SPATIO-TEMPORAL MODELS OF COUNTY-LEVEL ECONOMIC GROWTH

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by

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The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled:

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Professor Zack Miller

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ABSTRACT

This dissertation focuses on the growth of aggregate and sectoral earnings per worker in the counties of the state of Missouri in 1969-2000. Using the fact that industrial structure presented with employment composition differs for Missouri counties and applying measures of structural change to separate counties into clusters, in the second chapter of this dissertation we build spatial vector-autoregressive models of first order and estimate effects that spatial spillovers across counties have on growth of aggregate earnings per worker. An innovative approach to modeling spatial correlation among counties in a neighborhood shows that aggregate earnings in counties with different industrial structures have different and, sometimes, opposite effects on aggregate earnings of their adjacent neighbors. This approach when used for modeling spatial dependence shows that counties with large employment share of manufacturing sector have the biggest impact on their neighbors – a fact that may be used to assess possible economic policies to accelerate growth in some neighborhoods. In the third chapter we use a new variable to model spatial dependencies for three-dimensional panel data – sectoral portions of aggregate earnings per worker – with separate temporal and spatio-temporal lags of first order which allow estimation of external shocks across and within counties as well as across and within sectors of the economy. Estimation results for this spatial vector-autoregressive model of first order show that earnings per worker in some, although not all, sectors influence earnings per worker in other sectors with these effects differing by magnitude and direction. They also show that inter-sectoral spillovers within a county are stronger than spatial inter-sectoral spillovers in a neighborhood.

Chapter 1

Introduction

1.1 Motivation and hypotheses

Economic growth theories have not been able to explain differences in growth of income per capita in different countries to the full extent. Many factors that have been considered in the economic growth literature include both fundamental causes such as geography, institutions, culture, and so-called correlates of economic growth that include physical capital, human capital, and technology. These factors and correlates are called to explain the differences in the growth of productivity of workers as well as income per capita in different countries.

Cross-country studies that either consider particular sample of countries, e.g., OECD countries, or all countries in the world deal with both fundamental causes and correlates since all of them proved to be influential in countries' income growth paths. Although in order to concentrate on correlates and safely assume that fundamental causes are absent or their influence is mitigated, the lower level of economic entities has to come under scrutiny. Either state- or county-level study is able to shed light on the role of correlates on economic growth.

The advantage of county-level study of economic growth and development does not come without complications in terms of closeness of counties in space. If we assume that growth of income per capita (or earnings per worker as a proxy for worker's productivity) is not randomly scattered in space then geographical proximity of counties should be taken into account while studying income growth. Spatial and spatio-temporal models allow an inclusion of geography into study of economic growth in counties or other small geographical areas.

Although geographical proximity might be considered an unavoidable complication in county-level studies, it has another advantage in terms of the differences in industrial structure of the counties' economies. Structural change[1] has been considered as one of the sources of non-balanced economic growth. Structural change is closely related to technological change, for if different sectors of the economy grow at different rates due to different pace of technological progress, then it might be the case that both process and product innovations influence different sectors of the economy at different rates. Thus, technological and knowledge spillovers within and across counties as well as within and across sectors of the economy can be observed at the level of counties. While studying growth of incomes or earnings in geographically close economies, it is important to account for possible differences in the way that technological and knowledge spillovers or productivity shocks propagate within

[1]This structural change represents change in industrial composition of the economy measured either in earnings shares or employment shares and should not be confused with a structural break notion from time series analysis.

neighborhoods of counties. Modeling average effect for all counties in neighborhoods might not produce desired results because structural change might differ significantly in counties of the same neighborhood. We demonstrate this feature of the neighborhoods on the Figure 1.1 below. These maps show that for two sectors – manufacturing and services – the employment shares grow and shrink during 1969-2000 and in any neighborhood we can find counties with different changes in the employment shares of the presented on the maps sectors as well as other sectors of the economy.

Thus, we propose to adopt a new view on dimensionality of the growth process. The first, and most important one, is the time dimension, for it defines the growth dynamics. The second dimension is the geographical dimension – determines interaction of entities located close in physical space. Evidence of this dimension to be important in analysis is plentiful in spatial econometrics literature. And the third dimension is an interaction between economic sectors, for they grow at different rates for various reasons. In order to combine these dimensions in a model we build a spatial VAR (vector autoregressive) model of first order for two-dimensional panel of aggregate earnings per worker in which time and geographical dimensions are employed directly while space of sectors is used indirectly to allow for heterogeneous spatial dependence; and another VAR model for three-dimensional panel of sectoral portion of aggregate earnings per worker in which all three dimensions – time, geographical space and virtual space of sectors – are modeled directly.

Economic growth theories build a framework that helps to answer questions such as: What are the determinants of economic growth? How long does it take for economies to reach their steady states? Why do economies grow differently? At the same time, these theories have not been able to explain differences in growth of income per capita in different countries to the full extent. The determinants of economic growth include both fundamental causes such as geography, institutions, culture, and correlates of economic growth that include physical capital, human capital, and technology (Acemoglu, 2009, p. 19 [5]). They are called upon to explain the differences in the growth of earnings of workers as well as income per capita in different countries.

The fundamental causes of economic growth, when absent, play a role of barriers to it. These barriers can be divided into 5 main groups: policies, institutions, culture, composition of economic sectors, and distance between economies. (Acemoglu (2009) [5] lists only 4 of them, excluding composition of economic sectors, but does not include it into the list of covariates either.) When subjects of economic growth study are countries, all 5 groups of barriers are at work, for countries have different policies implemented in a fabric of different institutions and function in different cultural environments; the composition of their economies are different as well, partly because of different natural endowments and partly because of different past economic histories. The distance between different countries also differs due to the actual size of their territory as well as their being located on different continents. These difference are accounted for in empirical studies but they complicate the analysis and may affect the results.

Cross-country studies that consider either particular sample of countries, e.g., OECD countries, or all countries in the world deal with both fundamental causes and correlates since all of them proved to be influential in countries' economic growth. They are intertwined and, thus, have to be separated or isolated in empirical studies. Lowering the level of analysis from countries to states or counties allows elimination of some fundamental causes and concentration on covariates – the ones that play an important role in growth models and the ones that so far received limited attention. But one important fundamental cause – employment composition of the economies – is still at work. Significant difference in this composition becomes more evident and has more pronounced effect on economic growth of earnings for states and counties.

While state-level studies of economic growth ignore institutions and culture as fundamental causes of economic growth because of their absence on the level of states, county-level studies focus on composition of sectors and distance between counties. Absence of other fundamental causes of economic growth and similarity of its correlates presume growth of counties' economies in accordance with economic theories. The classical (Solow) growth model implies that labor productivity is the most important driving force of growth and thus, the output per worker is a good proxy for the standard of living and level of prosperity of the economy. The main idea behind the Solow model is such that countries with lower output per worker grow faster than countries with higher output per worker given assumptions adopted by the model. The implication of such a feature is that output per worker in different countries, both fast- and slow-growing, eventually converges.

Economists distinguish two types of convergence of economies' income – β- and σ-convergence. The first one, also known as the absolute convergence, refers to the hypothesis that 'poor economies tend to grow faster per capita than rich ones' (Barro, Sala-i-Martin, 1995 [9], p. 26) and depending on whether other characteristics of economies are accounted for conditional or absolute convergence is present. In other words, if the level of income that countries reach is common for them then there is an absolute convergence of income, if the levels are different then there is a conditional convergence. The speed of β-convergence depends on the initial amount of capital in the country (amount of capital per worker in the model setup), savings rate, type of technology that is represented with production function, and some other parameters including population growth rate and capital depreciation. The second kind of convergence occurs if the dispersion of income levels across countries declines over time.

There are also competing theories such as endogenous growth theory that model economic growth process on the basis of different sets of assumptions. These assumptions include endogenously determined growth rate of capital and non-decreasing returns to scale property of production function. These theories do not imply any possibilities of convergence of output per worker and, consequently, income per capita across different countries or any other regional entities within an economy.

Recent development of spatial econometrics introduced new modifications into theoretical framework as well as to empirical work of economic growth as the current growth models "do not integrate the spatial factor satisfactorily from the theoretical point of view" (Zhang, 2003 [105], p. 1). If the introduction of increasing return to scale and imperfect competition found their way into neoclassical growth theory, integration of this 'new' geographical aspect into growth models have not been realized fully because the prevailing way to do this is to adjust the models to account for any spatial interaction (in the form of technology spillovers or core-periphery interaction) on the last stage of analysis when growth rates or whatever other measures of the economic performance are chosen and then their spatial interaction is analyzed (see, for example, Giovanni and Francesco (2010) [55]).

Thus, we propose to include multiple dimensions into the growth process. The first, and most important one, is the time dimension, for it defines the growth dynamics of the levels of earnings. The second dimension is the geographical dimension – determines interaction of entities located in spacial proximity. Evidence of importance of this dimension important in empirical analysis is plentiful in spatial econometrics literature. And the third dimension is an interaction between economic sectors, for they grow at different rates for various reasons. In order to combine these dimensions in a model we build a reduced-form statistical model, namely, a spatial VAR (vector autoregressive) model of first order for two-dimensional panel of aggregate earnings per worker in which time and geographical dimensions are employed directly while space of sectors is used indirectly in order to allow for heterogeneous spatial dependence; and another VAR model for three-dimensional panel of sectoral portion of aggregate earnings per worker in which all three dimensions – time, geographical space and virtual space of sectors – are modeled explicitly.

We pose several hypotheses. The first hypothesis is related to the growth of aggregate earnings per worker at the county level. We conjecture that aggregate earnings not only grow at different rates across counties but also have non-random geographical distribution, e.g., counties with higher aggregate earnings are clustered together. This fact points to possible spatial dependence of aggregate earnings among counties and existence of spatial spillovers across counties' economies. It also raises questions about estimates of the growth rates of aggregate earnings in these counties if the underlying data-generating processes are assumed to be independent. We pose several hypotheses. The first hypothesis is related to the growth of aggregate earnings per worker at the county level. In the second chapter we conjecture that aggregate earnings not only grow at different rates across counties but also have non-random geographical distribution, e.g., counties with higher aggregate earnings are clustered together. This fact points to possible spatial dependence of aggregate earnings among counties and existence of spatial spillovers across counties' economies. It also raises the questions about estimates of the growth rates of aggregate earnings in these counties if the underlying data-generating processes are assumed to be independent. Thus, we hypothesize that spatial spillovers exist. At the same time, if change in sectoral composition is different in the counties within these clusters then it might be the case that this change affects growth of aggregate earnings per worker differently. So our second hypothesis is that the spillover effects are different within the same neighborhood. Then the empirical question is whether it can be measured with conventional modeling techniques. We offer an approach that allows one not only to measure this effect but also distinguish the effect that counties with different sectoral structure have on each other. The third hypothesis we consider is the significance of these spillover effects on the growth rates of earnings per worker in counties. The next, forth, hypothesis is that spillover effects are present not only in the space of counties but also in the space of economic sectors and sectoral earnings per worker, if modeled properly, can show how spillovers flow across sectors within and across counties and within sectors within and across counties. The last hypothesis related to it is that the sectoral earnings per worker in some sectors have consistently positive or negative spillover effects on sectoral earnings per worker in other sectors.

We offer an approach that allows one not only to measure this effect but also distinguish the effect that counties with different employment composition have on each other.

In the third chapter we show that a different from conventional approach should be used for study of the spatial spillover effect across counties as well as across sectors of the economy. For that instead of the aggregate earnings per worker we focus on sectoral portion of aggregate earnings per worker (it shows the portion of aggregate earnings per worker earned in a sector) at the county level. Then it is plausible to think that technological innovations propagate across sectors within and across counties and within sectors within and across counties. The existence of technological or knowledge spillover effects in the geographical space of counties and virtual space of sectors and the relative importance of the cross-section versus cross-county spillovers are tested in this chapter. Another hypothesis related to it is whether the sectoral portion of aggregate earnings per worker in some sectors has consistently positive or negative spillover effects on sectoral portion of aggregate earnings per worker in other sectors.

The research questions that we try to answer in this dissertation are the following.

1. Does spatial vector autoregressive model with a scalar coefficient associated with spatio-temporal (diffusion) term do well in terms of goodness of fit of the county-level data? Is there a way to improve the fit by offering different model specification?

2. How do the results of growth accounting exercise change when it is performed for clusters of counties instead of all counties in the state of Missouri?

3. Based on impulse response functions of the aggregate earnings per worker in a neighborhood of counties to an exogenous shock to a core/center county, what are the effects that counties in different clusters have on counties in other and/or the same cluster? And how does existence of spillover effects affect the growth

in counties that receive the shock initially?

4. How does spillover effect, when isolated from the growth effect due to internal forces, affect convergence of aggregate earnings per worker across counties?

5. What would be an appropriate measure of earnings per worker that would take into account both sectoral earnings per worker and the number of the workers in a sector?

6. How does an exogenous shock applied to a portion of aggregate earnings in a sector in a county affect portions of aggregate earnings in other sectors in the same county and the same and other sectors in other, neighboring, counties?

7. How does an exogenous shock applied to all sectors in a county simultaneously, e.i., county shock, affect portions of aggregate earnings in other sectors in the same county and the same and other sectors in other, neighboring, counties?

8. How does spillover effect, when isolated from the growth effect due to internal forces, affect convergence of sectoral earnings per worker across counties?

1.2 Economic growth literature

Empirical literature on the convergence of income per capita for different levels of economies contains evidence of different degrees of convergence of income per capita on different levels of economy. Sala-i-Martin (1996) [97] demonstrates that GDP per capita of 110 countries in the world from 1960 to 1990 converged at an average rate of 1.3% per year, conditional on regional dummies and structural variables, while OECD countries during the same period showed an average rate of about 2% for conditional convergence and 1.4% rate for absolute convergence.

Barro and Sala-i-Martin (1991) [8] show that, for U.S. states, the rates of absolute and conditional convergence are both close to 2% per year. Lower barriers for states' convergence increase the rate of absolute convergence and make it very close to the rate of conditional convergence. In the same paper, Barro and Sala-i-Martin estimate the convergence of Gross State Product (GSP) per worker from 1963 to 1986 for different economic sectors and find that all sectors combined converge at a rate of 2.13%, while construction converges at 1.7%, manufacturing at 4.6%, services at 1.49%, government sector at 1.6%, transportation at 2.5%. Other authors also estimated the convergence of other measures of economic activity and found mixed results. Bernard and Jones (1996) [13] found that the total factor productivity (TFP) converged at a rate of 3% in 14 OECD countries from 1970 to 1987, while the manufacturing sector showed an increased dispersion of productivity and, thus, the least evidence for convergence, and utilities, and services in general, the most. Later research by Rodrik (2013) [96] found a lack of convergence for manufacturing sector as a whole and evidence of substantial convergence for more disaggregated data for more than 100 countries over recent decades.

Empirical analysis of county-level data emphasizes the following features of counties as economic units: they function as small open economies and can be analyzed as such. They enjoy even lower than states barriers to growth, for to some degree they share the same policies and institutions, they perform in favorable environments of high factor mobility for both capital and labor, and practically all of them include both tradable and non-tradable sectors of the economy. If counties within one state are considered, even regional dummies can be omitted in the analysis. Higgins, Levy, and Young (2006) [61] show that income per capita for U.S. counties converges at 1.6 to 2.3% depending on the region.

While most of empirical work on economic growth focuses on convergence hypothesis testing, a model based on levels of earnings (development accounting) instead of growth rates (growth accounting) offers some advantages. First, using county-level data preserves degrees of freedom provided by the data and improves efficiency of the estimates. Second, model based on levels of earnings allows studying temporal dynamics of observed variables combined with application of spatio-temporal effects. Besides, these two kinds of models can provide different answers (as it has been pointed out in some of empirical research such as Hulten and Isaksson (2007) [66]).

When analysis of different sectors is performed, the main feature of underlying process of development that arises from the development of each sector separately comes from different nature of these different parts of the economy. Mostly 3 main sectors are considered: agriculture, manufacturing and services. While the first one is resource-based and obliges the decreasing returns to scale, the second one being knowledge-based is more prone to increasing returns. We also should keep in mind recent technological development that occurred in biotechnologies and possibly changed the nature of the agriculture. As for services sector, it is not simple to determine the nature of this production process since services are different on their own. Some services are customer-based, or non-tradable, e.g., dentistry and other health-related services, while others are tradable and might have different properties of production function.

Empirical literature focused on the role of structural change in growth of productivity demonstrates evidence that support its importance. Fagerberg (2000) [40] shows that if countries increase their presence in the technologically most progressive industry in the period under study (electronics in 1973-1990) they experience higher productivity growth than other countries. This study is done for 39 countries of the world and 24 low- and high-tech industries. Peneder (2003) [87] find evidence of industrial structure being a significant determinant of growth in the 1990s in 28 OECD countries by means of shift-share analysis. The same approach is used in study of regional convergence and industry mix in the European Union by Esteban (2000) [38] which shows that differences in the sectoral composition of sectors of the economy are responsible for the existing interregional inequality in aggregate productivities per worker and not the productivity gaps within sectors. These empirical findings support our view on the role that structural change (or change in employment composition) has on economic growth and speed of convergence.

1.3 Spatial, temporal, and spatio-temporal modeling literature

Some empirical literature on economic growth has space included into analysis as its factor and a determinant in income convergence. All three main econometric techniques used in empirical analysis of economic growth – cross-sectional data, panel data, and time series analysis – employ some elements of spatial modeling.

