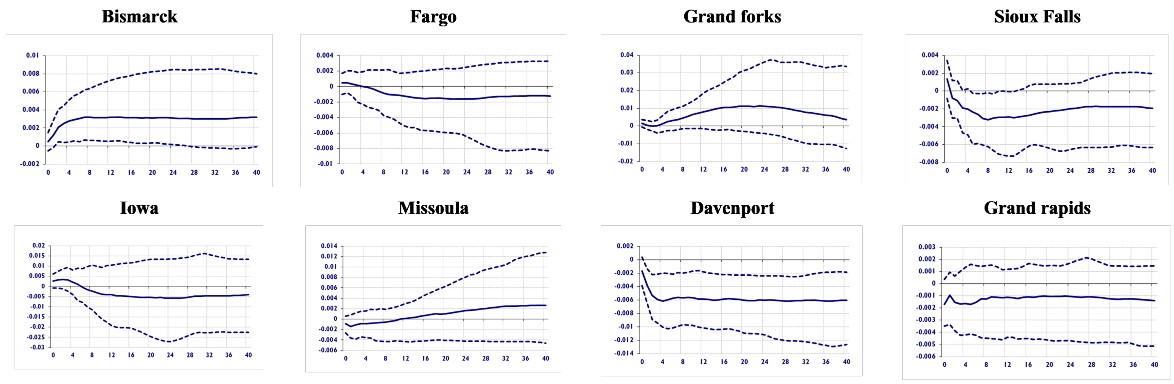


Figure 6: Bootstrapped GIRFs from one SE positive shock on Rig Count in Bismarck on Regional Average Hours Earnings

Unemployment Rate. Figure 7 display the GIRFs for a one percent s.e. increase in "rig count" on the regional unemployment for the 7 closest MSAs to Bismarck. One can notice a persistent decline of the unemployment rate, the shock transmit much more slowly and delay in all MSAs with exception of Sioux Falls and Sioux City. The reaction not only is quick and persistent as well as it is in the opposite direction - an increase of about 0.008% after 4 months. Not surprisingly, Bismarck absorbs most of the gains with the unemployment rate reaching -0.002 percentage points (pp) after 16 months followed by the Fargo (-0.001pp) afte 12 months. Although a slow pace reaction, Grand Forks shows the largest MSA-specific impact with the unemployment rate decelerating continuously reaching by -0.005pp after 28 months.

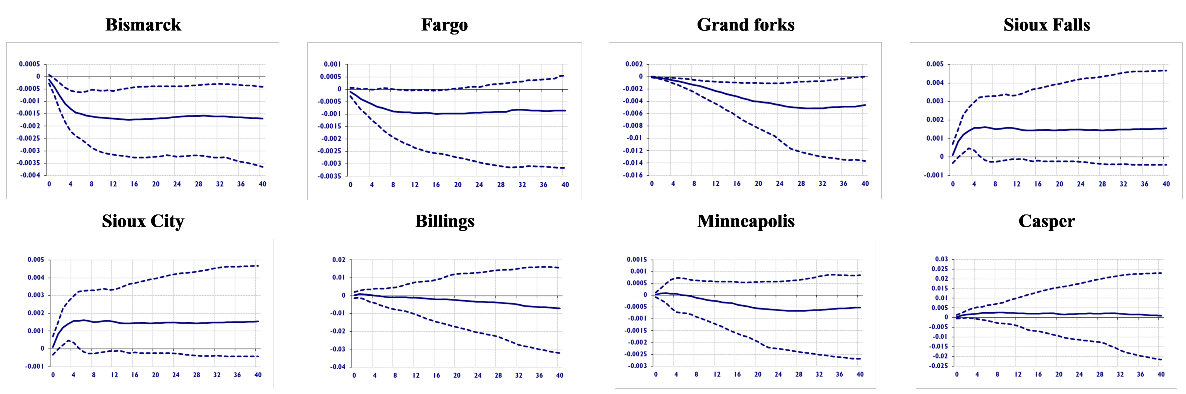


Figure 7: Bootstrapped GIRFs from one SE positive shock on Rig Count in Bismarck on Regional Unemployment

Housing Prices. Figure 8 and 9 provide the GIRFs for a one percent increase in rig count and average week earnings,respectively. The magnitudes are surprisingly more pronounced for rig count than week earnings. A great look, shows that housing prices reacts substantially with one month delay in all MSAs. Besides Bismarck, still the impact more pronounced in other two MSs in North Dakota (Fargo and Great Forks) and Billings. The responses are significant over the first 4 months, ranging from -0.01% to 0.12%. On the other hand, Figure 9 shows a almost muted response of housing prices to 1 s.e. shock in average week earning for the MSAs further distant and two neighboring MSAs to Bismarck (Sioux Falls and Sioux City). These finds are consistent with effect of the proximity and the size of the the MSAs in attracting new residents, effect partially captured in the migration weight matrix. Sioux Fall and Sioux City observed a net out-migration which is significant for small MSAs. Furthermore, distant MSAs not only are less integrated as well as workers from these regions may decide to immigrate to closest MSAs to Bismarck pressuring the new relocated housing prices.

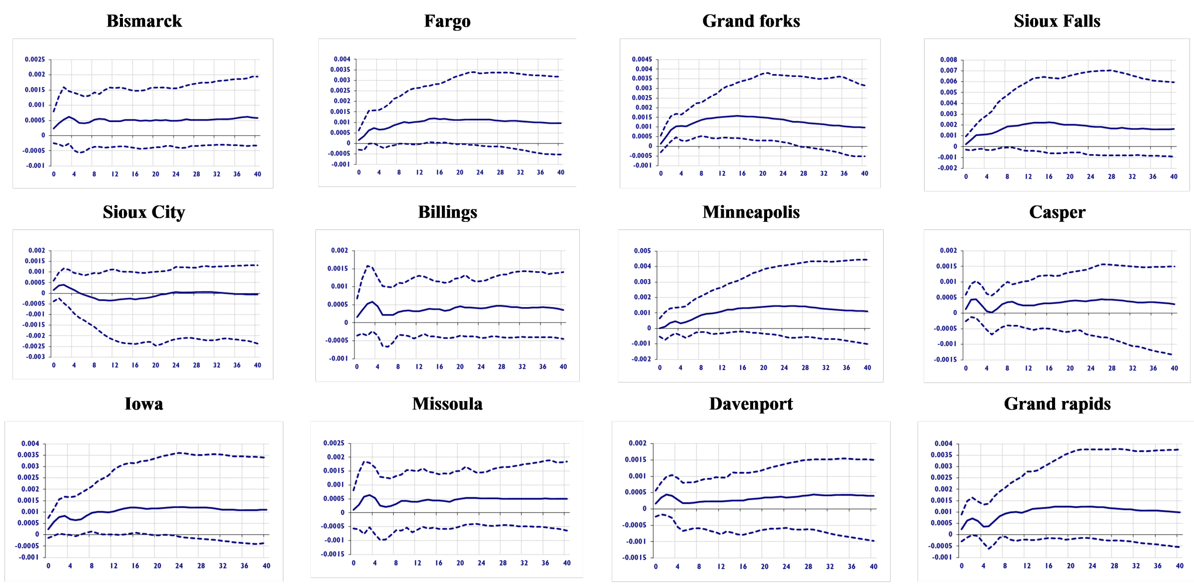


Figure 8: Bootstrapped GIRFs from one SE positive shock on Rig Count in Bismarck on Regional Housing Prices

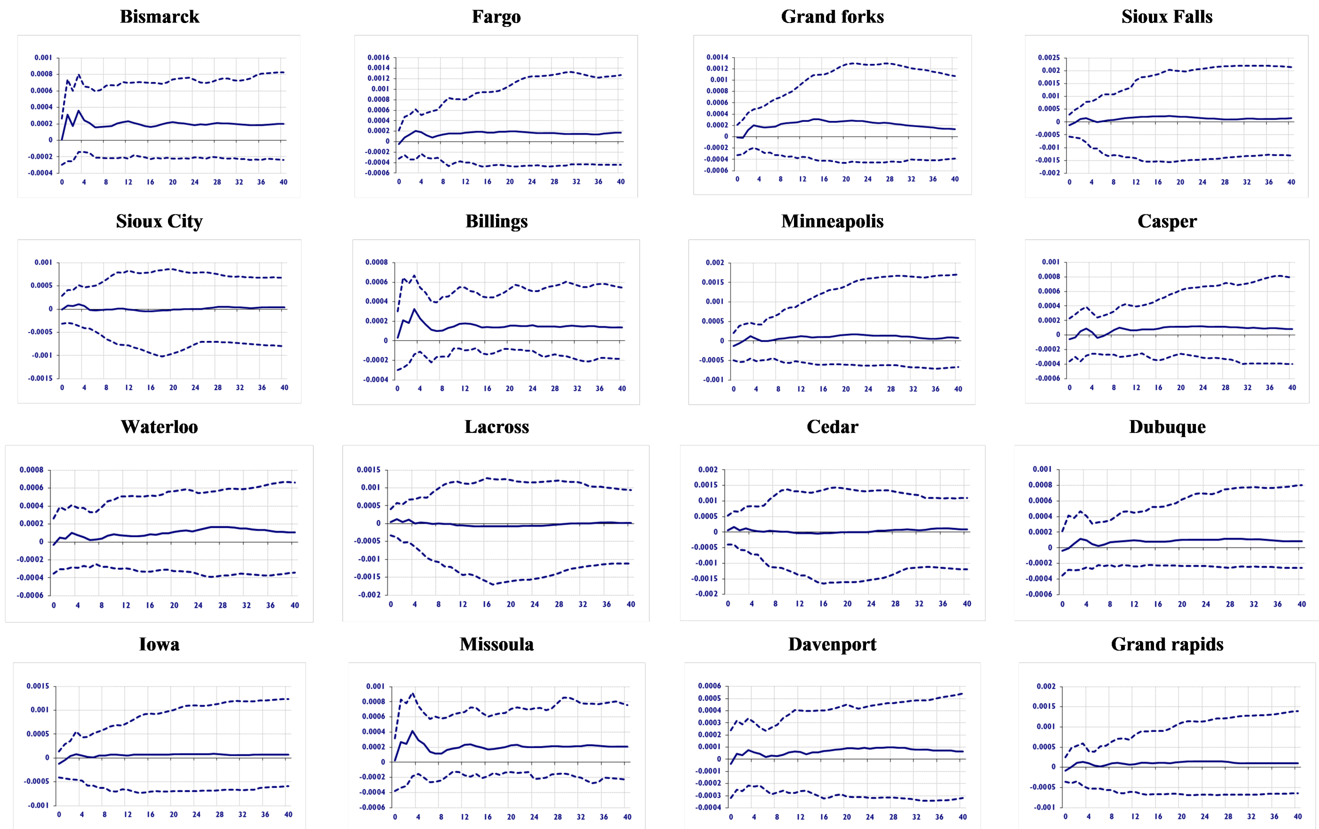


Figure 9: Bootstrapped GIRFs from one SE positive shock on Average Week Earnings in Bismarck on Regional Housing Prices

7 Conclusion

This paper investigates the spatial and temporal propagation of regional productivity shock by looking dynamic interactions between labor market outcomes, and housing prices. I employ Bartik instrument to generate a measure labor demand shock, and employed data on oil and gas production from fracking to integrate in a spatial dynamic model. Consistent with the theoretical model, I find evidence of substantial employment, wages and housing price spillovers However, the estimated heterogeneous effects are fundamentally influenced by housing supply constraints which in turn determine workers mobility. In response to a positive labor demand shock, areas with a less responsive housing supply will experience higher wages, higher housing prices, and a lower level of employment. Moreover, the four alternative specification for the weight matrices show that workers respond to a positive localized labor demand shock migrating to neighbor regions with lower commuting times.