Space may be included in models as either absolute or relative location. The absolute location models are similar to spatial heterogeneity models, for they allow parameters of growth vary across countries or regions depending on their location –

coastal vs. landlocked, or other specifications of a location. The absolute location models are used more often when the club convergence is considered. For example, the absolute location model was used in Gallup et al. (1999) [50] empirical work on influence of geography on economic development of countries in the world. They used dummy variable for landlocked countries in regression equation for transport costs as a factor of economic growth. The authors also divided countries into different categories based on their climate and looked for the effect of climate on agricultural output. They also employed these geographical variables in a baseline growth model as in Barro and Sala-i-Martin (1995) [9] and found strong effects these geographical variables have on economic growth.

The relative location models determine location of a country relative to others so that an observation at one location depends on observations at other locations. These models allow spatial dependence as well since the spatial connections among areas are explicit. These models are used more often in spatial econometrics while the absolute location models are used more often in non-spatial econometrics literature. An example of a relative location model used in non-spatial economic growth research is in Keller (2002) [69] where the effect of R&D expenditures in neighboring countries on domestic productivity is modeled using bilateral distance between counties without explicit application of weights matrix.

Space may also be modeled in terms of either spatial heterogeneity or spatial dependence. While spatial heterogeneity allows parameters to vary across locations or groups of locations, spatial dependence may be modeled in either substantive or nuisance specifications (see Fingleton and López-Bazo (2006) [46] for discussion). The choice of specification is determined by the role that externalities across locations play in the growth process.

Commonly used linear spatial dependence models include, first of all, spatial autoregressive model (SAR)(Anselin, 2003 [4]) or spatial lag model of the following form:

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \rho\boldsymbol{W}\boldsymbol{y} + \boldsymbol{u}$$

where $\boldsymbol{y}$ is a vector of observations of a dependent variable, $\boldsymbol{X}$ is a vector of independent variables, ρ (scalar) the spatial autoregressive parameter, $\boldsymbol{W}$ the weights matrix, and $\boldsymbol{u}$ a vector of errors. The weights matrix $\boldsymbol{W}$ represents spatial proximity of the areas under consideration in such a way that the elements w_{ij} have non-zero value if areas i and j are neighbors of each other. The term $\boldsymbol{W}\boldsymbol{y}$ denotes the interaction effects for the dependent variable while spatial effect associated with particular location is defined by the term $\rho\boldsymbol{W}$. This term can be either homogeneous if $\boldsymbol{W}$ is a contiguity matrix or heterogeneous if the weights in $\boldsymbol{W}$ are based on distances, length of shared borders, etc. The former case is the most restrictive, since it imposes constraints on both elements of $\rho\boldsymbol{W}$ term, and sometimes produces infeasible results. The latter allows for some degree of heterogeneity among locations in the neighborhood but it is determined by the researcher a priori and based on the context of the phenomena under consideration. The choice of the weights in $\boldsymbol{W}$ is restricted with the information available to the researcher, i.e. length of borders between neighbors in real terms and linearized, contiguity [90], contiguity matrix with assignment of binary variables [81] or normalized rows, distance between centers [43], n nearest neighbors with a decision about n based on 'trial and error' methods, and combinations of the listed methods and others. Some degree of heterogeneity of the spatial or spatio-temporal association among regions within neighborhood is achieved through usage of either empirical weights matrix based on combination of different measures of spatial proximity or through several spatial terms with differently defined weights matrix.

Another linear model is a spatial error model:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u}$$
$$\boldsymbol{u} = \lambda \boldsymbol{W u} + \boldsymbol{\epsilon}$$

where $\boldsymbol{Wu}$ denotes the interaction effects among the disturbance terms. When the spatial interactions effects are modeled for the independent variables the model becomes spatial cross-regressive or SLX model:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \theta \boldsymbol{WX} + \boldsymbol{u}$$

where $\boldsymbol{WX}$ denotes the exogenous interaction effects among the independent variables.

Besides these models there exist other models that combine interaction effects: SAC model with $\boldsymbol{Wy}$ and $\boldsymbol{Wu}$ effects, spatial Durbin model with $\boldsymbol{Wy}$ and $\boldsymbol{WX}$ effects, and spatial Durbin error model with $\boldsymbol{WX}$ and $\boldsymbol{Wu}$ effects. These models are used in the studies of economic growth and convergence hypothesis testing with spatial econometrics techniques.

Rey and Montouri (1999) [93] estimated convergence parameters for U.S. states with spatial dependence modeled with three different specification: spatial error, spatial lag, and spatial cross-regressive term. They found (1) strong evidence of spatial effects in the unconditional convergence model, and (2) spatial error specification to be more appropriate for modeling, despite similarity of results for all three specifications. The authors favored spatial error model because it allows to observe propagation of a random shock applied to a specific state to other states. They also notice dampening of the spillover from the shock as the application point of shocks moves away from the central states (the random shock was applied to the state of Missouri as one of central states). They also hypothesized that presence of spatial error dependence may imply a possibility of a complex set of shock spillovers and that the only specification that allows propagation of a random shock throughout the locations in convergence models is spatial error specification while spatial lag or spatial cross-regressive models, to the contrary, do not allow random shocks to propagate through states. So, when spatial lag or spatial cross-regressive models are used, states' income per capita deviate from some steady state equilibrium only due to their own random shocks but not to their neighbors' random shocks.

Another approach used in cross-country studies of growth and convergence hypothesis testing that accounts for spillover considers measuring deviation of county's measure of income from world average (as in Bernard and Jones (1996) [13], Ramajo et al. (2008) [88] and others). In this case the cross-country interaction happens only due to a country belonging to a 'club' and affecting the club's average.

The spatial interaction is more pronounced between counties than between countries and even states, for their smaller territories presume lots of possibilities for workers to commute to work or interact socially, thus, changing geographic profiles of the economies. This fact is reflected in the income statistics that is observed, collected, and used for the economic analysis. Roberts (2004) [95], while studying convergence of GDP per capita in Great Britain counties, discusses possible reasons for overestimation of GDP per capita in different counties, in particular, due to commuters residing in one counties and working in others.

The same models described above are used for panel data estimations in similar way as for cross-sectional data. The main modifications to panel data models include introduction of fixed or random effects for the subjects under study or time periods. For example, Badinger et al. (2004) [6] introduce time-invariant region-specific effects and region-invariant time-specific effects into their panel convergence model to account for differences in the initial level of technology and temporal correlation of observed variables.

When time-series approach is employed in empirical work, convergence is identified in terms of relationship between long-run forecasts of output per capita while taking initial conditions as given. If in selected pairs of economies the difference between incomes per capita can be characterized as a zero-mean stationary stochastic process then convergence in these pairs of economies is observed (see Bernard and Durlauf (1996) [12]). The tests are done with standard unit root and cointegration procedures. The main caveat of this time-series approach is such that the data-generating process is assumed to be time-invariant (see Durlauf and Quah (1999) [31] for discussion). But this assumption is violated when economies are transitioning toward their steady states.

Spatio-temporal models have not gained popularity in economic growth empirical research probably because of the nature of convergence models widely used for study. Elhorst et al. (2010) [33] introduced space-time dynamics into income per capita convergence equation via estimation of cross-section time-series and panel data models along with cross-section model. In cross-section model they divided the time period under consideration into 5-year time spans and calculated average growth rates of income per capita for them while in panel data model they introduced time-period fixed effects. Ehorst (2001) [32] demonstrated general-to-specific approach to modeling relationship between labor force participation rate and unemployment rate at the regional level in EU. This approach consists of fitting and testing for significance of estimated coefficients a nested model for a cross-section of observations at time t that include temporal, spatial, and spatio-temporal lags of dependent and independent variables. His results suggest that 'both serial and spatial effects are likely to be present in the analysis of space-time data' (p. 23) and it is unclear how the spatio-temporal term is constructed – whether a spatial autoregressive lag model is corrected for serial autocorrelation or a serial autoregressive lag model is corrected for spatial autocorrelation.

Some researchers study spatio-temporal patterns of diffusion and interdependence of economic phenomena. Márquez et al. (2003) [83] use first order vector autoregressive model with interregional interaction term to estimate interregional linkages among 7 Spanish regions. They find asymmetric interregional spillover effects and build impulse responses functions to show transmission of exogenous shocks for the Spanish economy. Franzese and Hays (2006) [47] study policy diffusion and strategic policy interdependence for Active Labor Market policymaking in Europe. They claim that explanatory variables included into "spatial dynamics" models show only their pre-dynamic impetuses to the dependent variable which are unobservable, for they incur within observation period. To the contrary, spatio-temporal terms allow expression of the effects across spatial units and over time.

The propagation of random shocks through geographically close areas is attributable to both spatial and temporal connections of the areas. When only spatial connections are considered, the spatial effects are represented with spatial lag coefficient multiplied by the elements of weights matrix W and thought of as indirect effects for the nearest neighbors of an area of interest and induced effects for higher-order neighbors (the neighbors of the neighbors). These effects imply that all the areas in the system are linked, so that the spatial effects are global in nature, and induced effects are not equal to indirect effects.

There is another issue that the state of Missouri is not an island, i.e., there are other states which counties are located close enough to affect dynamics of economic processes in Missouri counties in a similar way that Missouri counties affect each other. The magnitude of the effects may not be the same for interstate connections as for intrastate connections but for the purpose of taking into account this fact it is not necessary to explicitly measure the interstate effects. In the literature this effect is called the edge effect and treated as a part of the more general boundary problem. Existence of borders may introduce considerable bias into parameter estimates for the region under study. Ignoring activities outside of the border to the ones inside of it may make the bias even more significant.

There are several ways to deal with the boundary effect in general and the edge effect in particular in empirical work that are offered in the literature. (Theoretical approaches mostly rely upon mapping finite surfaces onto an infinite surface such as a torus.) One of these ways is to construct a buffer (real or artificial) zone along the boundary and use areas in this zone to estimate spatial autocorrelation in the region. The width of the zone depends on the number of the spatial lags in Markov structure. Following statistical analysis is performed after discarding these units in the zone which brings about the fundamental shortcoming of this method related to information loss. Another, more conventional, way is to correct the weighting scheme for boundary area units. It can be done by appropriately weighting areas within boundary while taking into account areas outside of the boundary. Alternative way that may be thought as a combination of the first two is to construct the boundary zone and estimate spatial correlation for it separately from within the boundary region.

Most effectively these methods are used for geographical point processes in meteorology (Wikle, Berliner, Cressie, 1998 [102]), ecology, and other sciences. To our knowledge, in econometric empirical research this issue is mostly ignored or not discussed explicitly due to spatial models built for states or for all counties in the U.S. so that the edge effect is negligible.

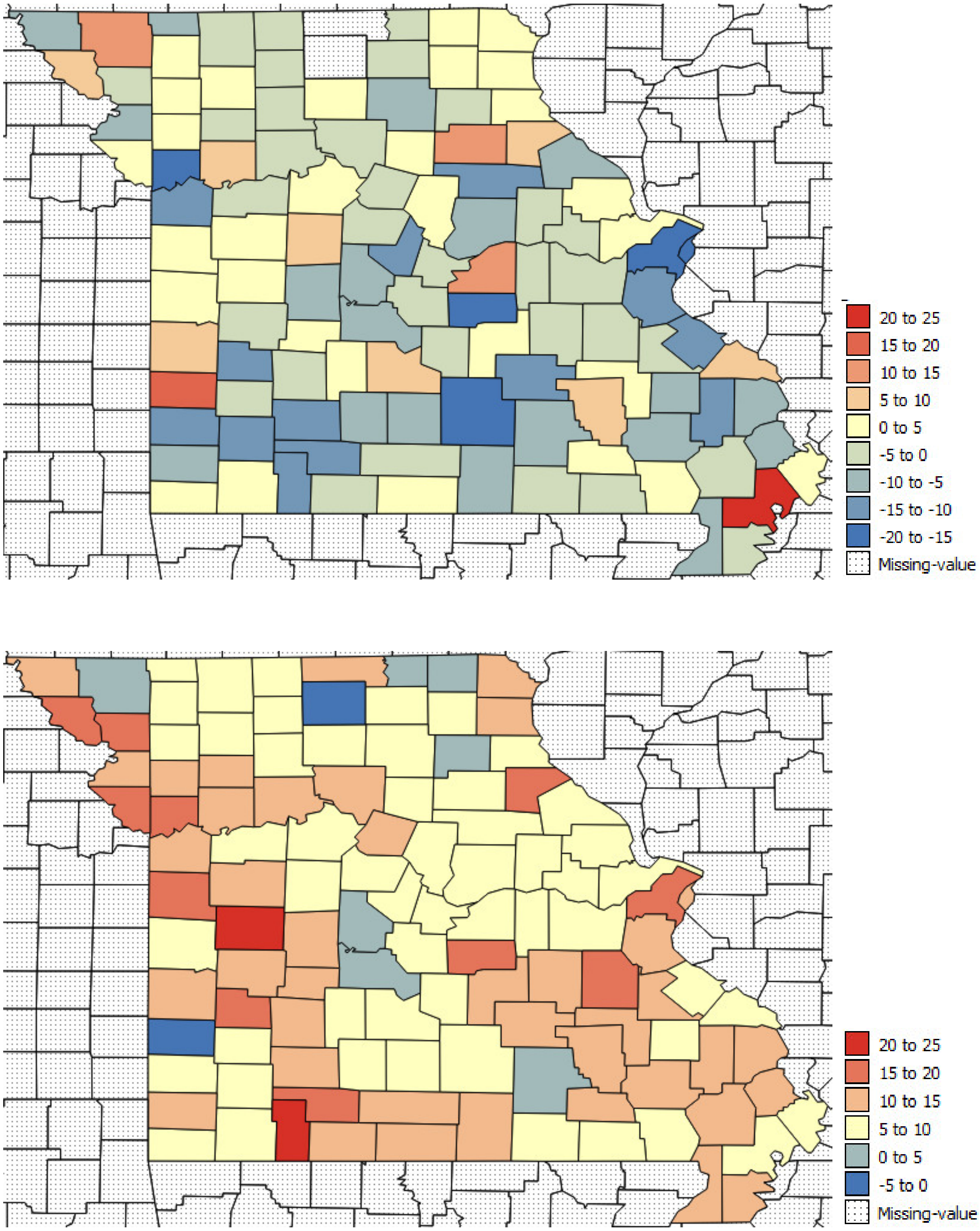

Figure 1.1: Maps of changes in employment shares for manufacturing and services sectors for counties in the state of Missouri in 1969-2000.

Chapter 2

Aggregate earnings per worker and industrial change

In this chapter we examine aggregate earnings per worker on county level. Since counties are located close to each other and behave as open economies we can expect some spillover effects to exist and affect dynamics of aggregate earnings per worker. In order to account for these effects spatio-temporal correlation between counties in a neighborhood is included into a model as a diffusion term along with temporal term. We test how a form of this diffusion term affects 'net' growth rates of counties' aggregate earnings per worker and their convergence.

2.1 Data and some stylized facts

2.1.1 Overview

The data we use are drawn from the Bureau of Economic Analysis Regional Economic Information System (BEA-REIS) database. The income per capita data are available for period from 1969 to 2000 on annual basis from BEA-REIS data sets. Our data contain 115 county-level observations for counties of the state of Missouri along with the observations for the whole state of Missouri for the same time period.

The measurement of income per capita is of particular importance for this paper so we want to address this issue separately. Income information collected by the Census Bureau for states and counties is based on the values self-reported by the Census Survey respondents as a part of the overall population census. These data are reported and recorded by place of residence. However, BEA's initial estimates of different components of personal income measure are done on a place-of-work basis. Consequently, a place-of-residence adjustment is made to the data to account for intercounty commuters and border workers[1].

The BEA-REIS data that used for the analysis are coming from tables CA05 and CA25. The main three measures of earnings and income are calculated in the manner presented in Table 2.1.

Table CA05 contains information on the earnings by sectors of the economy and table CA25 contains information on employment by the same sectors. So we calculate and use for the analysis earnings per worker by sector (by place of work), employment shares and earnings shares of the sectors, etc. The sectors reported in these tables are

[1]For more details on this issue see 'Local Area Personal Income and Employment Methodology' published by the BEA under the Regional Accounts Data, April, 2012.

farming (FA), agricultural services (AS), mining (MI), construction (CO), manufacturing (MA), transportation and public utilities (TU), wholesale trade (WT), retail trade (RT), finance and insurance (FI), services (SS), and government (GT).

2.1.2 Cross-county income differences in the state of Missouri

The state of Missouri's personal income per capita stayed within 92-94 percent of the national level, i.e., it was slightly lower than the average personal income per capita across all states. During period of 1969-2000 real aggregate earnings per worker by place of work on average for the state was growing consistently at an average annual rate of 0.4 percent, real net earnings per capita were growing at an annual rate of 1.1 percent, and real personal income per capita was growing at an annual rate of 1.6 percent (see Figure 2.1). The difference in growth rates between the first two measures of earnings might be attributed to two main factors: difference in the number of workers and the number of residents within an area (in this case, the state) and the change in contributions for government social insurance along with the change in adjustment for residence (which is related to the first factor, for more workers moving for residence into other areas increase this adjustment). The difference between the last two measures might be attributed to the increase in non-labor incomes that residents of the area receive, and some of these incomes come in the form of personal transfer receipts, so the ageing of the population of the area can bring the difference up as well.

Assessment of the convergence of the measures of earnings and income is done through assessment of absolute and conditional β-convergence and σ-convergence.