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A A Spatial Equilibrium Model with Homogeneous Labor

A.0.1 Firms

Consider a world comprising two "small Metropolitan Statistical Area (MSA), MSA_s : $S = 1, 2$, producing a single homogeneous good Y that is traded on the international competitive markets - we normalized price to 1. The production function for firm i in MSA_s is given by

$$Y_{i,s} = X_1 N_{i,s}^{(h)} K_s^{(1-h)} \tag{A.1}$$

where X is MSA - is local productivity shifter (Total Factor Productivity - TFP); N is the total number of workers in MSA_s and $h < 1$ to ensure labor demand is downward sloped ; and K is capital in MSA_s. We also assume that there is an international competitive capital market that is infinitely supplied at a given price i. The firm's production technology in log form is

$$lny_{i,s} = x_1 + hn_{i,s} + (1-h)k_s \tag{A.2}$$

The labor demand input derived from first order condition of the firm's problem has the usual log form.

$$w_s = x_s - (1-h)n_s + (1-h)k_s + lnh \tag{A.3}$$

$$\text{with } 0 < h < 1$$

where w_s is the log of nominal wage in msa_s.

A.0.2 Workers

There is a fixed number of workers $\overline{n}$ in each of the two MSA_s. Each worker provides one unit of labor, so that local labor supply is only determined by workers' location decisions. Utility of worker in MSA_1 depends on consumption of homogeneous traded good Y, housing H, the MSA_1's local amenities A, and an idiosyncratic location preference $e_{i,1}$.

$$U_{i,1} = Y_{i,1}^{(1-\beta)} H_{i,1}^{\beta} A_1 e_{i,1} \tag{A.4}$$

The log form indirect utility of worker i in msa_1 is given by:

$$v_{i,1} = w_1 - \beta r_1 + a_1 + e_{i,1} \tag{A.5}$$

where w_1 is the log of nominal wage, r_1 is the log of cost of housing, a_1 is the log value of amenities, and β measures the importance of housing consumption in utility and equals the budget share spent on housing (normalized to 1). The intuition is straightforward. If a worker i moves from one MSA_i to MSA_j with $i \neq j$ she will receive wage w_i, face housing costs r_i and will enjoy an amenity level a_1. The random term $e_{i,1}$ represents worker i idiosyncratic preferences for location MSA_1. A larger $e_{i,1}$ means that worker i is particularly attached to MSA_1, holding constant real wage and amenities. Worker *i's* relative preference for MSA_1 over MSA_2, $(e_{i,1} - e_{i,2})$, is uniformly distributed $U[-s, s]$. The parameter s mirrors the importance of idiosyncratic preferences for location and therefore the degree of labor mobility. If s is large, worker location preferences are stronger and, therefore, workers decision to move are less sensitive to differences in real wages and amenities; and the labor supply is steeper. On the other hand, a small s revels location preferences are weaker and, thus worker's decision to move are more sensitive to differences in real wage and amenities and regions face now a less steep labor supply curve. Thus, worker i chooses MSA_2, rather than MSA_1, if and only if the strength of location preferences exceeds any real wage premium and higher amenity value.

$$e_{i,2} - e_{i,1} > (w_1 - r_1) - (w_2 - r_2) + (a_1 - a_2) \tag{A.6}$$

A.0.3 Equilibrium

In equilibrium, the marginal worker is indifferent between two MSA_s. Thus, the labor supply for MSA_2 is

$$w_2 = w_1 + (r_2 - r_1) + (a_1 - a_2) + s\frac{(n_2 - n_1)}{\overline{n}} \tag{A.7}$$

where n_s is the log number of workers in MSA_s; and $\overline{n} = n_1 + n_2$ is the assumed to be fixed. This equilibrium condition implies that local labor supply is upward sloping, and its slope depends on the parameter s. From (A.7) one can observe that if the real wage in MSA_1 increases or local amenities improve, workers leave MSA_2 and move to MSA_1. We can also obtain the inverse of local demand for housing by rearranging equation (A.7) as it follows:

$$r_2 = r_1 + (w_2 - w_1) + (a_2 - a_1) + s\frac{(n_2 - n_1)}{\overline{n}} \tag{A.8}$$

Finally, the log form of the upward housing supply curve is given in as

$$r_s = k_s n_s \tag{A.9}$$

Contrarily to the standard Rosen-Roback model, Moretti's model assumes that workers have heterogeneous location preferences. Though workers and firms are mobile across MSAs, worker mobility is not necessarily infinite because they have idiosyncratic location preferences. Therefore labor supply is not infinitely elastic as prescribed in Rosen-Roback workhorse model. Here, the housing supply is not completely fixed which implies that the elasticity of local labor supply is not necessarily infinite and the elasticity of the housing supply is not certainly zero[41] where the number of housing units in MSA_s is assumed to be equal to the number of workers. The parameter k_s is exogenously determined and characterizes the elasticity of the supply of housing (Glaeser & Gyourko, 2005; Saiz, 2010; Enrico, 2011). On the other hand, k_s is small in cities where geography and regulations are less stringent. The equilibrium in the labor market is obtained by equating equation (A.3) and (A.7) for each MSA. Equilibrium in the housing market is obtained by equating (A.8) and (A.9).

Let us consider two periods, X_{21} as the initial Total Factor Productivity (TFP) and that the TFP increases in msa_2 by an amount δ. Then the TFP gain from period 1 to 2 in MSA_2 is $X_{22} - X_{21} = \delta$, where $\delta > 0$ represent a positive, localized unexpected productivity shock. The model assumes that amenities in the two MSA_s are identical and remain unchanged and no productivity changes take place in MSA_1. Thus, an increase in productivity in MSA_2 will shift the local labor demand curve to the right, resulting in higher employment and higher nominal wages. Consequently, housing costs increase due to higher local employment, higher wages. Essentially, workers are more productive in MSA_2 than MSA_1 and some of them move to MSA_2 attracted by this higher productivity. As employment declines in MSA_1, the cost of housing declines and real wages increase. The changes in equilibrium employment, nominal wage, and housing rent in MSA_2 are:

$$n_{22} - n_{21} = \frac{\overline{n}}{\overline{n}(k_1 + k_2) + 2s}\delta = \pi_1 \delta \geq 0 \tag{A.10}$$

[41]In Rosen-Roback standard model, in equilibrium any local demand or supply shock is fully capitalized in the price of land which is fixed and therefore, housing price. The elasticity of housing supply is zero.

$$w_{22} - w_{21} = \delta \geq 0 \tag{A.11}$$

$$r_{22} - r_{21} = \frac{k_2\overline{n}}{\overline{n}(k_1 + k_2) + 2s}\delta = \pi_3\delta \geq 0 \tag{A.12}$$

The size of these effects depend on the elasticities of labor supply and housing supply. From equation (12), the increase in housing costs is larger the smaller the elasticity of the housing supply in MSA_2 relative to MSA_1. However, because nominal wages increase more than housing costs, the real wages will reflect the difference in nominal wages and the budget-share weighted increase in housing cost in MSA_2 by:

$$(w_{22} - w_{21}) - (r_{22} - r_{21}) = \frac{k_1\overline{n} + 2s}{\overline{n}(k_1 + k_2) + 2s}\delta = \pi_4\delta > 0 \tag{A.13}$$

Although the original productivity shock only involves MSA_2, in general equilibrium, prices in MSA_1 are also affected. Out-migration in MSA_1 lowers the cost of housing. Because the nominal wages in MSA_1 does not change, the net effect is an increase in real wages in MSA_1 is:

$$(w_{12} - w_{11}) - (r_{12} - r_{11}) = \frac{k_1\overline{n}}{\overline{n}(k_1 + k_2) + 2s}\delta \geq 0 \tag{A.14}$$

Comparing (A.13) and (A.14), we observe that real wages in period 2 differ in the two MSA_s. Real wages are higher in msa_2 because this location is directly affected by the shock.