To test the absolute and conditional β-convergence hypothesis for the counties' earnings per worker by place of work and (net) earnings per capita by place of residence the regression model (as in Higgins, Young and Levi (2007) [62]) was estimated [2]. The results are presented in Table 2.2. The graphs with respective regression lines (for absolute β convergence only) are shown on Figures 2.2 and 2.3.

Since the actual convergence rates approximately equal to the β estimates, regressions estimation results show that when each decade is considered separately, for earnings by place of work absolute convergence is observed during 1980s and 1990s while in 1970s absolute divergence takes place. When we use average growth rates for all years (1969 through 2000) there is no evidence of convergence or divergence. This fact might be interpreted as an evidence in favor of endogenous growth rather than exogenous as non-zero estimates of β (and convergence rates) would suggest.

Income by place of residence shows completely different results. For this measure of income absolute β-convergence is observed during 1980s, 1990s, and for all period under consideration. For 1970s β estimate is not significant although its sign is correct.

Figures 2.4 and 2.5 show the distribution of the income per capita and earnings per worker across counties in 1969 and 2000. Visual assessment of the histograms allows us to conclude that the variation of the earnings per worker by place of work has increased during period of 1969-2009. Obvious question might be asked of whether there were movements of counties within the distributions from lower quantiles to upper quantiles. As results of cluster analysis for the earnings by place of work show (will be discussed in the next section) there was no significant movement; counties

[2] Estimates for decades are based on 11-year and 9-year period average growth rate with initial year being 1969, 1980, and 1990, respectively.

with aggregate earnings per worker by place of work above the state average in 1969 still had these aggregate earnings above the state average in 2000 (there are 5 of those). The rest of the counties with the earnings below the state average did not change their positions in the distribution significantly.

As for the per capita (net) earnings by place of residence, the histograms show that there is no visible change in the width of the distribution of these earnings during period of 1969-2000.

F-test of the difference between the variances of the real aggregate earnings per worker in 1969 and 2000 shows that the variance for 2000 is greater than the variance for 1969 ($F_{114,114} = 1.73496 > 1.265$) for one-sided test at 5 percent significance level. F-test of the difference between the variance of the real personal income per capita in 1969 and 2000 shows even stronger evidence of σ-divergence of personal income per capita ($F_{114,114} = 47.65 > 1.265$).

Empirical testing of convergence hypothesis based on income per capita might be very misleading precisely for the following reasons. Firstly, convergence hypothesis is an extension of Solow model which is based on the properties of production function but treats income and earnings in the same way. As we have seen above, income per capita includes transfers that redistribute income across individuals and households as well as non-labor income. Secondly, when analysis is done for smaller than country aerial units, adjustment for residence also plays an important role in redistribution of income but now across states/counties. Thus, if we want to study effect of industrial structure on well-being of population we have to concentrate on earnings per worker rather than income per capita.

Available data on aggregate earnings per worker can be considered as a set of 115 time series. Each of the time series is assumed to follow an AR(1) process. We can see it from the plots of autocorrelation function (ACF) and partial autocorrelation function (PACF) (see graphs on Figure 2.6).

At the same time, since in geographical space counties are neighbors of each other it is possible that these time series are not independent from each other. Local and global Moran's I tests of spatio-temporal randomness (the lack of pattern) has been performed for each of 31 pairs of consecutive years (1969-1970 through 1999-2000) and the results indicate presence of spatial clustering while positive spatial autocorrelation means that nearby counties have similar levels of aggregate earnings per worker (see Table 2.3 for global Moran's I values and Graph 2.7 for local clusters map). This test's results also show that clustering persists over time suggesting that time series of the aggregate earnings per worker are spatio-temporally autocorrelated.

Another feature of the spatio-temporal clustering of aggregate earnings per worker demonstrated on the maps of local clusters is that the number of clusters change over time as well as their location on the map. The number of clusters changes from as few as 5 (in 1998/99) to many as 14 (in 1979/80). Some clusters with high values for both center and neighbors are located persistently in St.Louis and Kansas City metropolitan areas while clusters with low values for center and neighbors located mostly near norhtern and southern borders of the state. Overall conclusion that these tests allow us to make is that there is no stable pattern of spatio-temporal dependence across counties and the existing ones are not identical in terms of the combinations of levels of values of variable under scrutiny for center and for neighborhoods.

During period of 1969-2000 the sectoral composition of the state's economy expressed in terms of employment shares (see Figure 2.8) followed the national trend which is shown on Figure 2.9. The main features of it are shrinking share of the manufacturing and farming and expanding share of services. Government and mining sectors are shrinking in both the country and the state while retail trade and construction sectors are expanding in both. For the counties in the state of Missouri there are other changes in the employment structure of the economy in place while they are not present in the employment structure of the U.S. economy as a whole. While the wholesale trade sector is not consistently shrinking in the country, it is shrinking in Missouri; the same pattern is observed for the finance and insurance sector. Transportation and public utilities sector is shrinking in the state while it stayed almost the same in the country during 1969-2000.

Since the employment shares by sector of the economy reflect the input share of the labor it is also important to take a look at the output share of the labor which is presented with the earnings share by sector. Earnings per worker by sector for the counties in the state of Missouri are shown on Figure 2.10. The national economy's earnings shares are presented on Figure 2.11. These structures are more similar than the employment structures. The earnings shares of services, finance and insurance and agricultural services are increasing both in the national economy and in the state's economy while earnings shares of retail trade, transportation and public utilities, manufacturing and farming are declining in both economies. Some differences in trends exist in governments, wholesale trade, construction and mining sectors. The shares of the earnings in government and construction sectors are steadily declining in the U.S. economy but do not follow the same trend in the state of Missouri while wholesale trade and mining sectors are not changing in the national economy and falling in the state's economy.

The overall results of changes in employment shares of the sectors and in earnings per worker within the sectors can be seen in the changes of the earnings shares of the sectors since this structure shows the contribution of each sector to the aggregate earnings per worker in the state of Missouri. The connection between these two structures happens due to two effects that can be either offsetting each other or working together – the increase in the employment share of the sector can either bring the average earnings in the sector up or down depending on the properties of the production process in the sector with possible effect coming from the resulting labor market effect when increase in supply of workers, given unchanged demand for them, brings the wages down. On the other hand, increasing wages in the sector can reduce employment of workers reducing the labor intensity of the production process. We do growth accounting exercise to see what happens with the earnings and employment in different sectors of the economy of the state of Missouri (see subsection 2.2.1).

If we want to take a loser look at how the counties in the state of Missouri do not converge to a common steady state level of aggregate earnings per worker, we can look at the plot of the average growth rates against the logarithm of the real aggregate earnings per worker in 1969 for all counties presented (see Figure 2.2).

On the graphs on Figure 2.12 we can see that employment shares change differently not only across sectors but across counties as well. The 45-degree lines on these graphs show how employment shares of the sector changed during 1969-2000 period. One of the conclusions that we can make is that the change in industrial structure may impact dynamics of the aggregate earnings per worker.

2.2 Cluster analysis

2.2.1 Growth accounting exercise

In order to see whether change in employment composition has any effect on aggregate real earnings per worker we perform growth accounting exercise. Growth accounting exercise is often used in economic growth analysis to assess the relative importance of changes in several components of the overall change (see example in Bernard and Jones (1996) [13]). For the purpose of our analysis we take a look at the relative importance of the change of the size of a sector (as determined by its employment share) and a change in earnings per worker in a sector in an overall change of aggregate earnings per worker which is of main interest for us.

We look at the sources of the change in earnings per worker aggregated over aforementioned sectors of the economy. Since aggregate earnings E can be written as a sum of sectoral earnings E_j

$$E = \sum_j E_j.$$

and earnings in each sector as a product of the sectoral earnings per worker e_j and the employment level L_j (number of workers)

$$\begin{aligned} E_j &= \sum_j \frac{E_j}{L_j} L_j \\ &= \sum_j e_j L_j, \end{aligned}$$

we can write aggregate earnings per worker e as a weighted sum of sectoral earnings per worker where the weights are employment shares s_j

$$e = \frac{E}{L} = \sum_j e_j \frac{L_j}{L} = \sum_j e_j s_j.$$

Using this framework we can decompose the growth of aggregate earnings per worker in each county into between- and within-sector components in the following way:

$$\Delta e = \sum_j \Delta e_j \cdot \bar{s_j} + \sum_j \Delta s_j \cdot \bar{e_j}.$$

Dividing this decomposition by the initial level of aggregate earnings per worker e_0 and rewriting it in terms of percentage changes yields

$$\%\Delta e = \sum_j \%\Delta e_j (\frac{e_{j,0}}{e_0}) \cdot \bar{s_j} + \sum_j \Delta s_j \cdot (\frac{\bar{e_j}}{e_0})$$

and in terms of effects yields

$$TE = EGE + SE,$$

where TE is a total effect, EGE is an earnings growth effect, and SE is a share effect. The EGE captures the contribution of within-sector change in earnings per worker to the change of aggregate earnings for the county, using the average sectoral weights for the period under consideration. So the sectors with faster growth of earnings make larger contributions to the growth of aggregate earnings. The SE shows the contribution of the change in sectoral composition on growth of the aggregate earnings per worker. Analogously to the EGE, the shares changes are weighted by the average relative earnings per worker for the sector over period under consideration. Thus, the sectors with a declining share as a fraction of total employment have negative share effect. It is also important to emphasize that these effects are calculated under ceteris paribus condition, i.e., the total effect of growth of earnings by sector shows the weighted average of the growth of earnings in all sectors with the average over time employment share of each sector. The actual growth rates are not reported in the table but occasionally mentioned when the results are described only to emphasize the difference in the growth of earnings in the counties within different clusters.

The third column in Table 2.4 shows that the change in industrial structure of the economies of Missouri counties has an effect on the growth of aggregate earnings per worker of the magnitude much smaller than the change of the sectoral earnings per worker. The actual calculated share effect is about a third of the earnings growth effect. Also it is noticeable that observed changes in the employment shares within counties are such that the increase in employment share of services sector has a positive effect on the aggregate earnings per worker of the size that is twofold of the size of the negative effect of the decrease in employment share of farming sector has on the same aggregate earnings. It is also noticeable that the overall effect of the services sector is the greatest among all sectors, and the share effect is twice bigger than the earnings growth effect for this sector.

2.2.2 Choice of clustering variables

The choice of clustering variables is determined by the research question asked. Since we are looking at the effect that industrial structure or its change have on the growth of aggregate earnings per worker, clustering variables have to reflect them.

The variation of potential clustering variables is presented in Table 2.5. It shows that industrial change in 1969-2000 is more diverse than the initial industrial structure. The coefficient of variation measured as a ratio of standard deviation over the mean ranges from 0.45 to 34.84 for the changes and only from 0.21 to 3.44 for the values in 1969. At the same time, when these variables are combined together into one measure of variability, as cluster analysis does, the results are such that the combined change in employment shares varies less than the combined initial structure. It can be demonstrated by the size of the clusters from clustering analysis performed separately for values in 1969 and changes in 1969-2000 of the employment shares of the counties in the state.

The cluster analysis based on the values of employment shares in 1969 shows that as the number of the clusters increase to 6 and more 3 counties are included into their own clusters and stay there. These counties are Pike (FIPS 29163), Platte (FIPS 20165), and Pulaski (FIPS 29169). In these counties, respectively, the following sectors have the greatest shares among all counties in the state: construction - 25.1 percent, transportation and public utilities - 50.8 percent, and government - 8.7 percent, respectively. In this case, even if the initial structure of the economy in the counties is important for the dynamics of the aggregate earnings per worker in the following years, the estimates of this effect are not going to be reliable because of the smaller number of the observations used for the clusters chosen.

On the other hand, the cluster analysis based on the changes in employment shares in 1969-2000 shows that the only one smallest cluster among 5 or more clusters includes 3 counties - Cass (FIPS 29037), Johnson (FIPS 29101), and Pulaski (FIPS 29169). Thus, it seems to be reasonable to use changes in employment shares for the cluster analysis since these clustering variables allow more even distribution of the counties among the clusters and make the estimates of the parameters in the models more reliable.

Another clustering variable that can be added to the change in employment shares may either provide information about the employment level in the counties or about their human capital. The human capital seems to be more feasible variable since growth theory tells us that level of human capital affects economic growth but the role of human capital in different sectors of the economy is not clear. Besides, if human capital is measured with the educational attainment, e.g., number of holders of bachelor's or higher degrees per 1000 persons or percentage of population with bachelor's or higher degree, it should be used with great cautious, for the educational attainment is observed for population or residents within counties while earnings are measured for workers within counties. Significant numbers for adjustment for residence in BEA-REIS tables suggest that residents commute a lot and approximation of the education of workers with education of residents might not be correct.

Thus, we choose to use the percentage change in total employment as additional clustering variable because it reflects the growth of the 'size' of the counties' economies. The reason for choosing such a variable is that the growth of the share of a sector might happen for at least two reasons – decrease in share(s) of other sector(s) or growth of the size of the sector only which is reflected with the growth in total employment. Thus, including percentage change in total employment allows separation of counties where total employment grows slowly from the counties where it grows fast.

Exclusion of the spatial variables (longitude and latitude coordinates) from the list of clustering variables is due to the main purpose of the cluster analysis – division of neighborhoods of counties into different clusters based on industrial change characteristics, not their geographical proximity. Including spatial coordinates restricts clusters spatially, thus, creating spatial clusters instead of clusters in the virtual space of sectors of the economy.

The cluster analysis is done using SAS 9.4 procedures. The first procedure, PROC STANDARD, standardizes the clustering variables to mean zero and variance one to reduce influence of their magnitudes on the resulting clusters and equalizes the weight of each variable. After the variables are standardized, PROC FASTCLUS, which is run separately for each number of clusters, divides counties treated as units of observations into convex k clusters using k-means method, i.e., locating each observation to the cluster with the nearest mean. Following this procedure, PROC CANDISC procedure is used to perform a canonical discriminant analysis of the clusters determined earlier, to calculate Mahalanobis distances between centers of the clusters, to perform multivariate analysis of variance and to report multivariate statistics used for decision about the optimal number of clusters.

2.2.3 Results of cluster analysis

As was shown above, the counties in the state of Missouri are heterogeneous in their aggregate earnings per worker by place of work and (net) earnings per capita by place of residence. Thus, modeling an average effect across all of them is meaningful since all counties as a whole include both high-performers and low-performers and present very heterogeneous mix. So, we have decided to divide them into classes (or clusters) depending on the change in industrial structure measured by a change in employment shares of the sectors (we use only 9 out of 11 of those presented in the data) and a percentage change in the employment level to account for a growth of the size of the county's economy. These 10 variables were used for cluster analysis. The reduction in the number of the sectors for which the change in employment shares has been used for cluster analysis is explained by the fact that there are many missing values for the change in employment shares for agricultural services and mining sectors (15 and 35, respectively.) When all 11 sectors' changes of employment shares are used for the cluster analysis the used number of observations is 26 while if these two sectors are removed from the list the number of used observations increases to 81. Greater number of used observations allows more efficient division of the counties into cluster since the multivariate statistics used for choosing the optimal number of clusters are calculated in a more precise manner.

Based on statistics for the cluster analysis that include Wilks' lambda, Pillai's trace, Hotelling-Lawley trace, and Roy's greatest root the decision is made in favor of 7 clusters (see Table 2.6). All these statistics use between subjects within clusters and between clusters sums of squares and cross-products to test the fit of the clusters. When the number of the cluster increases the first statistics has to decrease while the other 3 have to increase to confirm improvement of the cluster analysis results.

As we can see from Table 2.6 when the number of clusters increases from 5 to 6 and from 6 to 7 the statistics show that greater number of cluster in both cases produces better fit of the clusters to the data. When the number of cluster increases from 7 to 8 the first two statistics show improvement of the fit while the other two do not. When the number of clusters increase even further, to 9, the first two statistics show improvement again while the other two statistics both grow but not much enough (in the case of Roy's greatest root) to improve the fit in comparison with 7 clusters.

When the number of clusters increases to 10 all statistics show improvement of the fit while 11 and 12 clusters are not clearly better ones than 10. So we have a choice between using 7 or 10 clusters. We choose to use only 10 clusters because increase in the number of clusters from 7 to 10 increases the number of parameters in the model to be estimated exponentially – from 49 to 100.

The spatial map of these clusters is represented on Figure 2.13.

The employment structure changes demonstrated on the Figure 2.14 can also be seen in growth accounting results (see Table 2.7).

Counties in 7 clusters do not show the same changes in the structure of their economies as the state's economy and the national economy; decrease in the employment share of manufacturing sector and increase in the employment share of services sector. Counties in cluster 1 experienced largest decrease in the employment share of government sector and increase in the employment share of services sector but they still have government sector as the biggest sector of their economies. Platte county – the only county in cluster 2 – had largest transportation and public utilities (TU) sector which significantly shrank during 1969-2000 but still remains one of the two largest sectors along with services sector. Counties in cluster 3 experienced largest reduction of employment share in construction sector and farming and the largest increase in government sector which stays one of the largest three along with farming and services. Counties in cluster 4 experienced largest reduction in farming sector which is the second largest sector and increase in services sector that became the largest one with retail trade to be the third by the employment share. Counties in cluster 5 experienced reduction in the size of farming and increase in the size of services sector with services, government and retail trade sectors being the largest ones. Counties in clusters 6 and 7 have services, manufacturing and retail trade sectors as the largest by the employment share while experiencing reduction in employment share of manufacturing sector and increase in services, although both of slightly different magnitudes.