B Figures

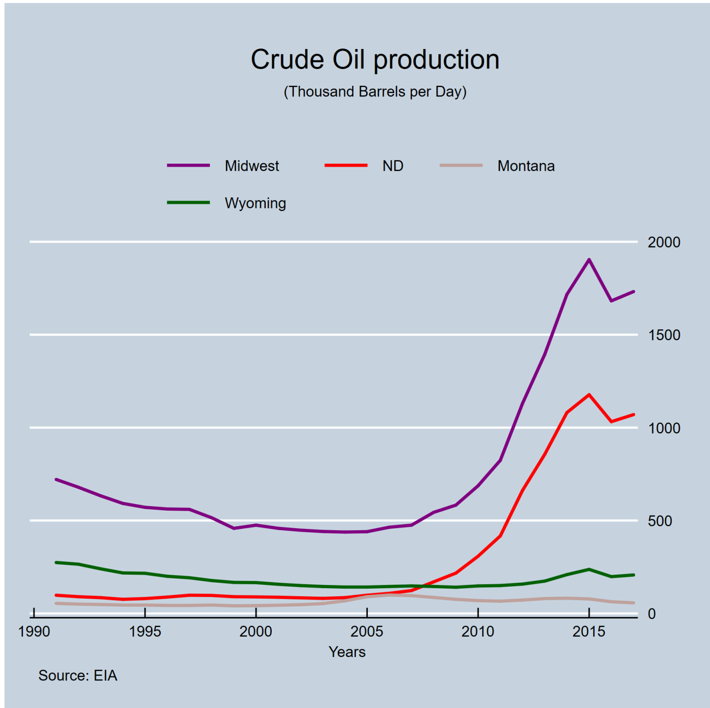

Figure B.1: Oil Production (1991 - 2017)

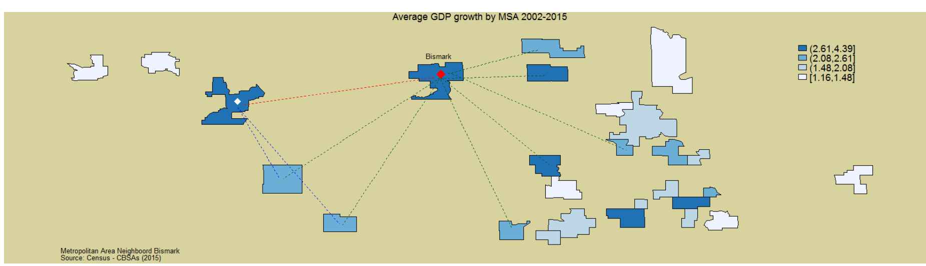

Figure B.3: GDP growth (2002 - 2015)

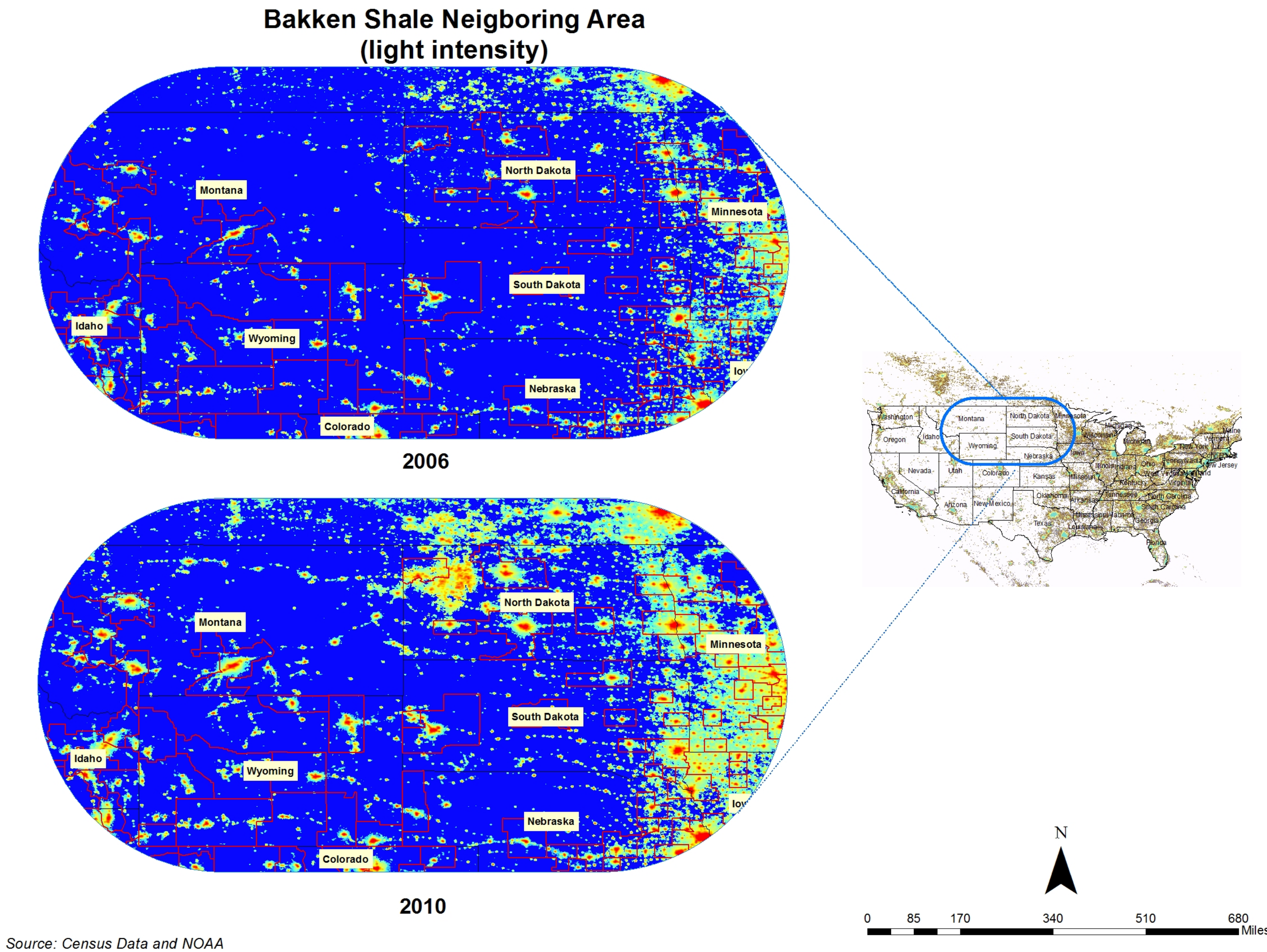

Figure B.2: Light Intensity Across Bakken Area

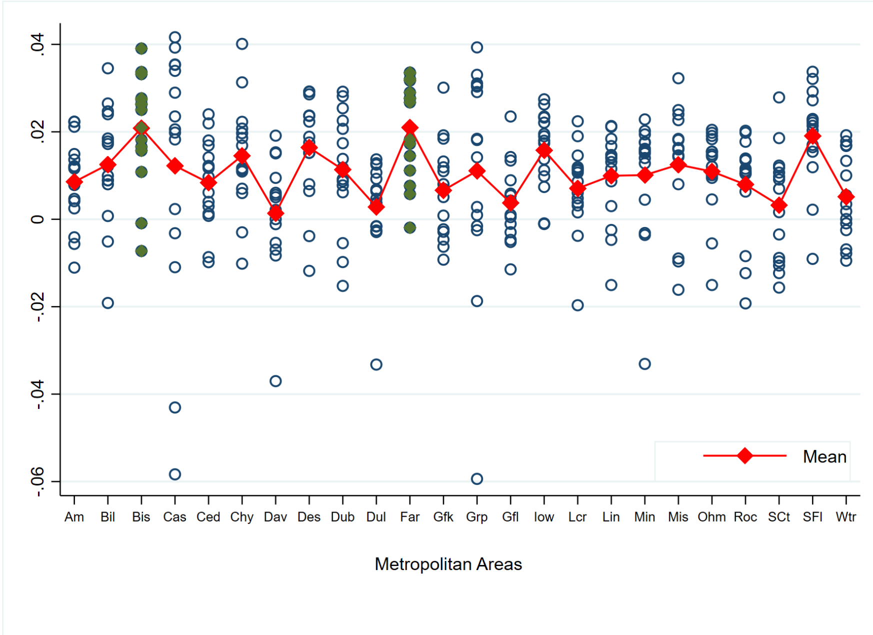

Figure B.4: Employment Growth (2003 - 2017)

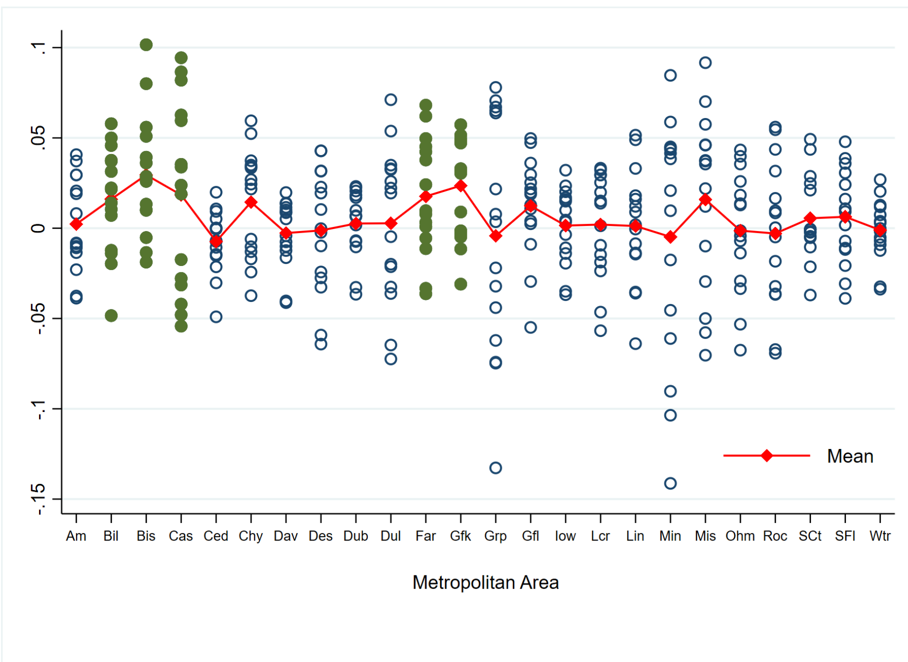

Figure B.5: Changes in Housing Price Index (2003 - 2017)