2.3 Models specification

As a variable of interest we use natural logarithm of aggregate earnings per worker on annual basis for all counties in the state of Missouri. The data are arranged into an $n \times T$ matrix $\tilde{\boldsymbol{Z}}$ with columns corresponding to time (years) and rows corresponding to spatial locations (counties). The underlying model that encompasses different formulations and numbers of parameters of consideration is Bayesian growth-diffusion model. This model includes an autoregressive temporal term of first order and an autoregressive spatio-temporal term of first order. The former describes growth of the variable of interest while the latter describes diffusion, inter-county spillover effects, or lagged in time spatial interaction between earnings in counties within a neighborhood. Different formulations of the model show spatio-temporal term with and without accounting for the assignment of clusters to the counties in a neighborhood. The model for all counties at time t has a particular form depending on the growth g and diffusion ρ parameters that may be either scalars or vectors of different dimensionality.

First three models have spatio-temporal parameter ρ assumed to equal to zero. The difference among these models comes from different number of coefficients of autoregressive parameter g.

In the first model autoregressive temporal coefficient g is a scalar that measures average over all counties correlation between any two consecutive terms in the temporal sequence. So the model for all counties at time t has the following form for a county i:

$$Z_{it} = gZ_{i,t-1} + \epsilon_{it},$$

where $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is an error term, and for all counties at time t:

$$\boldsymbol{Z}_t = g\boldsymbol{Z}_{t-1} + \boldsymbol{\epsilon}_t, \tag{2.1}$$

where $\boldsymbol{Z}_t$ is an $n \times 1$ vector of log-aggregate earnings per worker at time t.

In the second model the autoregressive parameter $\boldsymbol{g_m}$ is a vector of cluster-specific coefficients. If the number of cluster is m then it is a vector with m elements each of which measures average across counties within a cluster correlation between any two consecutive terms in the temporal sequence. So for a county i that belongs to cluster j $(j = 1, ..., m)$ at time t the model has the following form:

$$Z_{it}^j = g_j Z_{i,t-1}^j + \epsilon_{it},$$

and for all counties at time t:

$$\boldsymbol{Z}_t = \boldsymbol{Z^H}_{t-1}\boldsymbol{g_m} + \boldsymbol{\epsilon}_t, \tag{2.2}$$

where $\boldsymbol{Z^H}_{t-1}$ is an $n \times m$ matrix with the value Z_i for county i located in a column that corresponds to the cluster this county belongs to.

In the third model the autoregressive parameter $\boldsymbol{g_n}$ is a vector of county-specific coefficients. The number of elements in the vector is the same as the number of counties in the sample, so each element measures average correlation between any two consecutive terms in the individual temporal sequence for each county. The model has the following form for a county i at time t:

$$Z_{it} = g_i Z_{i,t-1} + \epsilon_{it},$$

and for all counties at time t:

$$\boldsymbol{Z}_t = diag(\boldsymbol{g_n})\boldsymbol{Z}_{t-1} + \boldsymbol{\epsilon}_t. \tag{2.3}$$

The second set of three models includes the same autoregressive terms as the first set and also a spatio-temporal diffusion term with a scalar coefficient ρ. This term is constructed with weights matrix $\boldsymbol{W}$ and applied to the temporal lag of the latent variable, vector $\boldsymbol{Z}_{t-1}$. For a county i at time t the spatio-temporal term is $\rho \boldsymbol{W}_i \boldsymbol{Z}_{t-1}$, the spatio-temporal coefficient ρ is multiplied by the weighted average of variable Z_{t-1} for the county i's neighbors where the weights are elements of the respective row of weights matrix $\boldsymbol{W}$.

The fourth model for a county i at time t is

$$Z_{it} = gZ_{i,t-1} + \rho \sum_{l \in N_i} w_{il} Z_{l,t-1} + \epsilon_{it},$$

where N_i is the neighborhood of county i, w_{il} is an element of weights matrix $\boldsymbol{W}$ located in i^{th} row and l^{th} column, and for all counties at time t is

$$\boldsymbol{Z}_t = g\boldsymbol{Z}_{t-1} + \boldsymbol{Z^W}_{t-1}\rho + \boldsymbol{\epsilon}_t, \tag{2.4}$$

where $\boldsymbol{Z^W}_{t-1}\rho = \rho \boldsymbol{W} \boldsymbol{Z}_{t-1}$.

The fifth model for a county i at time t is

$$Z^j_{it} = g_j Z^j_{i,t-1} + \rho \sum_{l \in N_i} w_{il} Z_{l,t-1} + \epsilon_{it},$$

and for all counties at time t is

$$\boldsymbol{Z}_t = \boldsymbol{Z^H}_{t-1} \boldsymbol{g_m} + \boldsymbol{Z^W}_{t-1}\rho + \boldsymbol{\epsilon}_t. \tag{2.5}$$

The sixth for a county i at time t is

$$Z_{it} = g_i Z_{i,t-1} + \rho \sum_{l \in N_i} w_{il} Z_{l,t-1} + \epsilon_{it},$$

and for all counties is

$$\boldsymbol{Z}_t = diag(\boldsymbol{g_n}) \boldsymbol{Z}_{t-1} + \boldsymbol{Z^W}_{t-1}\rho + \boldsymbol{\epsilon}_t. \tag{2.6}$$

The third set of models includes modified spatio-temporal term that accounts for the fact that counties in the neightborhood of county i belong to different clusters. The main idea behind the construction of these models is to allow heterogeneity of the parameter that measures strength of the spatio-temporal association among counties within a neighborhood.

As we have already discussed in the first chapter, the main feature of the spatial models that exploit weights matrices explicitly is their treatment of a neighborhood as a homogeneous entity. Recognition of the real world's complexity and desire to model it in a more realistic way – either for the purpose of studying it or for the purpose of making predictions/creating economic policies – make us think of replacing the scalar parameter with a vector that would enable capturing sufficient for the purpose of the task spectrum of relationships between counties within a neighborhood. The exact number of parameters to be estimated depends mainly on the choice of the measure of proximity of counties and on the number of unique pairwise spatial intercorrelations chosen to be modeled. (If in our model all counties are assumed to interact with each other asymmetrically then the introduction of such a vector will require estimation of $n^2 = 13225$ elements of spatial or spatio-temporal parameter-vector. Reduction of the number of neighbors will bring this number down significantly.)

The problem of having this kind of vector in the model is a computational complexity and the number of parameters to be estimated. One of the possible ways to handle this problem is to organize the neighboring counties into groups or other distinct separate formations; the most frequently used approach in geostatistical research is following north-south and east-west directions. When lattice data are used, the grouping can be applied to the counties themselves and then the spatial interaction between neighboring counties that belong to particular groups can be modeled separately. The division of the counties into groups can be based on any criterion. The number of parameters to be estimated is the squared number of groups or clusters that the counties are divided into. For example, the counties in our sample are divided into 7 clusters so we need to estimate 49 coefficients that will be associated with the relationships among these clusters of counties. So we reduce the number of parameters more that 200-fold (from 13225 to 49 even if we assume that all groups interact with each other).

Another complication of building such terms arises from difficulties of specification. This problem has been attacked from different perspectives. Some researchers empirically find suitable weights which are derived as a mixture of different commonly used proximity measures and then applied to model the spatial correlation. Resulting weights allow both estimation of ρ coefficient and some degree of idiosyncrasy to each location. Another way of getting similar results would be to apply different weights matrices with their own ρ coefficients attached to the choice of dependent or independent variable. The combination of weights with coefficients attached to them will also create site-specific measure of spatial dependence. There is another approach taken by Aldstadt and Getis (2006) [2] that uses local spatial autocorrelation statistic to identify the geometric form of clusters in space and apply this knowledge to construction of weights matrix. This endogenously specified weights matrix is used in the models to describe proximity of the regions under consideration.

We approach this problem from a different perspective. The choice of the weights matrix remains to be prerogative of the researcher but the regions under study are divided into clusters. The clustering procedure is not based upon the same variables that are being studied and modeled later on but a set of different variables from the ones used in the model that describe the same areas from different perspective. For example, we have information about counties that we are not using explicitly in the model for the aggregate earnings, e.g., industrial structure of the economy in the counties or a change in the industrial structure. If we think of all sectors of the economy as a quasi-space then we can divide the counties in this quasi-space into clusters and then map them into the original geographical space and study their interaction within the clusters framework. The reason for doing this is the following.

The homogeneity of the coefficient of spatial association ρ restricts us from effectively modeling the spatial interaction among counties and properly catching the spatial and temporal features of underlying dynamical process. One of the most important assumptions of this modeling technique is that all counties in the neighbourhood are treated in the same way. The only difference regarding the counties is their physical proximity to the center/core. We think that if the neighboring counties have different features related to the dependent and/or independent variables then they affect the center in different ways. So we can divide the counties within a neighbourhood into clusters based on their similarities and model the spatial correlation taking these clusters into consideration. The division of the counties into clusters can be done using cluster analysis with an appropriate choice of clustering variables. After the clusters are determined we design the weights matrix that consists of the same elements as the familiar weights matrix but they are rearranged in a different way. The whole weights matrix can be thought of as a three-dimensional matrix n x n by m where n is the number of counties and m is the number of clusters.

Since when modelling the spatial dependence the $\boldsymbol{\rho W}$ term serves as a linear filter for the values of the lagged variable, there are particular properties that the weights matrix should satisfy. One of them is that it has to be row-stochastic. This condition is satisfied when the three-dimensional matrix is turned into its two-dimensional equivalent of the size n x (nm). Then sum of the elements of each row is equal to 1 (if the edge effect is not accounted for). Any weights matrix can be rearranged into this new matrix but since the division of the counties into clusters allows for distinction between effects that different neighboring counties have on central county, properly recalculated binary contiguity matrix gets the work done.

Some researchers may have a concern regarding endogeneity of the constructed spatio-temporal term which is reasonable and can be addressed in the following way. As long as the clustering variables used for cluster analysis are not entering the model explicitly they do not create endogeneity. At the same time if the weights matrix is chosen based on exogenous measures of the proximity of counties to each other, simple division of the weights matrix into several matrices that when added together recreate the original matrix does not seem to create any problems.

Construction of the modified weights matrix for the purpose of deriving full conditional posterior distributions is described in Appendix A.

The seventh model for a county i that belongs to cluster j at time t is

$$Z_{it}^{j} = gZ_{i,t-1}^{j} + \sum_{j=1}^{m}\sum_{k=1}^{m}\rho_{jk}\sum_{l\in N_i} w_{il}^{jk} Z_{l,t-1}^{k} + \epsilon_{it},$$

and for all counties

$$\boldsymbol{Z}_t = g\boldsymbol{Z}_{t-1} + \boldsymbol{W}_{\boldsymbol{H}}^{\boldsymbol{\rho}}\boldsymbol{Z}_{t-1} + \boldsymbol{\epsilon}_t, \tag{2.7}$$

where $\boldsymbol{W}_{\boldsymbol{H}}^{\boldsymbol{\rho}}$ is an $n \times m^2$ matrix created from the weights matrix $\boldsymbol{W}$ modified according to the assignment of the counties to the clusters represented with incidence matrix $\boldsymbol{H}$, and the $m^2 \times 1$ vector of spatio-temporal coefficients $\boldsymbol{\rho}$.

The eighth model for a county is

$$Z_{it}^{j} = g_j Z_{i,t-1}^{j} + \sum_{j=1}^{m}\sum_{k=1}^{m}\rho_{jk}\sum_{l\in N_i} w_{il}^{jk} Z_{l,t-1}^{k} + \epsilon_{it},$$

and for all counties is

$$\boldsymbol{Z}_t = \boldsymbol{Z^H}_{t-1}\boldsymbol{g_m} + \boldsymbol{W}_{\boldsymbol{H}}^{\boldsymbol{\rho}}\boldsymbol{Z}_{t-1} + \boldsymbol{\epsilon}_t. \tag{2.8}$$

The last, ninth, model for a county is

$$Z_{it}^{j} = g_i Z_{i,t-1}^{j} + \sum_{j=1}^{m} \sum_{k=1}^{m} \rho_{jk} \sum_{l \in N_i} w_{il}^{jk} Z_{l,t-1}^{k} + \epsilon_{it},$$

and for all counties is

$$\boldsymbol{Z}_t = diag(\boldsymbol{g_n}) \boldsymbol{Z}_{t-1} + \boldsymbol{W_H^{\rho}} \boldsymbol{Z}_{t-1} + \boldsymbol{\epsilon}_t. \tag{2.9}$$

Prior distributions to the parameters in the model are the following:

$$\boldsymbol{\rho} \sim N(\boldsymbol{\rho_0}, \boldsymbol{I_{m^2}} \sigma_\rho^2)$$

$$\boldsymbol{g} \sim N(\boldsymbol{g_0}, \boldsymbol{I_n} \sigma_g^2)$$

$$\sigma_\epsilon^2 \sim IG(\tilde{q}_\epsilon, \tilde{r_\epsilon})$$

These distributions are adjusted to the change in the number of parameters of interest.

The following prior distributions for hyperparameters are general because of little intuition about the parameters of the model:

$$\sigma_\rho^2 \sim IG(\tilde{q}_\rho, \tilde{r_\rho})$$

$$\sigma_g^2 \sim IG(\tilde{q}_g, \tilde{r_g})$$

Full conditional distributions are derived from the joint distribution of the parameters of the model. The represented formulas are suitable for the last model among described above. The full conditional distributions for the models with a fewer parameters are adjusted appropriately.

$$\begin{aligned}
\boldsymbol{Z}_t &= \boldsymbol{R}\boldsymbol{Z}_{t-1} \\
&= diag(\boldsymbol{g})\boldsymbol{Z}_{t-1} + \boldsymbol{Z^W}_{t-1}\boldsymbol{\rho} \\
&= diag(\boldsymbol{Z}_{t-1})\boldsymbol{g} + \boldsymbol{Z^W}_{t-1}\boldsymbol{\rho} \\
&= \tilde{\boldsymbol{Z}}_{t-1}\boldsymbol{g} + \boldsymbol{Z^W}_{t-1}\boldsymbol{\rho}
\end{aligned}$$

$$\boldsymbol{g} \sim N(\boldsymbol{v}_g\boldsymbol{a}_g, \boldsymbol{v}_g)$$

$$\boldsymbol{v}_g = (\frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}\tilde{\boldsymbol{Z}}'_{t-1}\tilde{\boldsymbol{Z}}_{t-1} + \frac{1}{\sigma_g^2}\boldsymbol{I_n})^{-1}$$

$$\boldsymbol{a}_g = \frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}\tilde{\boldsymbol{Z}}'_{t-1}(\boldsymbol{Z}_t - \boldsymbol{Z^W}_{t-1}\boldsymbol{\rho}) + \frac{1}{\sigma_g^2}\mathbf{g_0}$$

$$\boldsymbol{\rho} \sim N(\boldsymbol{v}_\rho\boldsymbol{a}_\rho, \boldsymbol{v}_\rho)$$

$$\boldsymbol{v}_\rho = (\frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}\boldsymbol{Z^W}'_{t-1}\boldsymbol{Z^W}_{t-1} + \frac{1}{\sigma_\rho^2}\boldsymbol{I_{m^2}})^{-1}$$

$$\boldsymbol{a}_\rho = \frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}\boldsymbol{Z^W}'_{t-1}(\boldsymbol{Z}_t - \tilde{\boldsymbol{Z}}_{t-1}\boldsymbol{g}) + \frac{1}{\sigma_\rho^2}\boldsymbol{\rho_0}$$

$$\sigma_\epsilon^2 \sim IG(\frac{n(T-1)}{2} + \tilde{q}_\epsilon, \frac{1}{\tilde{r}_\epsilon} + \frac{1}{2}\sum_{t=2}^{T}(\boldsymbol{Z}_t - \boldsymbol{R}\boldsymbol{Z}_{t-1})'(\boldsymbol{Z}_t - \boldsymbol{R}\boldsymbol{Z}_{t-1}))$$

These formulas are suitable for estimation of model 2.9 only since they represent vector coefficients, and are simplified respectively by removing the identity matrices or replacing them with matrices of lower dimensions in the precision and mean formulas for the parameters.

There is an identification issue regarding the diffusion parameter $\boldsymbol{\rho}$ that should be taken into account while estimating the model. Since each element of the parameter vector specifies the relationship between two particular clusters of counties, it is fully identifiable as long as the relationship exists, i.e., the counties that belong to two clusters are neighbors to each other. In our case, only 37 out of 49 elements are identifiable because some of the clusters' counties do not have any counties that belong to some clusters as their neighbors. Thus, during the estimation procedure $\boldsymbol{\rho}$ vector is collapsed to its shorter version for estimation and then expanded back to its full length for estimation of the rest of the parameters.

Since we choose normal (Gaussian) distributions with conjugate prior distributions, the derivation and implementation of the full conditional distributions needed for the Gibbs sampler are quite straightforward. As the choice of starting values, length of the chain before convergence and best ways of monitoring the chain and performing the desired estimation might be an issue. Initially we run two short pilot simulations with different starting values. Then the final, longer, simulation is performed, some part of its resulting sequence is discarded as 'burn in' period, and remaining iterates are thinned. The resulted mean and standard deviations for the parameters estimates as well as DIC values are based on the thinned sample of drawings.

We use DIC (deviance information criterion) for model selection, since it is one of the measures of the fit of a model and of prediction error used in Bayesian model selection problems (Gelman et al., 2004 [52], p. 180-182). The deviance is defined as

-2 times the log-likelihood:

$$D(z, \theta) = -2logp(z|\theta),$$

where z is data and θ is a set of parameters in a model.