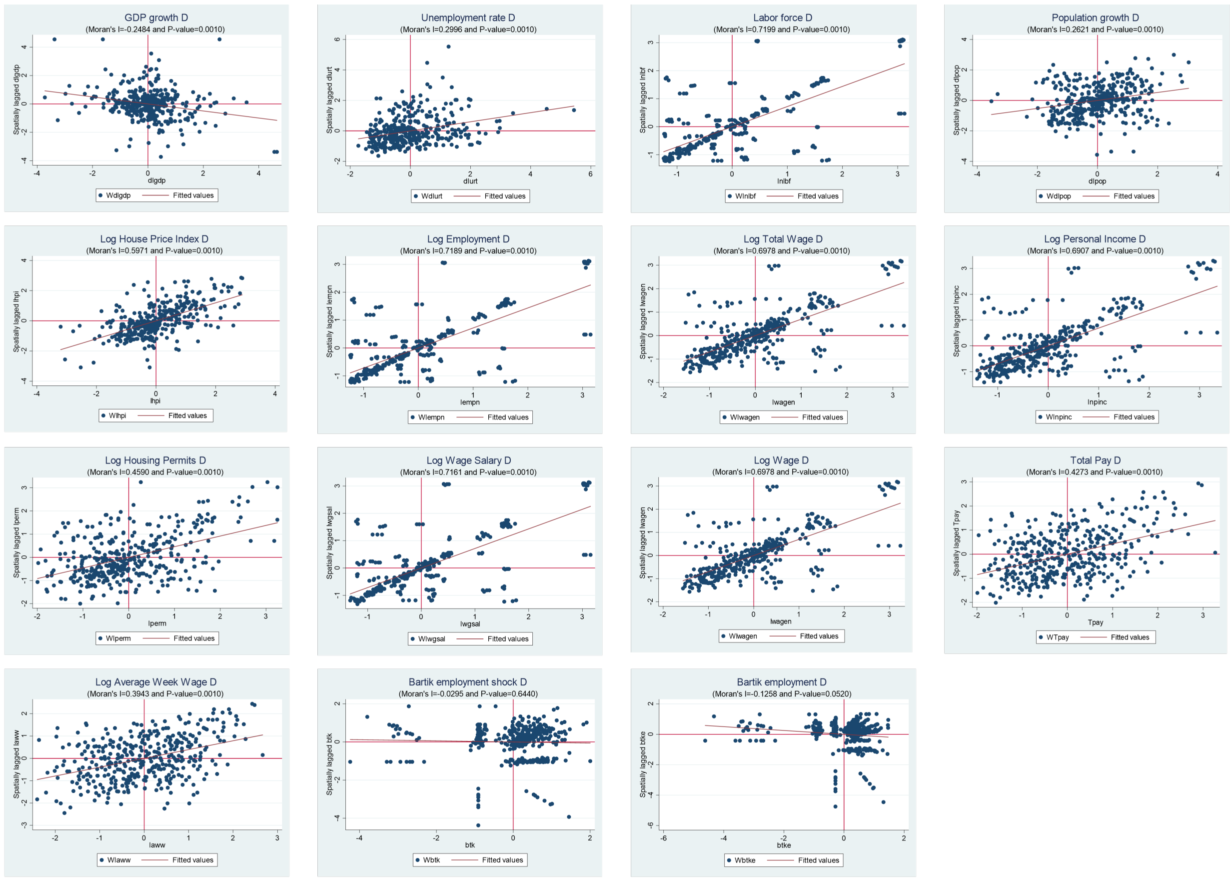

Figure B.6: Net Migration weight Matrix

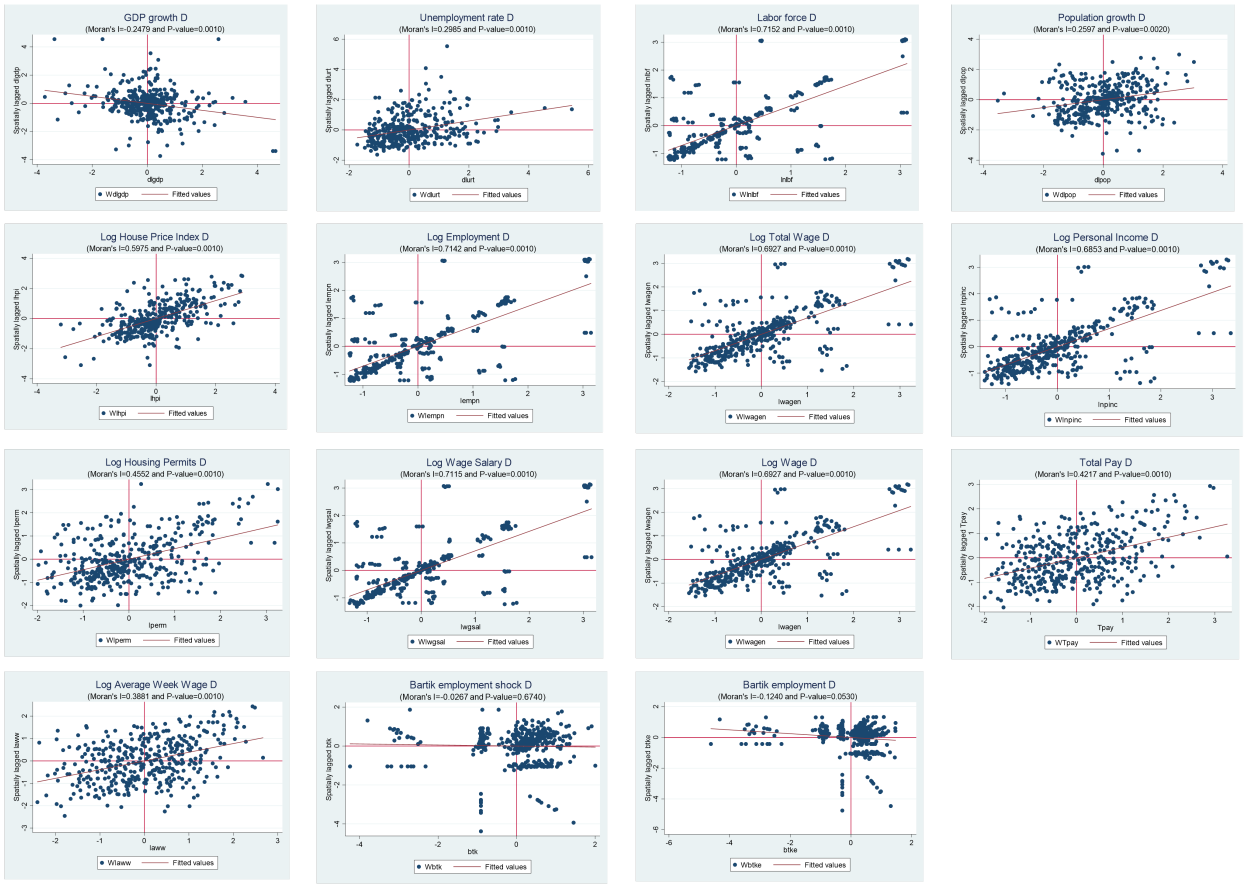

Figure B.7: Gravity Weight Matrix

C Tables

Table C.1: Data Sources

Variaveis	Measure	**Frequency**	**Years**	**Transformation**	**Source**
GDP	Real Dollar Chained	Year	2002 - 2017	Log form	Bureau of Economic Analysis (BEA)
Unemployed	Rate	Monthly/ annual	2002 - 2017	Log form	BEA and Bureau of Labor Statistics (BLS)
Employment	Level	Monthly/annual	2002 - 2017	Log form	QCEW and BLS
Personal Income	Millions of dollars	Annual	2002 - 2017	Log form	BEA
Labor force	Level	Monthly/annual	2002 - 2017	Log form	BLS
Average Hourly Earnings of All Employees	Dollars	Monthly	2002 - 2017	Log form	QCEW
Average Weekly Earnings of all Employees	Dollars	Monthly	2002 - 2017	Log form	QCEW
Total Annual Wages	Dollars	Monthly/annual	2002 -2017	Log form	QCWE
Total Private Payroll	Thousand of dollars	Monthly	2007 - 2017	Log form	QCWE
Consumer Price Index - all consumers sa	Index	Monthly	2007 - 2017	Level	BLS
Housing Prices Index	Index	Monthly	2007 - 2017	Log form	Freedie Mac
Building Permits	Units	Monthly	2007 - 2017	Log form	Census Bureau
North Dakota - ND (Bakken) Oil Production	Millions of barrels	Monthly	2007 - 2017	Log form	ND State Government, Dept. Mineral Resources
ND wells producing	Units	Monthly	2007 - 2017	Log form	ND State Government, Dept. Mineral Resources
ND Crude Oil First Purchase Price	Dollars per Barrel	Monthly	2006 - 2017	Log form	US Energy Information Administration (EIA)
ND Average Rig Count	Units	Monthly	2007 - 2017	Log form	ND State Government, Dept. Mineral Resources
ND Oil permits	Units	Monthly	2007 - 2017	Log form	ND State Government, Dept. Mineral Resources
ND Well Spud	Units	Monthly	2007 - 2017	Log form	ND State Government, Dept. Mineral Resources
ND New Wells Producing	Units	Monthly	2006 - 2017	Log form	ND State Governmen, Dept. Mineral Resources
Labor Productivity in Oil and Gas Extraction (NAICS 211)	Index	Year	2002 - 2017	Log form	BLS
Metro Area-to-Metro Area Migration Flows	Units	Average	2010 - 2014	Level	Census Data - American Community Survey (ACS)

Table C.2: Reduced Form - Instruments

	Log change in employment		Log change in wages
Bartik Employment		1.274***	
		[0.377]	
Bartik Employment[1]	1.655***		
	[0.436]		
Bartik Wage bill			3.269***
			[0.463]
Constant	0.00580	0.0133**	-0.00541
	[0.00630]	[0.00657]	[0.0116]
Observations	360	360	360
R-Squared	0.4315	0.4571	0.5042
Year and MSAs, FE	Yes	Yes	Yes

Standard errors in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Another variation of Bartik shock in which we include all MSAs.

Table C.3: Shock, Population, Housing Price and Housing Supply Elasticity

	$\triangle$ *Population*				$\triangle$ *HousingPrices*
	More elast.	Less elast.	More Elast.	Less elast.	
Bartik Wage bill	13.79	-40.44			
	[1.74]	[-1.90]			
Bartik Employment			32.89***	33.20	
			[3.47]	[1.90]	
Popul. growth x shock					0.00984*
					[2.46]
Popul. growth x hous. elasticity					0.00489***
					[6.33]
Constant	0.925***	0.150	0.943***	0.0215	0.0234**
	[5.75]	[1.34]	[6.02]	[0.20]	[3.01]
Observations	304	80	304	80	285
R-Squared	0.669	0.851	0.680	0.851	0.673

t statistics in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.4: Selected Metropolitan Statistical Areas

1	Ames, IA (Metropolitan Statistical Area)
2	Billings, MT (Metropolitan Statistical Area)
3	Bismarck, ND (Metropolitan Statistical Area)
4	Casper, WY (Metropolitan Statistical Area)
5	Cedar Rapids, IA (Metropolitan Statistical Area)
6	Cheyenne, WY (Metropolitan Statistical Area)
7	Davenport-Moline-Rock Island, IA-IL (Metropolitan Statistical Area)
8	Des Moines-West Des Moines, IA (Metropolitan Statistical Area)
9	Dubuque, IA (Metropolitan Statistical Area)
10	Duluth, MN-WI (Metropolitan Statistical Area)
11	Fargo, ND-MN (Metropolitan Statistical Area)
12	Grand Forks, ND-MN (Metropolitan Statistical Area)
13	Grand Rapids-Wyoming, MI (Metropolitan Statistical Area)
14	Great Falls, MT (Metropolitan Statistical Area)
15	Iowa City, IA (Metropolitan Statistical Area)
16	La Crosse-Onalaska, WI-MN (Metropolitan Statistical Area)
17	Lincoln, NE (Metropolitan Statistical Area)
18	Minneapolis-St. Paul-Bloomington, MN-WI (Metropolitan Statistical Area)
19	Missoula, MT (Metropolitan Statistical Area)
20	Omaha-Council Bluffs, NE-IA (Metropolitan Statistical Area)
21	Rochester, MN (Metropolitan Statistical Area)
22	Sioux City, IA-NE-SD (Metropolitan Statistical Area)
23	Sioux Falls, SD (Metropolitan Statistical Area)
24	Waterloo-Cedar Falls, IA (Metropolitan Statistical Area)