The DIC is a sum of the average of deviances over the posterior distribution and half of the posterior variance of deviances:

$$DIC = \bar{D} + p_D$$

$$\bar{D}_z = \frac{1}{L}\sum_{l=1}^{L} D(z, \theta^l)$$

$$p_D = \frac{1}{2}\frac{1}{L-1}\sum_{l=1}^{L}(D(z, \theta^l) - \bar{D}_z)^2$$

where L is the number of posterior drawings.

The estimated average deviance is a summary of model error while the posterior variance of deviances is used as a measure of the effective number of parameters of a Bayesian model or a model complexity.

2.4 Assessing the Gibbs sampler

In order to control convergence of the drawn posterior values of the parameters to the appropriate stationary distributions, we account for the possible influence of the initial values and length of 'burn in' period, using quantitative as well as visual assessment tools. Initially, we run two pilot simulations with different initial values for each model – one represented by the OLS estimates and the other beyond the range of the distribution determined with the OLS mean and standard error of the estimates. These sequences are visually assessed for the length of the 'burn in' period. The remaining (after discarding the 'burn in') iterates are used to calculate the convergence monitor $\hat{R}$ from Gelman et al. (2004 [52], p. 296-297). According to these authors, $\hat{R}$ should be close to one since it represents 'the factor by which the scale of the current distribution for each scalar estimated variable might be reduced if the simulations were continued in the limit $n \to \infty$'.

For each scalar parameter ψ we calculate between- and within-sequence variances:

$$B = \frac{n}{m-1}\sum_{j=1}^{m}(\bar{\psi}_{\cdot j} - \bar{\psi}_{\cdot\cdot})^2, W = \frac{1}{m}\sum_{j=1}^{m} s_j^2$$

where ψ_{ij} is the simulation draw, $\bar{\psi}_{\cdot j} = \frac{1}{n}\sum\limits_{i=1}^{n}\psi_{ij}$, $\bar{\psi}_{\cdot\cdot} = \frac{1}{n}\sum\limits_{j=1}^{m}\bar{\psi}_{\cdot j}$, $s_j^2 = \frac{1}{n-1}\sum\limits_{i=1}^{n}(\psi_{ij} - \bar{\psi}_{\cdot j})^2$. The marginal posterior variance of the estimated variable $var(\psi|y)$ can be estimated as a weighted average of W and B

$$v\hat{a}r^{+}(\psi|y) = \frac{n-1}{n}W + \frac{1}{n}B.$$

$\hat{R}$ is then estimated by

$$\hat{R} = \sqrt{\frac{v\hat{a}r^{+}(\psi|y)}{W}}.$$

It declines to 1 as n $\to \infty$. The recommendations of the authors regarding the closeness of $\hat{R}$ to unity are such that values below 1.1 are acceptable but a higher levels of precision may be required.

2.5 Estimation results

The sequences for the parameters in all models converge to the stationary posterior distributions in about 500 iterations regardless of the initial values chosen ($\hat{R}$ stays within 0.999 to 1.100 for all parameters.) Two sequences of 2000 iterations are ran for each model and $\hat{R}$ is calculated for the last 1500 iterates. The long sequence of 15,000 iterations is ran for the purpose of calculating the parameters' estimates, 5000 iterations are discarded as 'burn in' period and the rest 10,000 are thinned so that each 10th value is used for plotting histograms of posterior distributions and calculating posterior means and standard errors of parameters.

The histograms for the growth coefficient g and error variance σ_ϵ^2 for model 2.1 are presented on Figure 2.15.

The histograms for the growth coefficient g, spatio-temporal coefficient ρ and error variance σ_ϵ^2 for model 2.4 are presented on Figure 2.18.

The histograms for some of the growth coefficients g_j, spatio-temporal coefficient ρ and error variance σ_ϵ^2 for model 2.5 are presented on Figure 2.19.

The histograms for some of the growth coefficients g_i, spatio-temporal coefficient ρ and error variance σ_ϵ^2 for model 2.5 are presented on Figure 2.20.

The histograms for the growth coefficient g, some spatio-temporal coefficients ρ_{jk} and error variance σ_ϵ^2 for model 2.7 are presented on Figure 2.21.

The histograms for the growth coefficients g_j, some spatio-temporal coefficients ρ_{jk} and error variance σ_ϵ^2 for model 2.8 are presented on Figure 2.22.

The histograms for some growth coefficients g_i, some spatio-temporal coefficients ρ_{jk} and error variance σ_ϵ^2 for model 2.9 are presented on Figure 2.23.

The results of MCMC estimation of models' scalar temporal and spatio-temporal autoregressive parameters (2.1, 2.4, 2.5, 2.6, and 2.7) are presented in Table 2.8.

The results of MCMC estimation of models' vector cluster-specific temporal autoregressive parameters (2.2, 2.5, and 2.8) are presented in Table 2.9.

The results of MCMC estimation of vector of spatio-temporal autoregressive coefficients for model 2.7 are presented in Table 2.10. The star marks statistically significant estimates at 10 percent level in all three tables below.

The results of MCMC estimation of vector of spatio-temporal autoregressive coefficients for model 2.8 are presented in Table 2.11.

The results of MCMC estimation of vector of spatio-temporal autoregressive coefficients for model 2.9 are presented in Table 2.12.

The map of the results of MCMC estimation of vector of county-specific temporal autoregressive coefficients for model 2.3 is presented on Figure 2.24, for model 2.6 on Figure 2.25, and for model 2.9 on Figure 2.26. These coefficients estimates are reported in Table in Appendix B.

2.6 Interpretation of results and conclusions

2.6.1 Models' fit of the data

Since our main interest lies in building a model that adequately incorporates spatio-temporal connection between counties into the process of growth of aggregate earnings per worker, we want to demonstrate how fitted values from different models look like in comparison to the actual data. Graphs for actual and fitted values from all models estimated earlier for St. Louis City are presented on Figure 2.27, for Boone County on Figure 2.28, and for Platte County on Figure 2.29.

These three counties belong to 3 different clusters – cluster 6, cluster 5, and cluster 2, respectively. These graphs suggest that if the spatio-temporal term is not included into the model then there is no difference whether the growth coefficient estimated for all counties, for clusters of the counties, or for individual counties. Inclusion of spatio-temporal term with a scalar coefficient does not have an effect on common growth coefficient but affects the fit when a vector of spatio-temporal coefficients is introduced.

The effect of the vector spatio-temporal coefficient is more pronounced for the counties with more volatile dynamics of aggregate earnings per worker. Graphs of fitted and actual values for Dade County and Stoddard County presented on Figures 2.30 and 2.31 are examples of the counties' growth coefficients which are the smallest for the last model (with both terms including vectors of coefficients) – 0.089 and 0.141, respectively. For these counties the graphs for the last model show the difference that the vector of spatio-temporal coefficients makes to the fit.

The combined results of the estimation of the models are presented in Table 2.13. These results show that the model with county-specific growth coefficients and vector spatio-temporal parameter allows better fit than others, for DIC is the smallest for model 2.9. Spatio-temporal term with a vector of coefficients reproduces temporal and spatio-temporal dynamics of the counties better than spatio-temporal term with a scalar coefficient.

2.6.2 Impulse response functions

We are also interested in responses of the aggregate earnings per worker to an exogenous shock or innovation of the size of one standard deviation σ_ϵ. For that we use only estimation results for model 2.9 so the shock applied equals 0.1. The traditional impulse response functions show more pronounced effects in places where counties that belong to different clusters are close to each other. These places might be at the edge of a metropolitan area where its counties are neighbors of non-metropolitan counties or any other places where counties with different industrial structure are located.

The first place we take a look at is the Kansas City area. The main 3 counties in or near this area are Jackson, Clay, and Clinton. The impulse response functions to a shock for Jackson County and its first ring neighbors – Clay, Ray, Lafayette, Johnson, and Cass counties – are presented on Figure 2.32.

Jackson county belongs to cluster 6 and, as all counties in this cluster, affects strongly counties in cluster 4 which both Ray and Lafayette counties belong to while it does not affect significantly all other counties in its neighborhood that belong to clusters 7 (Clay county) and 1 (Cass and Johnson counties). So the shock to aggregate earnings per worker in Jackson county increases aggregate earnings per worker in Ray county by up to 2.9 percent by year 7 after shock although it becomes statistically insignificant at year 6. This total increase consists of 1.7 percent coming from diffusion (or spillover) effect only and the rest coming from growth based on spillovers from neighboring counties. After year 7 the potential (statistically insignificant) effect decreases to the level of growth effect only, i.e., the diffusion effect goes down to zero. A clearer picture of dynamics of the effect for Ray county during first 5 after-shock years is presented on Figure 2.33.

For Lafayette county the total effect is close to 4.5 percent while statistically significant and consists of 1.6 percent due to growth effect and 2.9 percent due to diffusion effect. Potentially this total effect rises until the end of the forecast period due to rise in both growth and diffusion effect. A closer look at a dynamics of impulse response functions for Lafayette county for the first five years is presented on Figure 2.34.

To assess the influence of the diffusion effect from the neighborhood on the growth in Jackson county we take a look at the difference between the growth impulse responses without diffusion effect taken into account and the growth impulse responses with diffusion effect allowed to go through. These impulse response functions are presented on Figure 2.35. This graph shows that diffusion effect slows down growth in Jackson county by 1 percent – by year 10 the growth without diffusion is 14 percent while with diffusion it is 13 percent. This reduction in the growth rate of aggregate earnings in Jackson county happens due to the spillover effect of the shock.

Another county in the Kansas City area that shows strong interaction with the neighboring counties is Clay county. The impulse response functions for Clay county and its first ring neighbors – Platte, Clinton, Ray, and Jackson counties – are represented on Figure 2.36.

The potential of the shock in Clay county is not fully realized because of the spillover effect to the neighboring counties which affect positively some of them. For instance, member of cluster 2 Platte county's aggregate earnings per worker grow by 14.4 percent at year 3 due to diffusion from Clay county and other neighboring counties (see Figure 2.37). After 3 years the total change in Platte's aggregate earnings per worker becomes statistically insignificant but has a potential of growing by 45 percent by year 10.

In Clinton county which belongs to cluster 5 aggregate earnings per worker grows by 15 percent by year 5 (see Figure 2.38) after which the growth rate becomes statistically insignificant, and this total growth rate consists of 9.2 percent of growth rate due to county's internal forces and 5.8 percent of growth rate due to spillover effects from Clay and other neighboring counties.

In Ray county which belongs to cluster 4 aggregate earnings per worker grows by 11.5 percent total by year 7 after which the growth rate becomes statistically insignificant. This total growth rate consists of 3.4 percent growth due to county's internal forces and 8.1 percent due to spillovers from Clay and other neighboring counties (see Figure 2.39).

The growth of aggregate earnings in Clay county after shock is represented on Figure 2.40. This graph shows that the growth of aggregate earnings in Clay county is slower with the presence of spillover effect than without one – by year 6 when both growth rate are still statistically significant the growth rate is 56.5 percent without spillover effect and only 37.4 percent with it. This diffusion effect reduces growth rate of aggregate earnings per worker in Clay county by almost 20 percentage points but this reduction is the reason of the growth of aggregate earnings per worker in Clay's neighbors.

Another county in the Kansas City area that, when exposed to external shock, influences its neighbors is Clinton county which belongs to cluster 5. The graphs of impulse response functions for Clinton county and its first ring neighbors are represented on Figure 2.41.

These graphs show that the impulses responses are not statistically significant for most of the counties in the neighborhood of Clinton counties such as Buchanan, DeKalb, Platte, and Clay counties, for Caldwell and Ray counties the shock to aggregate earnings per worker in Clinton county affects dynamics of their aggregate earnings per worker. In Caldwell county the growth rate of aggregate earnings per worker due to internal forces reaches 0.9 percent by year 4 after which it becomes statistically insignificant while the growth rate due to spillover effect starts at 1.2 percent at year 1 after the shock and declines to 1 percent at year 2 after which it becomes statistically insignificant as well, so the total growth rate for this county reaches 1.7 percent by year 3 (see Figure 2.42).

The impulse response functions for aggregate earnings per worker in Ray county to the shock in Clinton county show (see Figure 2.43) that the initial growth of aggregate earnings per worker due to internal forces from zero to 0.5 percent by year 3 becomes statistically insignificant starting from year 4 while the total growth rate as a combination of internal growth and spillover effect reaches 1.3 percent by year 2 and declines for the rest of the forecast period.

As for the impact of the shock on aggregate earnings per worker in Clinton county itself, the graph on Figure 2.44 show that similarly to the dynamics of the post-shock effects in Clay county in Clinton county the growth of aggregate earnings per worker with spillover effect is slower than what it is when there would be no spillover effect. The difference between these growth rates increases with time and to the end of the period when the growth rates stay statistically significant (year 3) it reaches 5.8 percentage points. After year 3 the growth rate with spillover effect becomes statistically insignificant so if it is assumed to be zero percent then the growth rate without accounting for the diffusion effect reaches more than 300 percent by year 10.

The graphs of impulse response functions for the aforementioned counties in the Kansas City metropolitan area and their neighbors show that exogenous shocks to counties produce different effects in their neighbors and the former are determined by not only the relationship of the center and the neighboring counties but also by the composition of the neighborhoods of the neighboring counties.

In St.Louis metropolitan area the only county shows influence of the shock applied to its aggregate earnings per worker influences aggregate earnings per worker in its neighbors is St.Charles county. The graphs of impulse response functions for St.Charles counties and its neighbors are represented on Figure 2.45.

Among the neighbors of St.Charles county Warren and Lincoln counties (both belong to cluster 4) are the only ones whose impulse responses are statistically significant for a part or a whole forecast period. The aggregate earnings per worker in Warren county starts growing from 2 percent at the first year after shock to St.Charles county's aggregate earnings per worker due to spillover effect and reaches 6.2 percent at year 8 after which it becomes statistically insignificant. At year 8 the total growth rate consists of 4.8 percent growth due to internal forces and the rest – 1.4 percent – due to spillover effect from the neighboring counties (see Figure 2.46). The overall trend of the growth of aggregate earnings per worker in Warren county shows positive impact of the positive shock to St.Charles county's aggregate earnings per worker on this neighbor.

Impulse response functions of aggregate earnings per worker in Lincoln county show even stronger and longer lasting effects of the shock to St.Charles county's aggregate earnings per worker than in Warren county. These functions for the first

5 years are shown on Figure 2.47. The growth of aggregate earnings per worker in Lincoln county is statistically significant for all 10 year of the forecast and at the end of this period it reaches 13.8 percent of which the growth due to internal forces is 7.1 percent and the growth due to spillover effect from the neighboring counties is 6.7 percent.

The impulse response functions graphs for Warren and Lincoln counties show again that even if two counties belong to the same cluster the effects that a shock to their common neighbor has on the growth of their aggregate earnings per worker differ due to different growth rates due to internal forces and to different composition of the neighborhoods of these counties.

One more area where a shock to a county produces significant impact on its neighbors is the neighborhood of Pulaski county. The graphs of impulse response functions for Pulaski county and its first ring neighbors are represented on Figure 2.48.

The impulse response functions do not show statistically significant effects of the shock to Pulaski county for Maries, Camden, and Texas counties while for other counties – Miller, Phelps, and Laclede – the responses are significant. The graph of impulse response functions for Miller county (see Figure 2.49) shows that initial total growth rate of aggregate earnings per worker of 1.9 percent due to spillover effect rises to 2.7 percent by year 3 after shock which consists of 2 percent of growth to spillover effect and 0.7 percent due to internal growth forces. After year 3 the effects become statistically insignificant but potentially internal growth rate continues to grow and diffusion effect declines.

The impulse response functions of aggregate earnings per worker in Phelps county (see Figure 2.50) that growth due to spillover effect exceeds growth due to internal forces during the first 6 years after shock (later these rates become statistically insignificant). The total growth rate at year 6 is 5.6 percent of which 3.5 percent is due to spillover effect and remaining 2.1 percent is due to internal growth forces.

The growth of aggregate earnings per worker in Pulaski county after the shock shows a difference between growth rates with spillover effect and without spillover effect (see Figure 2.51). At year 5 after the shock the growth rate of aggregate earnings per worker with spillover effect taken into account – 12 percent – exceeds the growth rate without spillover effect – 10.2 percent – by 1.8 percentage points. This difference shows that spillover effect enhances growth of aggregate earnings per worker in Pulaski county and makes Pulaski county a recipient of the positive spillover effect from its neighbors. The same comparison of growth rates for other counties showed, to the contrary, negative spillover effect.

The impulse response functions show that presence of spillover effect induces growth of aggregate earnings per worker in counties-neighbors of the center – county that experiences an exogenous shock – and in the center's own aggregate earnings per worker. This impact does not necessarily slows down the growth of aggregate earnings per worker due to internal forces, for in some counties such as Pulaski county it enhances the growth.

The impact that counties in some clusters have on counties in other clusters can be seen in the columns of the table with spatio-temporal correlation coefficients estimates 2.12 since they represent correlation of counties in a neighborhood in the previous period with counties in a center in the current period. From these columns we can see that counties in clusters 6 and 7 have the largest impact in their neighbors with the strongest impact on cluster 3 and cluster 2, respectively. Weaker impact these clusters have on clusters 4 and 5. These same clusters also are affected by the counties in cluster 1 counties in which have government as a largest sector by employment share. Clusters 2 and 3 do not have any significant impact on other clusters and clusters 4 and 5 counties have mixed (both positive and negative) impact on other clusters – negative on clusters 1 and 2 counties, respectively, and on each other.