D Global Vector Auto-regression

Table D.1: Unit Root Test - domestic variables

Unit Root Tests at the 5% Significance Level

Domestic Variables	Statistic	Critical Value	AMES	BILLINGS	CASPER	CEDAR	CHEYENNE	DAVENPORT	DESMOINES	DUBUQUE	DULUH	FARGO	GFORKS	GRAPIDS	GRFALLS	IOWA	LACROSSE	LINCOLN	MINNEAPOLIS	MISSOULA	OMAHA	ROCHESTER	SIOUXCITY	SIOUXFALLS	WATERLOO	BISMARCK
urate_nsa (with trend)	ADF	-3.45	-2.13	-1.61	-1.03	-2.18	-0.37	-1.37	-1.67	-0.83	-1.16	-1.67	-3.10	-2.39	-2.02	-2.16	-1.62	-1.44	-2.20	-3.06	-2.14	-2.82	-1.65	-2.11	-2.24	-1.82
urate_nsa (with trend)	WS	-3.24	-2.31	-1.64	-1.40	-2.17	-0.74	-1.22	-1.50	-1.11	-0.98	-1.64	-3.05	-0.22	-2.28	-2.36	-1.26	-1.81	-1.05	-0.77	-2.37	-1.54	-2.00	-2.02	-2.48	-1.51
urate_nsa (no trend)	ADF	-2.89	-0.90	-1.56	-1.15	-2.13	-1.93	-2.07	0.11	-1.33	-0.30	0.16	-2.86	0.27	-1.83	-0.99	0.35	-1.03	0.11	0.13	-1.22	0.73	-1.68	-0.10	-1.22	-0.09
urate_nsa (no trend)	WS	-2.55	0.04	-1.65	-1.48	-2.18	0.10	-0.10	0.54	-1.00	-0.74	0.38	-2.98	-0.46	-1.76	-0.63	-0.20	-0.11	-0.54	-0.46	0.23	0.16	-2.04	0.57	-1.28	-0.49
Durate_nsa	ADF	-2.89	-7.84	-6.88	-4.91	-6.54	-7.37	-6.55	-7.11	-6.32	-3.38	-3.48	-2.04	-5.52	-7.25	-1.71	-4.36	-2.99	-2.23	-2.44	-6.74	-3.31	-2.78	-7.35	-5.41	-5.85
Durate_nsa	WS	-2.55	-7.96	-7.03	-5.06	-6.68	-7.51	-6.70	-7.23	-6.28	-3.60	-3.68	-2.32	-5.62	-7.39	-2.00	-4.56	-3.24	-2.41	-2.53	-6.89	-3.51	-2.98	-7.49	-5.58	-6.00
DDurate_nsa	ADF	-2.89	-8.23	-8.18	-7.63	-7.95	-8.12	-9.57	-7.29	-8.00	-10.11	-11.33	-5.00	-9.53	-10.04	-5.13	-8.57	-7.15	-6.79	-5.05	-10.21	-9.38	-6.78	-11.08	-8.88	-9.74
DDurate_nsa	WS	-2.55	-8.45	-8.39	-7.85	-8.22	-8.32	-9.73	-7.53	-8.00	-10.44	-11.43	-4.72	-9.75	-10.21	-5.34	-8.83	-7.31	-7.07	-5.15	-10.43	-9.61	-7.02	-11.30	-9.06	-9.91
tppr_sa (with trend)	ADF	-3.45	-1.68	-1.54	-1.63	-2.19	-1.35	-2.77	-2.17	-1.62	-2.35	-0.96	-1.52	-2.09	-2.33	-1.94	-2.46	-1.73	-3.00	-1.78	-2.12	-2.56	-2.13	-1.89	-1.93	0.77
tppr_sa (with trend)	WS	-3.24	-0.48	-1.53	-1.91	-2.48	-1.62	-2.32	-1.48	-1.57	-1.88	-1.24	-1.70	-1.63	-2.35	-1.16	-1.90	-1.49	-2.28	-1.09	-1.84	-1.35	-2.26	-1.79	-2.16	-0.03
tppr_sa (no trend)	ADF	-2.89	0.61	-0.59	-1.72	-1.28	-0.84	-2.74	0.28	-0.68	-1.07	-1.24	-1.18	0.25	-2.30	-0.10	-0.44	-0.05	-1.34	-0.27	-0.29	0.32	-1.56	0.01	-1.71	-1.65
tppr_sa (no trend)	WS	-2.55	-0.17	-0.92	-1.95	-0.93	-1.04	-2.34	-0.28	-0.63	-1.47	-0.29	-1.07	-0.08	-1.80	-0.33	-0.77	-0.21	-1.66	-0.75	-0.52	-0.35	-1.89	0.12	-1.95	-0.12
Dtppr_sa	ADF	-2.89	-7.99	-6.09	-3.61	-4.18	-9.16	-2.48	-2.20	-8.58	-3.95	-3.74	-9.62	-7.52	-7.85	-10.40	-6.51	-2.65	-1.91	-3.94	-3.94	-6.39	-3.56	-3.68	-2.95	-2.32
Dtppr_sa	WS	-2.55	-7.89	-6.27	-3.73	-4.39	-9.15	-2.65	-2.50	-8.74	-4.08	-3.95	-9.60	-7.67	-8.04	-10.56	-5.79	-2.88	-2.18	-4.09	-4.13	-6.51	-3.79	-3.87	-3.15	-2.55
DDtppr_sa	ADF	-2.89	-9.28	-8.64	-14.62	-8.20	-7.26	-10.13	-8.75	-11.41	-9.43	-7.70	-8.29	-6.55	-8.24	-10.33	-5.61	-9.00	-9.17	-7.10	-10.89	-7.68	-11.71	-8.99	-8.23	-10.33
DDtppr_sa	WS	-2.55	-9.42	-8.90	-14.75	-8.45	-7.52	-8.85	-9.04	-11.62	-8.99	-7.84	-8.23	-6.74	-8.54	-9.97	-5.68	-9.28	-9.16	-7.31	-11.09	-7.88	-11.84	-9.04	-8.10	-10.64
hprgwtsa (with trend)	ADF	-3.45	-5.84	-6.55	-3.47	-6.62	-7.46	-6.92	-5.91	-6.29	-6.11	-4.76	-4.68	-5.27	-6.28	-6.50	-5.95	-7.09	-4.26	-6.17	-6.59	-6.38	-5.81	-5.75	-6.29	-3.90
hprgwtsa (with trend)	WS	-3.24	-5.97	-6.54	-3.02	-6.72	-7.61	-6.91	-5.95	-6.36	-5.61	-4.74	-4.70	-5.26	-6.22	-6.58	-5.79	-7.15	-3.94	-5.99	-6.64	-6.12	-5.91	-5.81	-6.42	-3.99
hprgwtsa (no trend)	ADF	-2.89	-5.13	-6.13	-3.34	-6.08	-5.63	-6.20	-1.78	-5.84	-1.70	-3.36	-4.51	-1.53	-5.84	-5.79	-4.54	-3.08	-2.00	-3.02	-2.96	-1.57	-5.26	-4.76	-6.20	-3.92
hprgwtsa (no trend)	WS	-2.55	-5.28	-6.23	-3.05	-6.23	-5.72	-6.32	-2.03	-5.99	-2.01	-3.56	-4.63	-1.40	-5.91	-5.95	-4.68	-3.23	-2.24	-3.23	-3.13	-1.79	-5.41	-4.92	-6.35	-4.00
Dhprgwtsa	ADF	-2.89	-8.73	-7.24	-7.74	-8.87	-8.02	-7.70	-8.63	-8.66	-8.37	-7.38	-9.24	-7.50	-9.77	-8.65	-9.28	-7.36	-7.22	-9.67	-8.00	-8.69	-8.36	-7.51	-8.92	-7.38
Dhprgwtsa	WS	-2.55	-9.03	-7.55	-7.84	-9.15	-8.28	-7.94	-8.89	-8.90	-8.39	-7.48	-9.35	-7.51	-9.95	-8.87	-9.36	-7.56	-7.19	-9.83	-8.13	-8.85	-8.64	-7.69	-9.17	-7.42
DDhprgwtsa	ADF	-2.89	-10.25	-8.79	-9.66	-10.03	-9.75	-9.39	-10.13	-10.35	-10.02	-8.94	-8.54	-8.98	-8.44	-10.01	-8.83	-9.09	-9.81	-8.48	-8.94	-10.27	-9.79	-8.28	-10.28	-8.41
DDhprgwtsa	WS	-2.55	-10.63	-9.11	-9.95	-10.35	-10.09	-9.71	-10.49	-10.72	-10.37	-9.26	-8.82	-9.26	-8.72	-10.36	-9.15	-9.44	-10.16	-8.77	-9.28	-10.64	-10.15	-8.61	-10.62	-8.75
ahe (with trend)	ADF	-3.45	-3.78	-3.34	-2.05	-2.99	-2.58	-1.68	-3.20	-2.06	-2.16	-2.76	-3.26	-2.97	-1.66	-2.05	-2.14	-1.77	-1.58	-1.91	0.42	-1.30	-2.16	-7.45	-3.22	-1.23
ahe (with trend)	WS	-3.24	-3.64	-3.38	-2.34	-3.15	-2.79	-1.95	-3.12	-2.22	-2.35	-2.98	-2.04	-1.99	-2.00	-2.25	-2.20	-2.07	-1.88	-2.05	-0.30	-1.70	-2.43	-1.36	-3.44	-1.66
ahe (no trend)	ADF	-2.89	-1.74	-2.40	-1.21	-1.44	-0.34	0.02	0.16	-1.55	-2.27	-0.70	-0.99	-2.72	-0.26	-1.61	-0.14	-1.13	0.04	-2.09	2.52	-0.91	-1.23	-0.23	-1.13	-1.36
ahe (no trend)	WS	-2.55	-0.71	-1.90	-0.88	-0.37	0.83	0.84	0.99	-0.62	-0.54	1.25	-1.39	0.91	0.08	-1.88	-0.08	-0.11	-0.03	-1.30	2.05	0.18	-0.41	-0.72	-0.22	0.47
Dahe	ADF	-2.89	-8.79	-8.37	-3.76	-8.44	-9.16	-7.81	-6.66	-7.54	-5.93	-12.88	-6.13	-9.18	-3.60	-8.14	-7.04	-7.05	-4.77	-3.31	-5.28	-4.22	-5.25	-3.68	-3.55	-6.48
Dahe	WS	-2.55	-8.31	-8.45	-3.97	-8.58	-9.23	-7.68	-6.24	-7.73	-5.80	-13.06	-6.29	-9.31	-3.68	-8.30	-7.25	-7.08	-4.85	-2.86	-5.54	-4.41	-5.44	-3.50	-3.69	-6.58
DDahe	ADF	-2.89	-9.10	-10.08	-6.92	-7.83	-5.92	-7.79	-8.74	-8.35	-7.79	-8.60	-8.67	-7.43	-5.68	-9.37	-9.87	-9.50	-8.75	-10.04	-8.05	-8.29	-8.40	-7.89	-10.77	-8.28
DDahe	WS	-2.55	-8.86	-10.32	-6.35	-8.03	-6.04	-7.99	-8.95	-8.69	-7.96	-8.86	-8.96	-7.39	-5.93	-9.68	-10.24	-9.38	-8.96	-10.36	-8.17	-8.43	-8.66	-7.11	-10.21	-8.18
awe (with trend)	ADF	-3.45	-4.25	-2.58	-1.81	-4.31	-2.59	-2.33	-2.48	-2.88	-2.65	-2.57	-4.90	-2.74	-2.75	-1.81	-3.35	-1.78	-1.82	-3.62	0.68	-1.60	-2.68	-4.34	-2.83	-0.83
awe (with trend)	WS	-3.24	-3.16	-2.68	-2.13	-4.52	-2.68	-2.57	-2.57	-2.87	-2.91	-2.75	-2.35	-1.63	-2.89	-2.07	-3.57	-2.11	-1.07	-2.75	-0.27	-1.93	-2.64	-2.16	-2.66	-1.33
awe (no trend)	ADF	-2.89	-1.55	-1.00	-1.23	-1.93	-0.92	-0.41	-0.65	-0.83	-1.95	-0.71	-1.23	-2.44	-0.69	-1.29	-1.97	-1.21	0.78	-2.90	2.49	-0.93	-1.37	-0.39	-2.31	-1.29
awe (no trend)	WS	-2.55	-0.20	-1.19	-1.01	-1.54	0.18	0.62	0.89	-0.74	-0.80	0.66	-1.46	0.24	-0.66	-1.41	-2.17	-0.08	0.14	-2.63	2.86	-0.37	0.31	-0.77	-0.80	0.16
Dawe	ADF	-2.89	-8.83	-9.18	-4.24	-9.04	-6.24	-11.87	-7.00	-9.26	-5.91	-5.26	-9.18	-3.26	-3.83	-6.42	-6.16	-7.20	-5.24	-13.68	-8.30	-3.86	-3.94	-4.91	-5.85	-4.86
Dawe	WS	-2.55	-7.69	-9.20	-4.49	-9.20	-6.42	-11.81	-6.25	-9.35	-6.00	-5.52	-9.33	-3.35	-3.91	-6.58	-6.34	-7.36	-5.36	-11.76	-8.36	-4.10	-4.19	-4.99	-6.00	-4.93
DDawe	ADF	-2.89	-10.76	-11.16	-6.97	-7.35	-6.89	-8.28	-9.33	-8.12	-8.91	-8.01	-7.59	-7.55	-6.19	-9.07	-10.69	-9.76	-8.30	-10.37	-9.00	-7.79	-9.04	-9.77	-7.45	-8.55
DDawe	WS	-2.55	-10.09	-11.39	-6.83	-7.62	-7.02	-8.46	-9.52	-8.40	-8.37	-8.20	-7.75	-7.75	-6.00	-9.29	-11.01	-9.88	-8.60	-7.15	-8.97	-7.87	-7.96	-8.55	-7.62	-8.71