It is also worth mentioning that the after-shock responses of counties' aggregate earnings per worker are not dying out as it is usually observed, i.e. the growth of the aggregate earnings per worker does not come back to its steady-state level. The reason for such non-standard responses is such that we do not impose any restriction in our model which reflects our belief in the absence of equilibrium for the state economy now or in the future.

2.6.3 Convergence of aggregate earnings based on estimation results

As we have already shown earlier aggregate earnings per worker in counties in the state of Missouri converge at a rate 0.25 percent if the growth of earnings is assumed to be independent across counties. We reproduce the convergence plot using the estimates of growth coefficients from model 2.3 reported in the third column of the Table in Appendix B. For that we rewrite the deterministic part of the AR(1) process in the following way:

$$Z_t - Z_{t-1} = g_i Z_{t-1} - Z_{t-1} = (g_i - 1)Z_{t-1}.$$

It allows us to calculate the average growth rate suitable for convergence test as a product of the difference between AR(1) coefficient and one and the log-level of aggregate earnings per worker in the previous period. The convergence plot for all counties in the state of Missouri without accounting for the clusters they belong to is represented on Figure 2.52. This graph shows that when the growth rates are derived from the estimated AR(1) coefficients the convergence rate is 3 times smaller (0.08 percent) than the convergence rate for the growth rates calculated from the original data. If we do the same exercise with the AR(1) coefficients from model 2.6 in which we separate the growth effect and diffusion effect but model the latter with a scalar parameter, then the aggregate earnings per worker slightly diverge for Missouri counties (see Figure 2.54). At the same time the growth rates are all negative and some of them seem to be concentrated around -3 percent. The same graph for the estimates of growth coefficients from model 2.9, the one with separated growth and diffusion terms with the latter modeled with a vector of coefficients, produces evidence of aggregate earnings per worker for Missouri counties strongly diverging over time (see Figure 2.56).

The same convergence plots with the counties belonging to different clusters and being presented with the respective color (see Figures 2.53, 2.55, and 2.57) show that while on the first two graphs there is no distinct pattern in the location of points associated with a particular cluster, on the last graph we can see that counties in cluster 6 have growth rates within about -2 to 1 percent range, counties in cluster 1 have growth rates within -0.5 to 1.5 percent range, and all counties in cluster 4 have negative growth rates.

An appropriate question to ask is whether the estimated growth coefficient are distinct for the counties in different clusters, for the estimated growth rates in the graphs above are products of initial log-levels of the aggregate earnings per worker and the estimated growth coefficients. To assess this difference we use boxplots for the estimated AR(1) coefficients for all three models – 2.3, 2.6, and 2.9 (see Figures 2.58, 2.59, and 2.60). While the first two graphs clearly show that the values of estimated coefficients are not distinct for clusters for models 2.3 and 2.6, the third graph does not allow visually assess whether they are significantly different. For that purpose we calculated 90% intervals for the coefficients for counties in different cluster and reported them in Table 2.14.

This table shows that for the first two model the estimates of growth coefficients for counties in different cluster do not differ from each other. The estimates from the last model show some difference between growth rates for clusters; the aggregate earnings per worker in counties in clusters 1, 7, and 6 on average grow faster than in clusters 3 and 5. The slowest growing aggregate earnings per worker is in clusters 2 and 4.

In order to assess how these results influence the growth of counties' aggregate earnings per worker relative to each other we use convergence test as a tool for it. As Young et al. (2008) [104] show, β-convergence is a necessary but not sufficient condition for σ-convergence. The direct connection between two types of convergence is presented by the authors with equation

$$\sigma_t^2 = (1-\beta)^2 \sigma_{t-1}^2 + \sigma_\epsilon^2.$$

This equation shows that for σ-convergence to occur it is not enough that $\beta<1$, σ_ϵ^2 also has to be quite small. If instead of convergence β-divergence is observed then it is enough for β to be negative regardless of the relative sizes of variances on the right-hand side.

In the first section we observed weak β-convergence and weak σ-divergence for 'gross' growth rates of the aggregate earnings per worker. It reasonably fits the explanation of Young and his co-authors. But when we look at the convergences of the 'net' growth rates (separated from the diffusion effect) we observe strong β-divergence and weak σ-divergence. One of the explanations that we can offer for this combination of convergences is that it is the absence of spillovers which we include as a diffusion term into the model that makes β-divergence so strong. If the diffusion effect is accounted for then the divergence of the some counties' aggregate earnings per worker gets smoothed out. As we have seen in the impulse responses of the counties' aggregate earnings per worker, presence of knowledge or technology spillovers across counties keeps fast growing counties from growing too fast and accelerate growth of those counties that stagnate.

We would like to make some conclusions. First, proper measurement of growth rates of aggregate earnings per worker for small geographical areas such as counties should be done while accounting for spatio-temporal correlation between counties. Second, models with a scalar coefficient in a spatio-temporal term do not allow to extract properly this correlation, for they do not account for heterogeneous neighborhoods. When a vector of coefficients for spatio-temporal term is incorporated into the model the estimates of these coefficients show that aggregate earnings per worker in counties within the same neighborhood affect each other differently not only in magnitude but in the direction of the effect (positive or negative) as well. The main issue in constructing such a model is a way to distinct between counties in the neighborhood. We propose to use means of cluster analysis for such purpose and use change in employment shares as a measure of change in industrial structure as clustering variables. Third, based on the estimates of the model with a vector of coefficients for spatio-temporal term we found the evidence that counties with large manufacturing sector have the biggest impact on their neighbors even when the share of manufacturing is declining over time and other sectors such as services or retail trade are growing as compare to the counties with declining share of farming sector and growing share of services sector. This pattern of change in employment composition of the economies has not been in focus of empirical research so far and needs to be explored more in order to design appropriate economic policy to help counties that have slow or no growth of their aggregate earnings per worker. Forth, and the last, the growth of aggregate earnings per worker in Missouri counties presents some evidence of agglomeration economy, i.e. counties with higher aggregate earnings per worker grow faster than counties with lower aggregate earnings per worker with simultaneous formation of clusters of fast-growing counties and slow-growing counties. Inter-county spillovers of knowledge and technology slow down this process and may be used as a measure to mitigate divergence of earnings across counties in the state.

Table 2.1: Different measures of earnings and incomes calculated from BEA-REIS data sets

Measure	Calculation	Data Source Location	Data Source Description
Aggregate earnings by place of work	a	Table CA05 line 35	Earnings by place of work
Number of workers	b	Table CA25 line 10	Total full-time and part-time employment
Aggregate earnings per worker (by place of work)	$c = \frac{a}{b}$		
	d	Table CA05 line 36	Contributions for government social insurance
	e	Table CA05 line 42	Adjustment for residence
Aggregate net earnings by place of residence	$f = a - d + e$	Table CA05 line 45	Net earnings by place of residence
Number of residents	g	Table CA05 line 20	Population
Aggregate net earnings per capita by place of residence	$h = \frac{f}{g}$		
	i	Table CA05 line 46	Dividends, interest, and rent
	j	Table CA05 line 47	Personal current transfer receipts
Aggregate personal income (by place of residence)	$k = f + i + j$	Table CA05 line 10	Personal income
Aggregate personal income per capita (by place of residence)	$l = \frac{k}{g}$		Per capita personal income

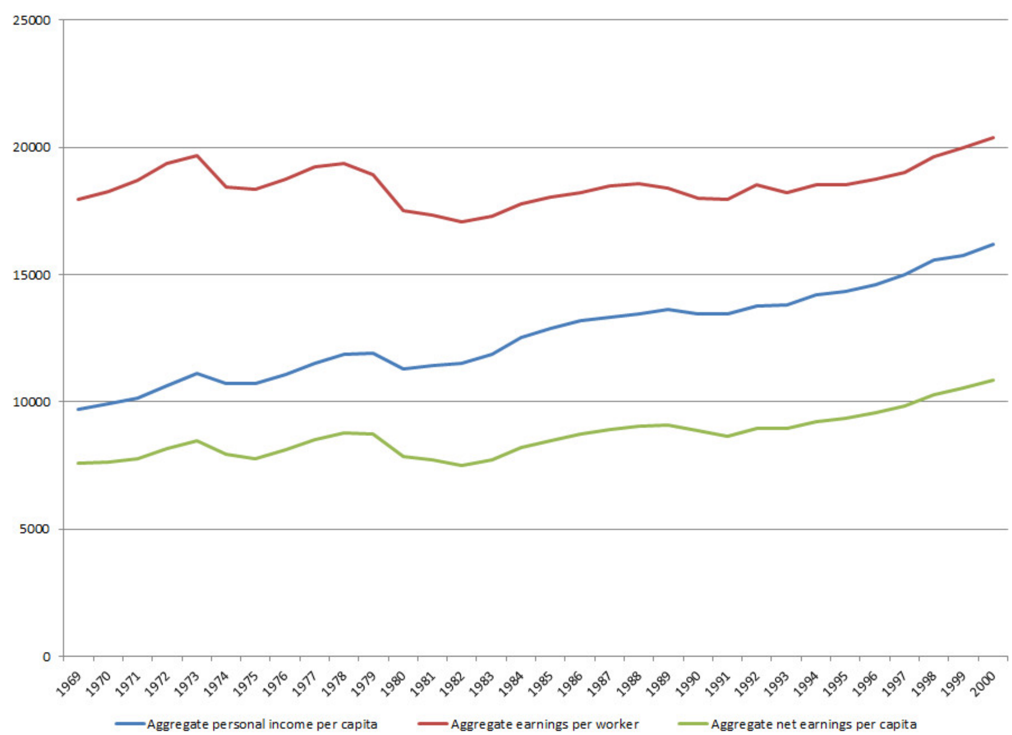

Figure 2.1: Time series plots of real aggregate earnings per worker by place of work, real net earnings per capita by place of residence and real aggregate personal income per capita by place of residence for the state of Missouri in 1969-2000.

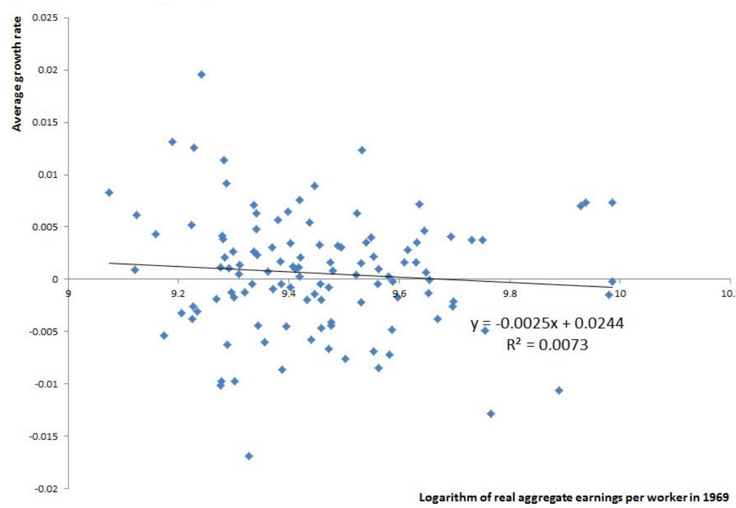

Figure 2.2: Plot of the average growth rates of the real earnings by place of work for counties in the state of Missouri during 1969-2000 against their log-earnings levels for year 1969.

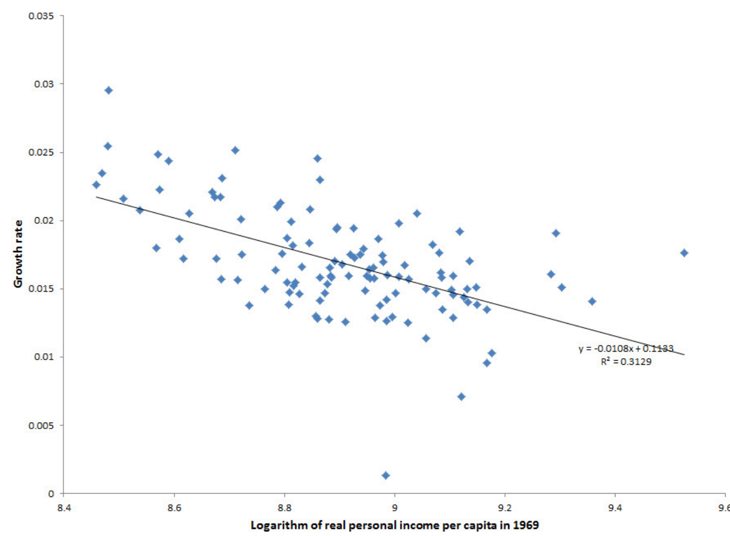

Figure 2.3: Plot of the average growth rates of the real income by place of residence for counties in the state of Missouri during 1969-2000 against their log-income levels for year 1969.

Table 2.2: Absolute β-convergence equation estimates for the earnings per worker by place of work and income per capita by place of residence.

	1970s		1980s		1990s		All years	
	(work)	(residence)	(work)	(residence)	(work)	(residence)	(work)	(residence)
Const	-0.133^c	0.068	0.064^c	0.215^a	0.081^a	0.096^a	0.024	0.059^a
	(0.073)	(0.052)	(0.039)	(0.035)	(0.032)	(0.029)	(0.026)	(0.014)
$\ln Y_0$	0.013^c	-0.008	-0.007^c	-0.024^a	-0.007^b	-0.008^b	-0.003	-0.006^a
	(0.007)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)

Standard errors are reported in parenthesis. “Work” abbreviates “earnings per worker by place of work” and “residence” abbreviates “income per capita by place of residence”.

[a] Significant at 1% level.

[b] Significant at 5% level.

[c] Significant at 10% level.

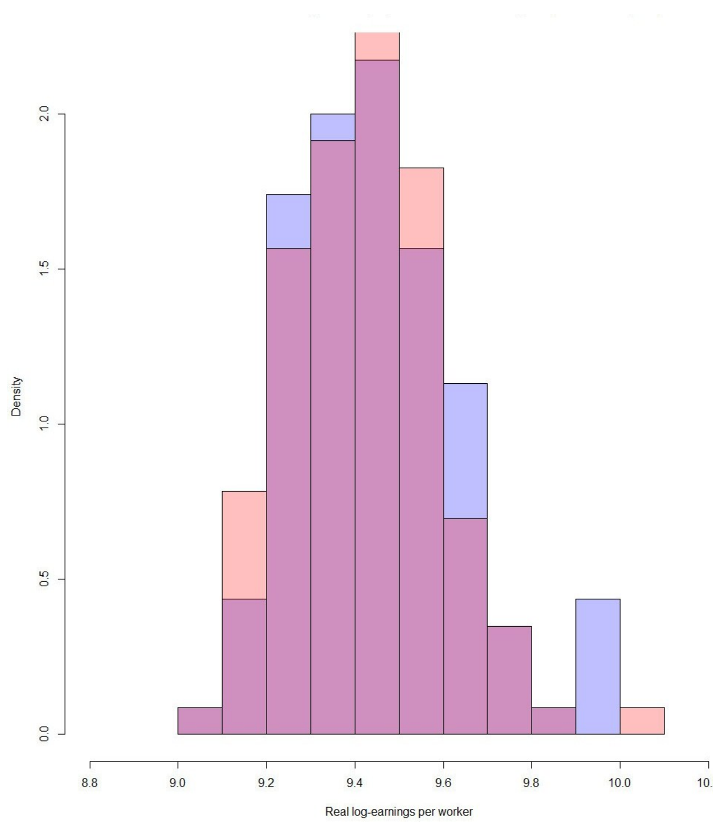

Figure 2.4: Histograms of the distributions of log-earnings per worker by place of work for Missouri counties in 1969 and 2000. (Distribution in 1969 is shown in pink and in 2000 - in purple.)

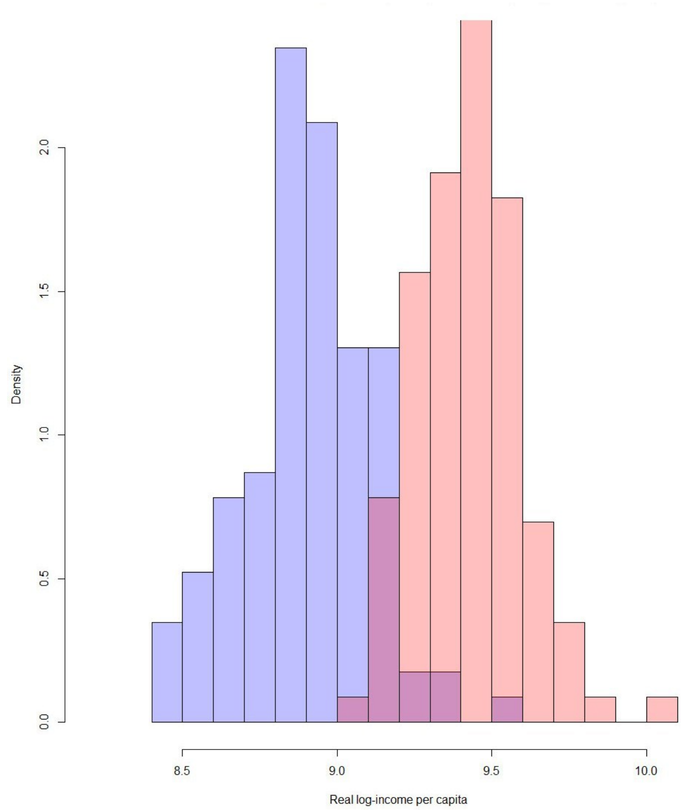

Figure 2.5: Histograms of the distributions of log-income per capita by place of residence for Missouri counties in 1969 and 2000. (Distribution in 1969 is shown in pink and in 2000 - in purple.)

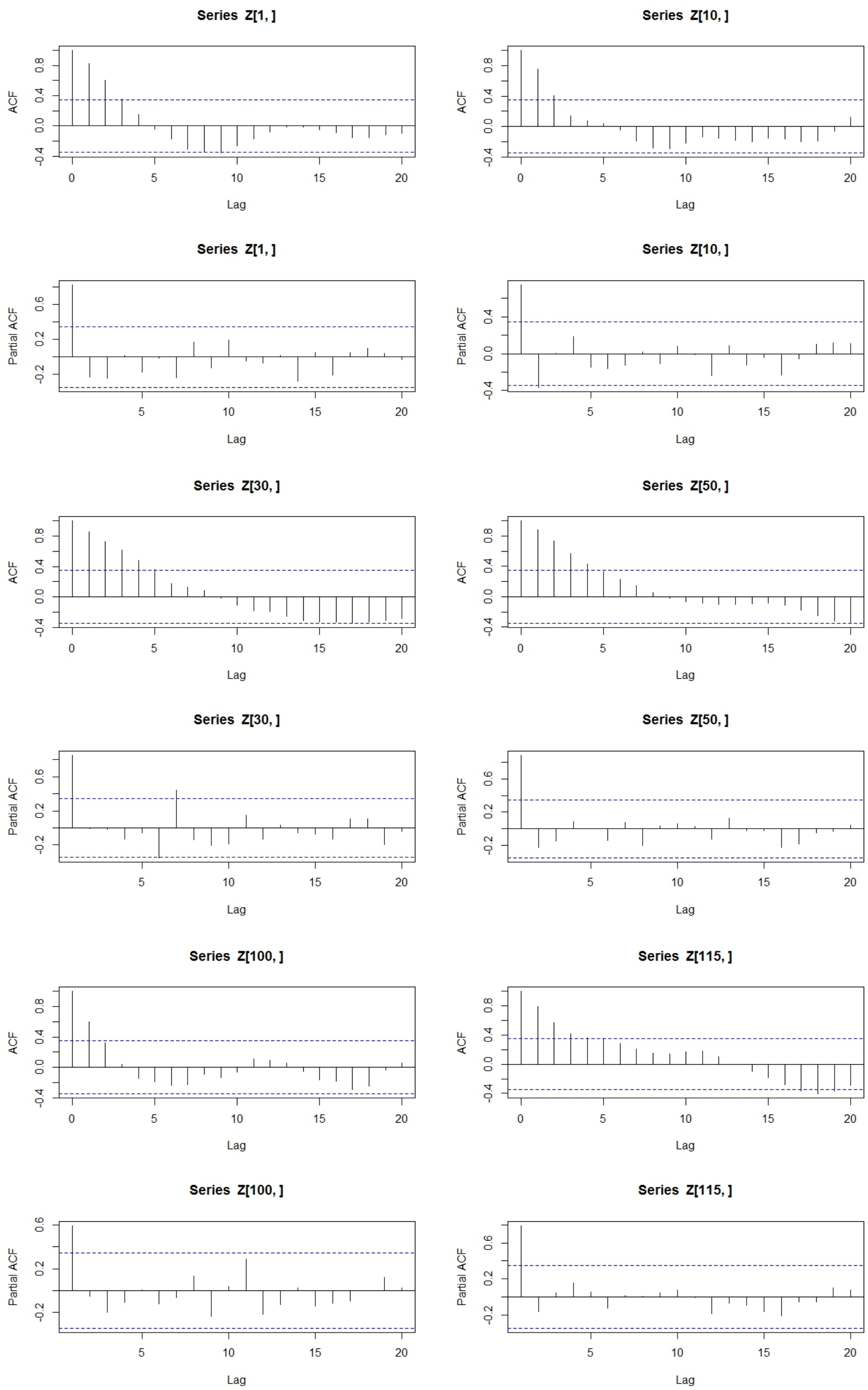

Figure 2.6: ACF and PACF of aggregate earnings per worker time series for some counties in the state of Missouri in 1969-2000.

Table 2.3: Bivariate Moran's I test for global spatio-temporal randomness for aggregate earnings per worker in the counties of the state of Missouri in 1969-2000.

Year for center	**Year for neighbors**	**Global Moran's I**
1970	1969	0.3883
1971	1970	0.3839
1972	1971	0.3753
1973	1972	0.3648
1974	1973	0.2826
1975	1974	0.3404
1976	1975	0.3167
1977	1976	0.3087
1978	1977	0.3423
1979	1978	0.3460
1980	1979	0.2262
1981	1980	0.3008
1982	1981	0.3156
1983	1982	0.3370
1984	1983	0.3472
1985	1984	0.3295
1986	1985	0.3593
1987	1986	0.3556
1988	1987	0.3782
1989	1988	0.3993
1990	1989	0.3760
1991	1990	0.3716
1992	1991	0.3606
1993	1992	0.3568
1994	1993	0.3456
1995	1994	0.3531
1996	1995	0.3641
1997	1996	0.3825
1998	1997	0.3598
1999	1998	0.3659
2000	1999	0.3606

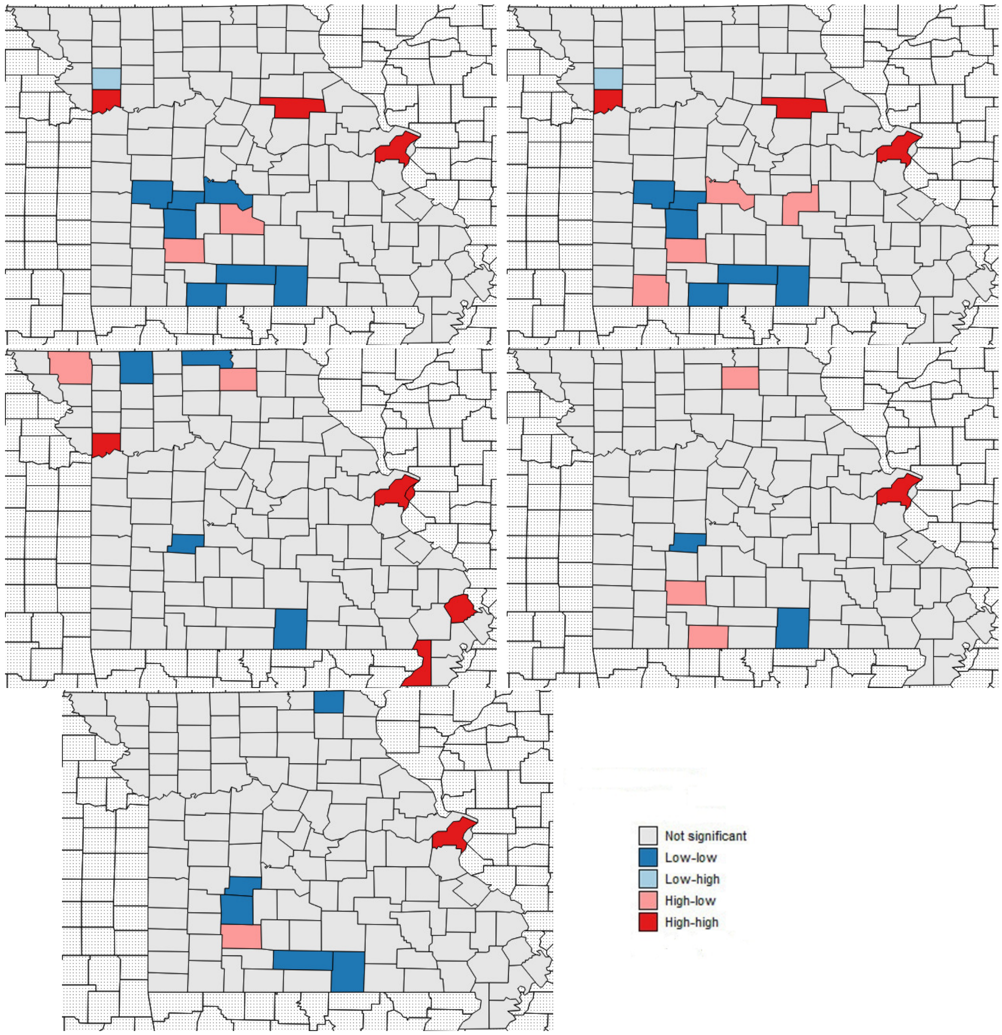

Figure 2.7: Maps of spatio-temporal clusters for aggregate earnings per worker in the state of Missouri in 1973, 1979, 1988, 1994, and 1997 (for neighbors and consecutive years for center).

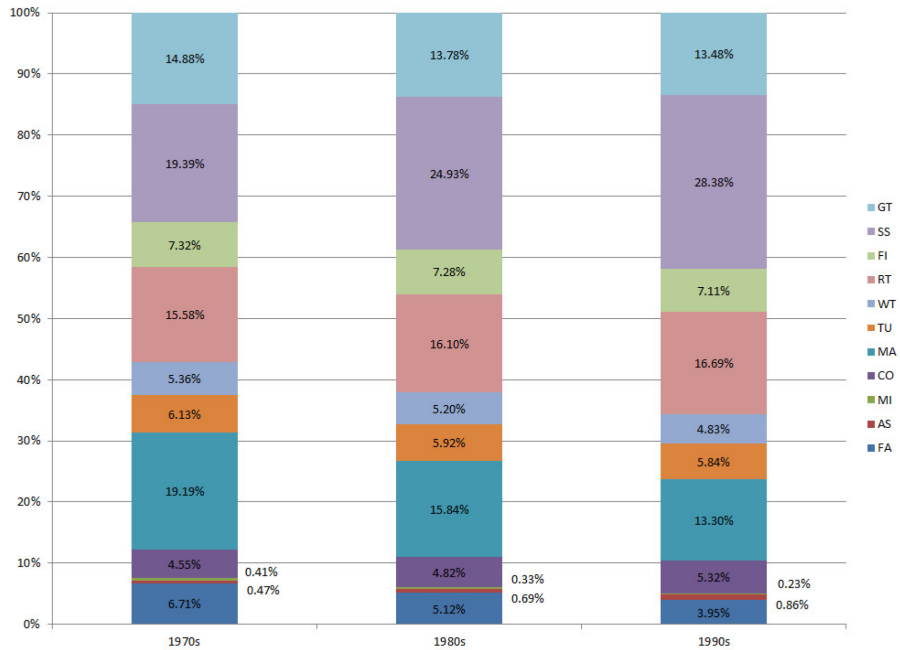

Figure 2.8: Structure of the state of Missouri economy by sector's employment shares in 1969-2000.

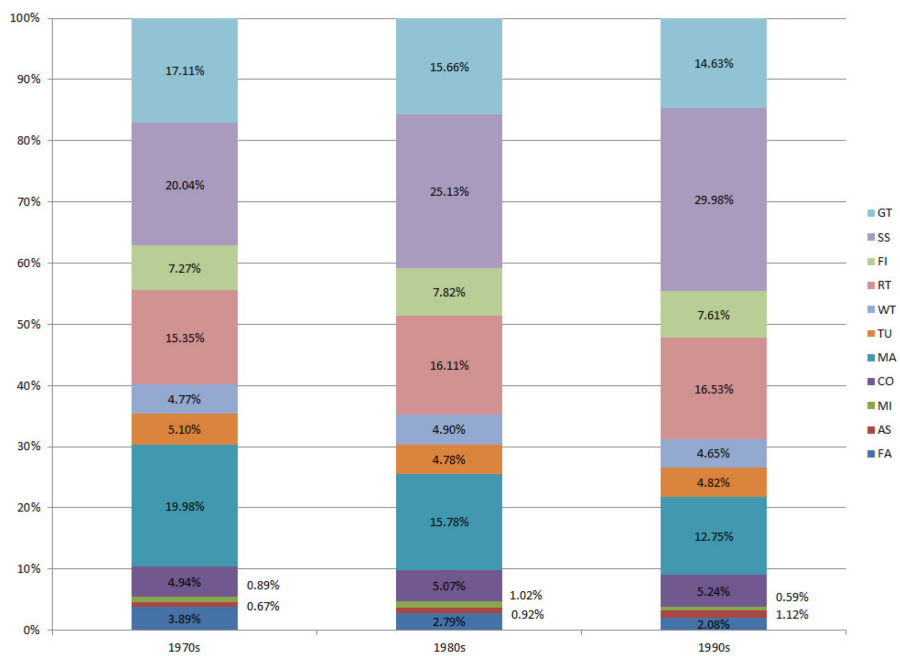

Figure 2.9: Structure of the U.S. economy by sector's employment shares in 1969-2000.

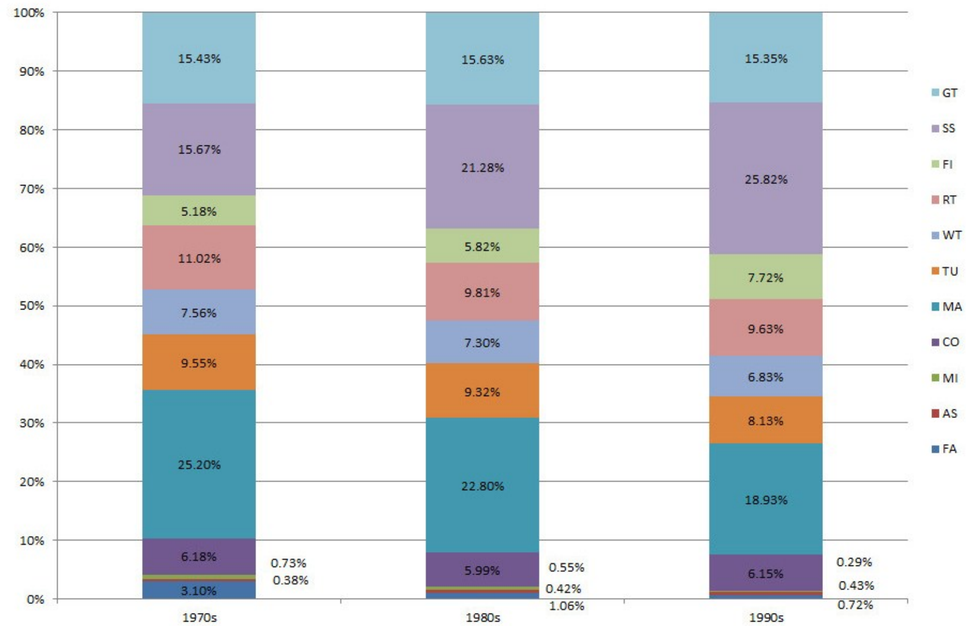

Figure 2.10: Structure of the state of Missouri's economy by sector's share in earnings on average during 1969-2000 by decades.

Figure 2.11: Structure of the U.S. economy by sector's share in earnings on average during 1969-2000 by decades.

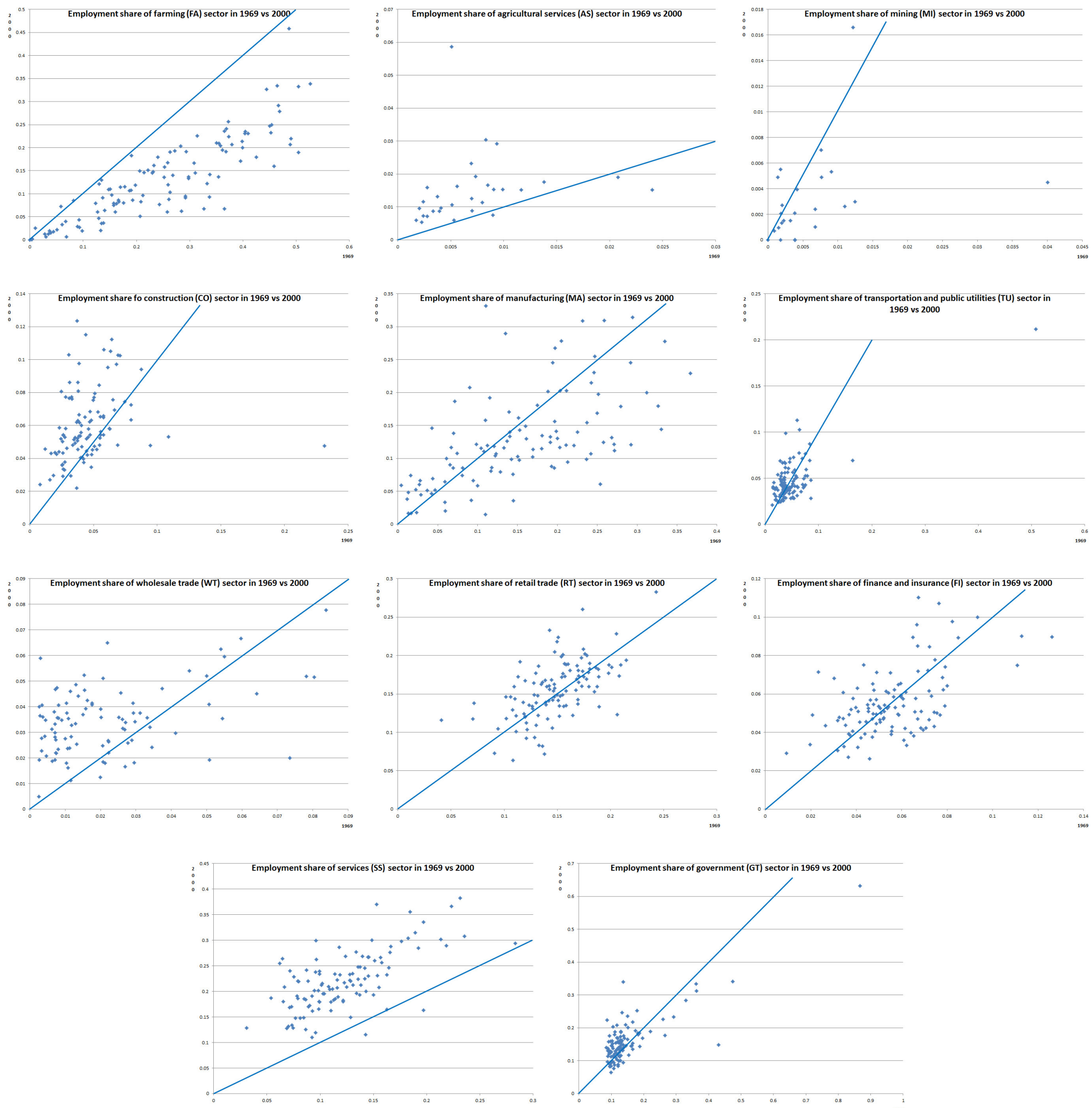

Figure 2.12: Change in employment shares of sectors of economy for Missouri counties in 1969-2000. Blue line is 45-degree line.