Table D.2: Unit Root Test - foreign variables

Unit Root Tests at the 5% Significance Level

Foreign Variables	Statistic	Critical Value	AMES	BILLINGS	CASPER	CEDAR	CHEYENNE	DAVENPORT	DESMOINES	DUBUQUE	DULUH	FARGO	GFORKS	GRAPIDS	GRFALLS	IOWA	LACROSSE	LINCOLN	MINNEAPOLIS	MISSOULA	OMAHA	ROCHESTER	SIOUXCITY	SIOUXFALLS	WATERLOO	BISMARCK
urate_nsas (with trend)	ADF	-3.45	-2.10	-1.78	-1.16	-2.55	-1.51	-2.01	-2.30	-2.00	-2.76	-2.08	-2.39	-1.78	-1.87	-2.55	-1.75	-2.23	-2.02	-2.48	-1.64	-1.85	-1.67	-1.58	-2.52	-1.81
urate_nsas (with trend)	WS	-3.24	-1.58	-1.19	-1.39	-2.53	-1.66	-2.25	-2.44	-0.46	-0.53	-1.35	-0.56	-1.35	-0.84	-1.55	-2.08	-2.27	-1.90	-2.72	-1.98	-0.65	-1.38	-1.47	-2.39	-1.71
urate_nsas (no trend)	ADF	-2.89	-0.16	-0.71	-1.79	-0.60	-1.32	-0.99	-0.87	0.85	0.16	0.05	-0.16	-0.11	-0.66	-1.81	-0.84	-0.49	-0.07	-2.48	-1.11	0.65	0.18	0.26	-0.37	0.29
urate_nsas (no trend)	WS	-2.55	-0.54	-1.14	-0.12	0.39	-1.69	-0.87	-0.74	0.05	-0.48	-0.52	-0.54	-0.09	-0.83	-1.62	-0.51	0.14	0.12	-2.71	-0.70	-0.17	0.44	0.56	0.79	0.38
Durate_nsas	ADF	-2.89	-4.23	-5.50	-7.65	-8.35	-5.11	-3.57	-7.36	-5.16	-2.81	-1.94	-2.88	-5.69	-5.53	-4.17	-3.79	-7.22	-6.24	-7.86	-2.60	-4.03	-6.89	-5.04	-8.38	-4.08
Durate_nsas	WS	-2.55	-4.39	-5.66	-7.78	-8.45	-5.26	-3.73	-7.51	-5.13	-2.77	-2.24	-2.87	-5.76	-5.67	-4.18	-3.85	-7.34	-6.37	-7.89	-2.73	-4.19	-6.99	-5.10	-8.51	-4.28
DDurate_nsas	ADF	-2.89	-8.53	-7.51	-8.56	-8.43	-7.47	-6.85	-7.96	-9.19	-7.56	-7.03	-6.95	-8.85	-7.98	-8.29	-7.42	-11.04	-10.20	-8.37	-7.74	-8.87	-7.23	-7.85	-8.50	-7.02
DDurate_nsas	WS	-2.55	-8.61	-7.80	-8.76	-8.61	-7.76	-7.12	-8.17	-9.27	-7.85	-7.31	-7.21	-9.06	-8.17	-8.34	-7.72	-11.26	-10.41	-8.50	-8.01	-9.08	-7.43	-8.01	-8.71	-7.20
tppr_sas (with trend)	ADF	-3.45	-2.91	-1.79	-1.49	-1.43	-2.13	-2.45	-1.56	-2.99	-2.90	-2.73	-1.85	-2.50	-1.83	-3.18	-1.67	-1.40	-1.11	-1.03	-2.50	-3.23	-2.21	-0.65	-1.94	-1.26
tppr_sas (with trend)	WS	-3.24	-2.42	-1.61	-1.63	-0.53	-2.37	-2.41	-1.38	-2.08	-1.72	-2.17	-0.70	-2.19	-1.25	-2.15	-1.68	-1.63	-1.17	-1.16	-2.65	-2.61	-1.24	-0.74	-0.35	-1.61
tppr_sas (no trend)	ADF	-2.89	-1.04	-0.64	-0.66	1.43	-1.88	-0.87	-2.08	-0.88	-0.74	-0.96	-0.74	-0.98	-0.49	-1.03	0.03	-0.59	-0.70	-2.03	-1.00	-1.41	0.67	-0.91	1.15	-1.36
tppr_sas (no trend)	WS	-2.55	-1.35	-1.11	-0.83	0.72	-2.12	-0.91	-1.20	-1.27	-1.12	-1.25	-0.67	-1.26	-0.99	-1.36	-0.04	0.16	-0.34	-0.36	-0.89	-1.71	0.06	0.54	0.12	-0.07
Dtppr_sas	ADF	-2.89	-2.04	-6.15	-9.30	-7.43	-3.29	-2.61	-4.11	-1.93	-2.67	-2.06	-3.44	-2.80	-5.50	-3.11	-3.19	-8.07	-5.93	-10.73	-2.76	-1.82	-4.43	-6.89	-4.45	-4.05
Dtppr_sas	WS	-2.55	-2.34	-6.14	-9.38	-7.55	-3.45	-2.87	-4.06	-2.23	-2.90	-2.35	-3.61	-3.02	-5.66	-3.26	-3.44	-8.18	-6.03	-10.84	-2.99	-2.13	-4.61	-7.01	-4.53	-4.26
DDtppr_sas	ADF	-2.89	-9.55	-7.50	-7.56	-11.01	-15.59	-7.87	-8.65	-9.38	-9.30	-10.30	-8.63	-9.00	-7.83	-9.24	-8.80	-7.35	-9.34	-8.79	-7.25	-9.91	-8.33	-8.50	-8.58	-7.97
DDtppr_sas	WS	-2.55	-9.48	-7.62	-7.80	-11.18	-15.71	-8.15	-8.93	-9.47	-9.49	-9.86	-8.80	-9.00	-7.91	-9.13	-8.99	-7.61	-9.63	-9.06	-7.50	-9.63	-8.63	-8.77	-8.87	-8.12
hprgwtsas (with trend)	ADF	-3.45	-5.16	-5.88	-6.45	-4.89	-5.35	-6.42	-6.65	-4.58	-4.61	-4.46	-4.44	-4.61	-6.22	-5.50	-6.53	-6.36	-4.03	-3.86	-6.49	-4.56	-5.76	-5.30	-5.17	-5.56
hprgwtsas (with trend)	WS	-3.24	-5.08	-5.62	-6.59	-5.00	-5.00	-6.51	-6.76	-4.40	-4.31	-4.23	-4.07	-4.47	-6.03	-5.36	-6.61	-6.40	-4.10	-3.70	-6.57	-4.24	-5.79	-5.20	-5.23	-5.64
hprgwtsas (no trend)	ADF	-2.89	-1.68	-4.71	-4.61	-1.39	-4.16	-5.71	-6.47	-1.48	-2.07	-2.68	-1.94	-3.18	-4.81	-4.23	-5.61	-5.36	-3.99	-3.49	-5.90	-2.15	-1.75	-2.59	-1.49	-5.48
hprgwtsas (no trend)	WS	-2.55	-1.90	-4.79	-4.68	-1.68	-4.24	-5.86	-6.62	-1.70	-2.29	-2.90	-2.15	-3.37	-4.92	-4.38	-5.77	-5.52	-4.12	-3.57	-6.05	-2.40	-1.99	-2.79	-1.72	-5.60
Dhprgwtsas	ADF	-2.89	-8.18	-9.68	-8.07	-8.67	-7.52	-8.70	-8.85	-7.70	-7.51	-7.25	-7.23	-7.55	-9.80	-7.71	-7.91	-8.23	-9.46	-10.19	-8.53	-7.46	-8.57	-7.41	-8.76	-9.80
Dhprgwtsas	WS	-2.55	-8.34	-9.84	-8.35	-8.97	-7.72	-8.95	-9.10	-7.79	-7.56	-7.23	-7.21	-7.62	-9.95	-7.80	-8.23	-8.40	-9.64	-10.25	-8.79	-7.45	-8.83	-7.45	-9.03	-10.00
DDhprgwtsas	ADF	-2.89	-10.11	-8.63	-10.26	-11.00	-9.58	-10.01	-9.97	-10.03	-10.06	-9.28	-9.86	-9.92	-8.70	-9.75	-9.90	-8.05	-8.30	-8.11	-9.75	-9.83	-10.16	-9.12	-10.69	-8.39
DDhprgwtsas	WS	-2.55	-10.46	-8.93	-10.61	-11.39	-9.94	-10.35	-10.29	-10.40	-10.44	-9.62	-10.23	-10.29	-9.01	-10.12	-10.23	-8.36	-8.60	-8.41	-10.09	-10.18	-10.52	-9.45	-11.08	-8.70
ahes (with trend)	ADF	-3.45	-2.15	-2.01	-4.05	-2.66	-2.29	-3.29	-2.73	-2.48	-2.21	-3.87	-1.39	-1.52	-1.86	-2.67	-3.74	-3.40	-1.77	-2.42	-3.68	-2.33	-3.86	-1.77	-2.73	-2.67
ahes (with trend)	WS	-3.24	-2.45	-2.24	-3.60	-2.44	-2.49	-3.54	-2.96	-2.31	-2.51	-3.43	-1.75	-1.70	-1.98	-2.25	-3.92	-2.37	-2.02	-2.27	-3.94	-2.42	-4.03	-2.05	-2.96	-2.35
ahes (no trend)	ADF	-2.89	0.02	-1.23	0.02	-2.54	-1.52	-0.42	-1.44	0.95	-0.23	-0.34	-1.40	-1.08	-1.50	0.61	-2.12	-0.71	-1.36	-0.33	-0.72	-0.16	-0.27	-1.37	-2.11	-1.86
ahes (no trend)	WS	-2.55	0.76	0.00	0.57	-1.61	-0.29	0.43	-0.36	1.25	0.06	-0.14	-1.72	-1.43	-0.35	0.85	-1.60	-1.11	-1.45	0.06	-0.12	-0.05	0.83	-0.02	-2.27	0.58
Dahes	ADF	-2.89	-4.32	-4.33	-9.22	-8.50	-3.80	-6.79	-6.55	-7.01	-4.49	-4.17	-5.02	-8.73	-7.60	-6.51	-5.14	-3.86	-10.63	-9.71	-6.47	-4.18	-6.99	-6.34	-11.01	-7.09
Dahes	WS	-2.55	-4.51	-4.19	-9.23	-8.10	-3.94	-6.92	-6.42	-7.23	-4.64	-3.85	-5.08	-8.85	-7.40	-6.77	-5.35	-3.43	-10.28	-9.77	-6.64	-4.08	-6.60	-6.52	-10.54	-7.16
DDahes	ADF	-2.89	-9.44	-7.94	-9.77	-9.57	-6.75	-7.30	-7.61	-8.02	-8.44	-8.87	-8.78	-7.37	-7.82	-8.72	-6.72	-10.64	-7.63	-7.49	-6.82	-8.62	-8.39	-8.95	-7.55	-8.45
DDahes	WS	-2.55	-9.74	-8.08	-9.83	-9.63	-6.78	-7.56	-7.63	-8.24	-8.62	-8.81	-9.03	-7.65	-8.12	-9.00	-6.86	-10.42	-7.73	-7.75	-7.04	-8.89	-8.58	-8.96	-7.45	-8.68
awes (with trend)	ADF	-3.45	-3.03	-3.32	-2.58	-1.78	-2.07	-2.34	-2.63	-2.99	-2.36	-3.25	-1.27	-1.29	-4.05	-3.03	-2.83	-3.56	-2.02	-2.24	-2.67	-2.33	-2.66	-1.66	-2.24	-2.26
awes (with trend)	WS	-3.24	-3.29	-2.54	-2.79	-1.86	-2.37	-2.62	-2.87	-3.12	-2.20	-1.31	-0.78	-1.64	-2.66	-2.97	-3.05	-2.68	-2.32	-2.43	-2.92	-0.79	-2.63	-1.63	-2.26	-2.62
awes (no trend)	ADF	-2.89	-0.36	-0.58	-0.83	-1.81	-1.08	-1.12	-1.51	-0.03	0.02	0.13	-0.75	-1.18	-2.25	0.06	-2.07	-0.72	-1.49	-0.83	-1.24	0.84	-1.17	-0.96	-2.15	-0.61
awes (no trend)	WS	-2.55	0.87	-1.03	0.14	-1.82	-0.17	0.08	-0.61	0.46	-0.13	-0.24	-0.74	-1.47	-2.31	0.19	-2.14	-0.97	-1.62	-0.09	-0.19	0.20	0.81	-0.56	-1.90	0.51
Dawes	ADF	-2.89	-9.48	-12.14	-10.98	-7.74	-4.68	-7.52	-7.65	-7.68	-4.97	-4.50	-5.54	-6.33	-12.33	-7.84	-8.59	-5.08	-4.83	-10.31	-7.19	-5.17	-9.36	-6.83	-9.25	-6.25
Dawes	WS	-2.55	-9.67	-10.89	-10.98	-7.76	-4.87	-7.70	-7.60	-7.86	-5.14	-4.26	-5.61	-6.26	-10.82	-8.10	-8.81	-4.90	-5.01	-9.59	-7.35	-5.07	-9.22	-6.92	-8.01	-5.91
DDawes	ADF	-2.89	-8.90	-9.45	-7.80	-9.87	-7.26	-10.22	-8.64	-8.36	-7.35	-9.54	-7.84	-7.15	-10.15	-7.61	-10.41	-8.77	-11.53	-6.76	-9.32	-9.85	-8.83	-7.55	-8.45	-7.98
DDawes	WS	-2.55	-9.20	-7.09	-8.09	-10.00	-7.07	-10.22	-8.58	-8.61	-7.64	-9.67	-8.12	-7.20	-7.37	-7.89	-10.66	-8.13	-10.63	-6.40	-9.39	-10.17	-9.00	-7.81	-8.27	-7.21

Table D.3: Unit Root Test - Global Variables

Unit Root Tests at the 5% Significance Level

Global Variables	Test	Critical Value	Statistic
rig (with trend)	ADF	-3.45	-2.145
rig (with trend)	WS	-3.24	-1.863
rig (no trend)	ADF	-2.89	-1.873
rig (no trend)	WS	-2.55	-1.832
Drig	ADF	-2.89	-4.230
Drig	WS	-2.55	-4.437
DDrig	ADF	-2.89	-8.371
Drig	WS	-2.55	-8.032
wellprd (with trend)	ADF	-3.45	-6.093
wellprd (with trend)	WS	-3.24	-6.166
wellprd (no trend)	ADF	-2.89	-0.768
wellprd (no trend)	WS	-2.55	-0.157
Dwellprd	ADF	-2.89	-8.346
Dwellprd	WS	-2.55	-8.574
DDwellprd	ADF	-2.89	-8.965
Dwellprd	WS	-2.55	-9.327

Table D.4: VARX* Order of Individual Models and Cointegrating Relationships

	p	q	Cointegrating relations [3]
AMES	1	1	2
BILLINGS	2	2	1
CASPER	2	2	1
CEDAR	3	2	1
CHEYENNE	2	2	3
DAVENPORT	1	1	2
DESMOINES	2	2	1
DUBUQUE	2	1	2
DULUH	3	1	3
FARGO	2	1	3
GFORKS	3	1	2
GRAPIDS	2	2	1
GRFALLS	2	2	2
IOWA	3	2	3
LACROSSE	3	2	3
LINCOLN	3	1	0
MINNEAPOLIS	3	1	1
MISSOULA	3	1	3
OMAHA	3	2	4
ROCHESTER	3	1	2
SIOUXCITY	3	1	2
SIOUXFALLS	2	2	3
WATERLOO	3	1	1
BISMARCK	2	1	2

Notes: [1] p: lag order of domestic variables (maximum lag is 3); [2] q: lag order of foreign variables (maximum lag is 2). [3] Number of cointegrating Relationships for the Individual VARX* Models

Table D.5: Test for Weak Exogeneity at the 5% Significance Level

Country	F test	Fcrit_0.05	urate_nsas	tppr_sas	hprgwtsas	ahes	awes	rig	wellprd
AMES	F(2,105)	3.08	2.65	**3.19**	0.11		0.17	1.24	0.69
BILLINGS	F(1,108)	3.93	0.53	0.14	**4.27**		0.04	1.30	1.47
CASPER	F(1,114)	3.92	0.03	0.75	3.21		0.86	0.04	0.42
CEDAR	F(1,114)	3.92	0.41	0.02	1.17		1.48	0.19	0.67
CHEYENNE	F(3,112)	2.69	0.37	1.30	2.13		1.58	1.28	3.27
DAVENPORT	F(2,100)	3.09	**4.69**	0.31	3.12		0.52	0.72	0.12
DESMOINES	F(1,114)	3.92	0.68	0.22	0.06		0.00	**4.24**	0.68
DUBUQUE	F(2,113)	3.08	1.57	**3.22**	**5.61**		0.78	1.38	0.25
DULUH	F(3,112)	2.69	1.41	**7.23**	5.34		0.28	0.68	1.81
FARGO	F(3,112)	2.69	0.95	1.32	1.38		1.08	0.70	1.88
GFORKS	F(2,113)	3.08	0.83	0.10	0.93		**10.19**	0.94	3.26
GRAPIDS	F(1,114)	3.92	1.17	0.29	0.02		0.76	**5.08**	**4.18**
GRFALLS	F(2,113)	3.08	0.83	0.83	0.22		4.68	1.00	1.05
IOWA	F(3,112)	2.69	**3.46**	1.10	2.60		0.65	0.71	2.32
LACROSSE	F(3,112)	2.69	2.22	0.95	**5.52**		**3.88**	0.15	0.98
LINCOLN	F(0,109)								
MINNEAPOLIS	F(1,114)	3.92	0.28	0.31	0.65		2.15	0.09	0.87
MISSOULA	F(3,112)	2.69	1.91	1.52	**3.79**		1.53	1.08	0.14
OMAHA	F(4,98)	2.46	2.91	1.04	0.16		1.07	0.78	1.58
ROCHESTER	F(2,113)	3.08	0.53	3.06	**4.32**		0.97	0.21	0.33
SIOUXCITY	F(2,113)	3.08	**3.79**	**5.00**	0.89		**3.69**	0.46	0.69
SIOUXFALLS	F(3,112)	2.69	**3.46**	**3.45**	0.25		2.33	0.68	2.77
WATERLOO	F(1,114)	3.92	0.17	0.01	**4.84**		0.17	0.29	0.06
BISMARCK	F(2,113)	3.0765743	0.1192651		0.0003127	1.38239			

Table D.6: Contemporaneous Effects of Foreign Variables on Domestic Counterparts

MSAs	urate_nsa	tppr_sa	hprgwtsa	ahe	awe
AMES	-0.74	0.37	0.94		0.52
	[-0.66]	[1.64]	[33.02]		[2.94]
BILLINGS	2.55	0.91	1.02		0.11
	[11.63]	[6.83]	[58.28]		[1.03]
CASPER	-0.44	0.03	0.86		0.37
	[-7.87]	[0.48]	[15.28]		[3.73]
CEDAR	-0.12	0.08	0.78		0.25
	[-3.86]	[1.72]	[20.46]		[3.47]
CHEYENNE	-1.02	0.27	0.94		0.72
	[-2.95	[2.05	[42.55]		[8.45]
DAVENPORT	0.98	0.73	1.02		0.48
	[2.87	[6.17]	[38.55]		[4.81]
DESMOINES	-0.37	0.32	0.99		0.17
	[-5.22]	[4.43]	[63.59]		[2.28]
DUBUQUE	0.27	0.45	0.85		0.53
	[1.95]	[2.38]	[23.41]		[2.53]
DULUH	0.42	0.57	0.82		0.29
	[4.04]	[2.99]	[29.75]		[2.62]
FARGO	0.18	0.84	0.86		0.60
	[1.15]	[7.24]	[25.27]		[3.78]
GFORKS	0.04	0.22	0.44		0.06
	[1.49]	[1.05]	[6.98]		[0.71
GRAPIDS	1.72	0.21	0.88		0.18
	[2.25[	1.43	[13.86]		[2.46]
GRFALLS	2.62	0.34	1.01		0.12
	[6.56]	[2.33]	[71.51]		[1.19]
IOWA	0.07	0.33	0.84		0.25
	[1.87]	[2.47]	[31.99]		[1.93]
LACROSSE	0.19	0.20	0.88		0.17
	[2.66]	[1.39]	[19.27]		[1.88]
LINCOLN	0.05	0.00	0.60		0.08
	[3.31]	[0.10]	[5.37]		[1.75]
MINNEAPOLIS	0.05	0.12	0.92		0.08
	[2.63]	[2.98]	[17.86]		[1.27]
MISSOULA	0.02	-0.09	0.85		-0.04
	[1.18]	[-2.15]	[12.53]		[-0.28]
OMAHA	-0.67	0.48	0.99		0.39
	[-1.60	[6.75]	[31.48]		[4.26]
ROCHESTER	-0.08	0.41	0.98		0.29
	-0.46]	[3.70]	[46.22]		[2.17]
SIOUXCITY	0.06	0.45	0.96		0.04
	[1.03	[4.09]	[43.21]		[0.33]
SIOUXFALLS	-1.83	0.40	0.82		0.33
	[-1.35]	[6.84]	[26.44]		[3.35]
WATERLOO	-0.45	0.04	0.97		0.13
	[-7.08	[0.54]	[41.89]		[1.17]
BISMARCK	0.04		0.89	0.05	
	[0.32]		[24.60]	[0.85]	

Notes: Newey-West's adjusted standard errors in brackets and heteroskedastic robust t-ratios.

Table D.7: Average Pairwise Cross-Section Correlations of variables using in GVAR model and associated model's residuals

	MSA	Levels	First Differences	VECMX* Residuals		MSA	Levels	First Differences	VECMX* Residuals
urate	AMES	0.45	-0.01	0.05	hpi	AMES	0.80	0.85	0.11
urate	BILLINGS	0.37	0.04	-0.11	hpi	BILLINGS	0.71	0.79	-0.03
urate	CASPER	0.12	0.09	0.03	hpi	CASPER	0.55	0.82	0.08
urate	CEDAR	0.17	0.08	0.04	hpi	CEDAR	0.77	0.85	0.11
urate	CHEYENNE	0.40	0.04	0.06	hpi	CHEYENNE	0.75	0.82	0.03
urate	DAVENPORT	-0.23	0.15	-0.04	hpi	DAVENPORT	0.81	0.86	0.03
urate	DESMOINES	0.57	0.09	0.10	hpi	DESMOINES	0.82	0.86	-0.03
urate	DUBUQUE	0.42	0.12	0.04	hpi	DUBUQUE	0.76	0.85	0.12
urate	DULUH	0.52	0.14	0.00	hpi	DULUH	0.77	0.83	0.16
urate	FARGO	0.55	0.14	0.02	hpi	FARGO	0.78	0.87	0.15
urate	GFORKS	0.33	0.17	0.02	hpi	GFORKS	0.73	0.85	0.17
urate	GRAPIDS	0.59	0.15	0.00	hpi	GRAPIDS	0.66	0.65	-0.03
urate	GRFALLS	-0.12	0.01	-0.04	hpi	GRFALLS	0.68	0.79	0.01
urate	IOWA	0.58	0.12	0.07	hpi	IOWA	0.78	0.86	0.05
urate	LACROSSE	0.59	0.18	0.02	hpi	LACROSSE	0.75	0.79	0.01
urate	LINCOLN	0.48	0.13	0.01	hpi	LINCOLN	0.75	0.81	0.07
urate	MINNEAPOLIS	0.60	0.23	0.03	hpi	MINNEAPOLIS	0.71	0.79	-0.15
urate	MISSOULA	0.59	0.15	-0.03	hpi	MISSOULA	0.75	0.78	0.06
urate	OMAHA	0.48	0.09	0.06	hpi	OMAHA	0.79	0.83	0.03
urate	ROCHESTER	0.56	0.02	0.07	hpi	ROCHESTER	0.75	0.80	0.01
urate	SIOUXCITY	0.34	0.06	0.02	hpi	SIOUXCITY	0.81	0.87	0.05
urate	SIOUXFALLS	0.56	0.08	0.04	hpi	SIOUXFALLS	0.77	0.81	0.07
urate	WATERLOO	-0.21	0.04	0.02	hpi	WATERLOO	0.72	0.85	0.09
urate	BISMARCK	0.55	0.09	0.00	hpi	BISMARCK	0.55	0.83	-0.08

	MSA	Levels	First Differences	VECMX* Residuals		MSA	Levels	First Differences	VECMX* Residuals
tppr	AMES	0.85	0.20	0.05	awe	AMES	0.68	0.15	0.00
tppr	BILLINGS	0.83	0.21	0.06	awe	BILLINGS	0.60	0.30	0.13
tppr	CASPER	0.31	0.21	0.09	awe	CASPER	0.67	0.37	0.13
tppr	CEDAR	0.84	0.24	0.11	awe	CEDAR	0.68	0.25	0.10
tppr	CHEYENNE	0.84	0.11	0.02	awe	CHEYENNE	0.76	0.38	0.01
tppr	DAVENPORT	0.47	0.33	0.11	awe	DAVENPORT	0.78	0.27	0.05
tppr	DESMOINES	0.84	0.28	0.11	awe	DESMOINES	0.80	0.31	0.08
tppr	DUBUQUE	0.77	0.18	0.06	awe	DUBUQUE	0.77	0.28	0.07
tppr	DULUH	0.81	0.16	0.03	awe	DULUH	0.76	0.25	0.10
tppr	FARGO	0.82	0.24	0.00	awe	FARGO	0.81	0.37	0.08
tppr	GFORKS	0.83	0.19	0.08	awe	GFORKS	0.70	0.20	0.10
tppr	GRAPIDS	0.86	0.25	0.13	awe	GRAPIDS	0.73	0.25	0.10
tppr	GRFALLS	0.66	0.09	0.06	awe	GRFALLS	0.76	0.36	0.13
tppr	IOWA	0.84	0.15	0.00	awe	IOWA	0.52	0.20	0.02
tppr	LACROSSE	0.82	0.17	0.10	awe	LACROSSE	0.56	0.31	0.09
tppr	LINCOLN	0.86	0.24	0.11	awe	LINCOLN	0.77	0.40	0.15
tppr	MINNEAPOLIS	0.85	0.37	0.13	awe	MINNEAPOLIS	0.75	0.38	0.08
tppr	MISSOULA	0.74	0.17	0.05	awe	MISSOULA	0.21	0.05	0.01
tppr	OMAHA	0.85	0.33	0.09	awe	OMAHA	0.76	0.45	0.11
tppr	ROCHESTER	0.83	0.19	0.02	awe	ROCHESTER	0.76	0.10	-0.03
tppr_sa	SIOUXCITY	0.75	0.19	0.11	awe	SIOUXCITY	0.77	0.22	0.08
tppr_sa	SIOUXFALLS	0.84	0.31	0.12	awe	SIOUXFALLS	0.78	0.32	0.07
tppr_sa	WATERLOO	0.68	0.15	0.06	awe	WATERLOO	0.68	0.27	0.10
tppr_sa	BISMARCK	0.77	0.22	0.14	awe	BISMARCK	0.81	0.34	0.13