Table 2.4: Sources of aggregate earnings growth for all counties in the state of Missouri (in percent).

Period	1969-2000			1969-1980			1981-1990			1991-2000		
Sector	**EGE**[a]	**SE**[a]	**TE**[b]	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**[c]
FA	-4	-4	-8	-7	-2	-9	-1	-1	-2	0	0	0
AS	0	0	0	0	0	0	0	0	0	0	0	0
MI	0	-2	-2	1	-1	0	-1	-1	-2	0	0	0
CO	0	2	2	0	0	0	0	1	1	1	1	2
MA	4	-3	1	1	-1	0	1	1	2	2	-2	0
TU	0	0	0	1	0	1	0	0	0	0	0	0
WT	1	2	3	0	2	2	0	0	0	1	0	1
RT	-2	0	-2	-2	-1	-3	-1	1	0	1	0	1
FI	3	0	3	0	0	0	1	-1	0	2	1	3
SS	4	8	12	-1	4	3	2	2	4	4	1	5
GT	4	1	5	1	0	1	2	1	3	1	0	1
Total Effect	10	3[d]	13	-6	2	-3	2	2	4	12	1	14

[a] The sector is omitted if the effect is close to zero or there is no information available.
[b] Total effect may not sum up to 100 per cent due to rounding.
[c] Overall total effect number comes from calculations for the actual aggregate earnings per worker.
[d] The discrepancy appears due to missing data for one or more sectors.

Table 2.5: Coefficient of variation for sectoral employment shares in 1969 and changes in employment shares in 1969-2000 for the counties in the state of Missouri.

Sector	**Value in 1969**	**Change in 1969-2000**
Farming	0.5590	0.6643
Agricultural services	0.6602	1.3832
Mining	3.4410	2.9374
Construction	0.5709	2.0598
Manufacturing	0.6087	3.0721
Transportation and utilities	1.0136	25.0620
Wholesale trade	0.8696	1.3952
Retail trade	0.2172	5.6157
Finance and insurance	0.3326	34.8361
Services	0.3574	0.4551
Government	0.6444	5.6428

Table 2.6: Multivariate statistics for the results of cluster analysis.

Clusters	**Wilks' Lambda**	**Pillai's Trace**	**Hotelling-Lawley Trace**	**Roy's Greatest Root**
5	0.0134	2.5399	8.6276	4.1013
6	0.0032	3.2512	12.3247	4.5268
7	0.0017	3.6480	14.2604	6.6443
8	0.0016	3.9755	12.2706	3.9447
9	0.0007	4.3437	14.4639	4.3776
10	0.0003	4.7353	17.9558	6.1065
11	0.0001	5.1407	19.9157	5.2812
12	0.0001	5.0301	19.4129	5.8070

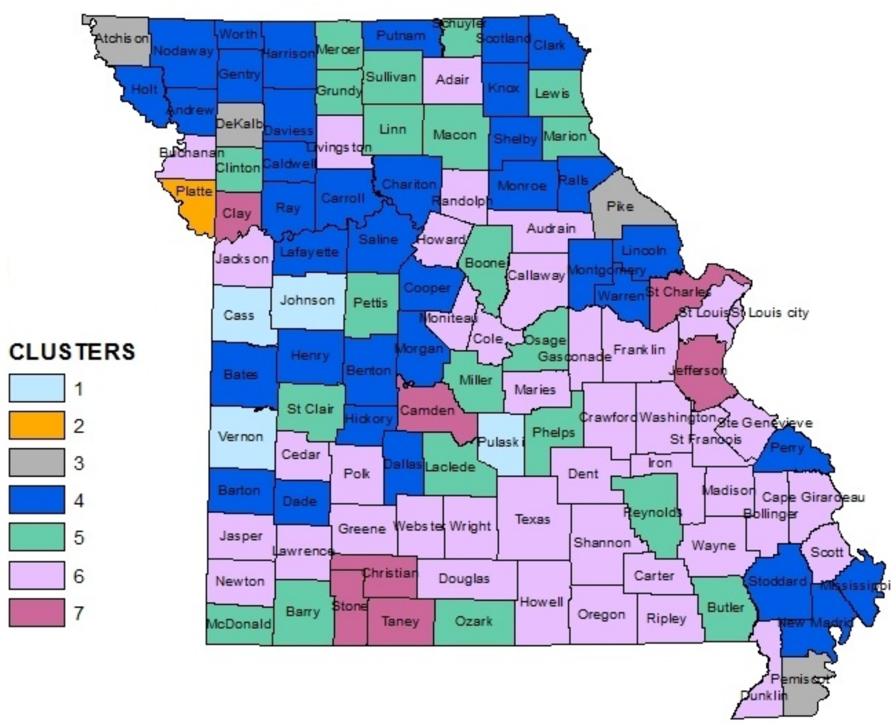

Figure 2.13: Spatial map of 7 clusters of counties of the state of Missouri.

Table 2.7: Sources of aggregate earnings growth for the clusters of the counties in the state of Missouri (in percent).

Period	1969-2000			1969-1980			1981-1990			1991-2000		
Sector	**EGE[1]**	**SE[1]**	**TE[2]**	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**
Cluster 1 counties												
FA	-2.8	-0.4	-3.2	1.5	0.7	2.2	1.4	-0.4	1.0	-0.5	-0.1	-0.6
AS	-0.5	0.2	-0.3	-0.4	0.4	0.0	0.0	0.1	0.1	-0.1	-0.2	-0.3
MI	0.1	0.1	0.2	0.4	0.4	0.8	-0.2	0.0	-0.2	0.1	-0.1	0.0
CO	-0.7	6.1	5.4	2.2	5.2	7.4	0.2	3.1	3.3	0.4	1.7	2.1
MA	1.7	3.3	5.0	2.0	4.4	6.4	0.2	1.4	1.6	1.7	-1.5	0.2
TU	0.3	1.4	1.7	1.0	1.8	2.8	-0.7	-0.2	-0.9	0.5	-0.1	0.4
WT	-0.1	1.0	0.9	0.4	2.1	2.5	-0.7	-0.7	-1.4	0.2	-0.1	0.1
RT	-2.3	5.9	3.6	-0.9	2.7	1.8	-0.7	2.0	1.3	0.9	0.6	1.5
FI	1.8	1.9	3.7	0.1	1.3	1.4	1.1	-0.5	0.6	0.9	0.6	1.5
SS	-2.8	12.4	9.6	-2.5	5.1	2.6	0.6	3.0	3.6	1.6	1.8	3.5
GT	31.9	-45.0	-13.1	13.5	-28.1	-14.6	11.4	-10.2	1.2	4.3	-5.3	1.0
Total Effect	26.5	-13.2	13.7	17.3	-3.9	13.4	12.6	-2.5	10.1	10.1	-2.6	7.8
Cluster 2 counties												
FA	0.8	-3.4	-2.6	4.7	-4.3	0.4	1.1	-1.6	-0.5	0.4	-0.4	0.0
AS	0.0	0.0	0.0	0.0	0.4	0.4	0.0	0.0	0.0	0.0	0.0	0.0
MI	0.0	0.0	0.0	0.2	-0.2	0.0	-1.1	0.9	0.2	0.0	0.0	0.0
CO	0.8	2.3	3.1	3.2	6.5	9.7	-1.9	1.5	-0.5	1.9	0.8	2.7
MA	1.9	6.5	8.4	-0.5	3.3	2.8	0.4	0.3	0.8	2.7	1.7	4.4
TU	-5.2	-60.3	-65.6	32.9	-27.9	5.0	-11.2	-7.7	-18.9	-7.9	-21.5	-29.4
WT	3.7	11.9	15.6	0.1	2.2	2.3	0.2	4.1	4.4	4.8	2.7	7.5
RT	-3.5	6.1	2.6	-2.4	3.2	0.8	-0.4	-0.3	-0.6	1.0	1.1	2.1
FI	2.9	5.3	8.2	-0.7	1.3	0.5	1.2	0.3	1.5	3.3	2.4	5.7
SS	-4.0	24.7	20.7	-2.6	4.2	1.6	4.6	10.1	14.7	-1.1	5.6	4.5
GT	5.0	-1.8	3.2	1.8	1.2	3.0	3.9	-6.8	-2.8	-0.2	-0.4	-0.6
Total Effect	2.2	-8.6	-4.5[4]	36.7	-10.0	18.8	-3.1	0.9	-0.9	5.0	-8.0	-1.7
Cluster 3 counties												
FA	0.2	-12.1	-12.0	15.0	-8.6	6.4	8.3	-1.3	7.0	-0.5	-2.4	-2.9
AS	0.0	0.0	0.0	-0.1	0.1	0.0	0.2	0.5	0.7	0.0	0.0	0.0
MI	0.0	0.0	0.0	0.4	0.1	0.5	-0.2	-0.1	-0.3	0.0	0.0	0.0
CO	-6.6	-18.3	-24.9	-11.0	-11.9	-22.9	0.0	0.1	0.1	1.3	-2.5	-1.1
MA	3.3	-6.3	-2.9	2.6	1.3	3.9	-4.8	-2.4	-7.3	4.8	-5.6	-0.8
TU	0.9	1.8	2.7	1.4	2.4	3.7	-1.4	-0.5	-1.9	1.8	0.1	1.9
WT	-0.8	3.9	3.1	-0.3	4.5	4.2	-0.2	0.0	-0.2	-0.3	-0.2	-0.6
RT	-1.5	1.7	0.2	-0.9	0.5	-0.4	-0.4	1.4	1.0	1.1	0.1	1.2
FI	0.9	0.6	1.5	0.8	0.6	1.4	-0.5	-0.9	-1.4	0.9	0.6	1.6

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Period	1969-2000			1969-1980			1981-1990			1991-2000		
Sector	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**[3]
SS	-1.4	8.3	6.8	-2.3	3.8	1.5	-1.3	1.8	0.4	3.4	1.1	4.4
GT	6.3	13.1	19.4	0.5	3.3	3.8	2.6	3.2	5.8	3.3	5.8	9.1
Total Effect	1.3	-7.4	-3.8	6.1	-3.9	3.0	2.2	1.7	3.0	15.8	-3.0	17.0
Cluster 4 counties												
FA	-4.4	-12.7	-16.9	16.0	-8.4	7.6	15.6	-1.7	13.9	0.5	-1.7	-1.2
AS	-0.4	-0.4	-0.9	-0.4	0.2	-0.3	0.1	0.1	0.2	-0.2	-0.7	-0.9
MI	0.0	-0.4	-0.4	0.3	-0.1	0.2	-0.2	-0.2	-0.3	0.0	-0.1	-0.1
CO	-0.9	2.1	1.3	-0.1	0.7	0.6	-0.3	0.6	0.3	0.7	1.0	1.7
MA	3.6	3.2	6.8	2.6	2.3	4.9	0.2	1.8	2.0	1.8	-0.4	1.3
TU	0.4	1.3	1.7	1.1	0.5	1.6	-0.2	0.3	0.2	0.9	-0.2	0.7
WT	-0.6	3.1	2.4	-0.2	3.3	3.1	-0.8	0.2	-0.6	0.4	-0.3	0.1
RT	-3.0	0.5	-2.4	-0.8	-0.4	-1.2	-0.9	0.7	-0.2	0.7	0.3	1.0
FI	2.2	-0.2	2.0	0.2	0.0	0.3	0.8	-0.8	0.0	1.1	0.6	1.7
SS	-2.6	7.4	4.8	-2.0	2.6	0.6	-1.4	1.7	0.3	2.4	1.0	3.5
GT	4.5	2.3	6.8	1.1	1.3	2.3	2.1	0.6	2.6	1.9	-0.1	1.8
Total Effect	-1.1	6.3	10.3	17.8	2.0	21.9	14.9	3.3	18.5	10.3	-0.7	14.5
Cluster 5 counties												
FA	-3.0	-3.9	-6.9	2.8	-2.7	0.1	3.0	-0.7	2.3	0.0	-0.5	-0.5
AS	-0.4	0.2	-0.2	-0.3	0.1	-0.2	-0.1	0.2	0.1	0.0	-0.2	-0.2
MI	-0.3	-0.9	-1.3	0.4	-0.3	0.1	-0.7	-0.5	-1.1	0.1	-0.1	0.0
CO	-0.9	0.1	-0.8	0.1	-0.4	-0.3	-0.5	0.5	0.0	0.4	0.5	0.9
MA	3.4	2.5	5.9	1.6	0.6	2.2	0.3	2.5	2.8	2.0	-0.3	1.7
TU	0.1	-1.3	-1.2	1.6	-1.2	0.3	-0.9	-0.3	-1.2	0.5	-0.1	0.4
WT	-0.3	0.6	0.4	0.1	1.2	1.3	-0.4	0.0	-0.4	0.4	-0.2	0.1
RT	-2.3	0.0	-2.2	-0.9	-0.3	-1.2	-0.6	0.8	0.2	0.8	-0.1	0.8
FI	3.8	-2.2	1.7	0.7	-0.3	0.4	0.8	-1.4	-0.6	2.0	-0.1	1.9
SS	0.3	8.2	8.5	0.7	-0.3	0.4	0.3	2.1	2.4	2.0	-0.1	1.9
GT	6.7	1.3	8.2	3.1	1.5	4.6	2.6	-1.2	1.4	1.8	0.6	2.4
Total Effect	7.3	4.7	13.3	6.8	1.4	8.4	4.1	1.9	5.6	12.0	0.3	14.7
Cluster 6 counties												
FA	-0.6	-0.3	-0.9	0.2	-0.2	0.1	0.2	-0.1	0.0	-0.2	0.0	-0.2
AS	-0.2	0.2	0.1	-0.1	0.2	0.1	0.0	0.1	0.0	0.0	-0.1	0.0
MI	0.1	-0.7	-0.6	0.4	-0.3	0.1	-0.4	-0.2	-0.6	0.1	-0.3	-0.2
CO	0.8	1.6	2.4	0.3	0.5	0.8	-0.5	0.2	-0.3	1.7	1.4	3.1
MA	8.6	-24.8	-16.2	4.4	-7.4	-3.0	2.6	-6.6	-4.0	3.4	-7.8	-4.4
TU	1.1	0.2	1.3	2.3	-0.3	1.9	-0.7	-0.6	-1.3	0.3	0.8	1.1
WT	2.0	-2.5	-0.5	0.7	-0.4	-0.4	0.8	-0.9	-0.1	1.0	-1.1	-0.1
RT	-2.7	0.9	-1.7	-1.5	0.7	-0.9	-0.9	0.7	-0.2	1.5	0.1	1.6
FI	7.6	1.0	8.6	-0.1	0.2	0.1	2.2	0.0	2.2	5.5	0.3	5.8

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Period	**1969-2000**			**1969-1980**			**1981-1990**			**1991-2000**		
Sector	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**	**EGE**	**SE**	**TE**[3]
SS	10.3	16.9	27.2	0.1	4.1	4.2	4.8	5.1	9.9	7.6	4.4	12.0
GT	4.2	-0.8	3.4	1.7	-0.2	1.6	2.1	-1.0	1.1	1.1	-0.3	0.8
Total Effect	31.3	-8.3	16.5	8.4	-3.1	3.9	10.1	-3.4	4.9	22.0	-2.5	19.5
Cluster 7 counties												
FA	-1.2	-1.1	-2.3	0.2	-0.9	-0.6	-0.1	-0.4	-0.5	-0.1	-0.1	-0.2
AS	-0.2	0.3	0.1	-0.1	0.1	0.0	0.3	0.2	0.5	-0.2	0.0	-0.2
MI	0.2	-0.5	-0.3	0.4	-0.3	0.0	-0.2	0.1	-0.1	0.2	-0.1	0.0
CO	-0.7	4.4	3.7	-0.2	1.0	0.8	-1.1	2.2	1.1	2.3	1.8	4.1
MA	6.4	-22.3	-16.0	2.5	-11.1	-8.6	2.9	0.2	3.1	2.0	-8.1	-6.0
TU	-1.6	-4.7	-6.4	1.1	-2.8	-1.7	-0.6	-1.8	-2.3	-0.6	0.5	-1.2
WT	0.1	-0.9	-0.8	0.1	2.4	2.5	-0.6	-2.9	-3.4	0.7	0.3	0.9
RT	-4.6	4.1	-0.5	-1.4	0.9	-0.5	-1.2	2.8	1.5	1.3	0.0	1.3
FI	3.2	1.1	4.3	-0.8	0.8	0.0	1.3	-0.7	0.6	2.3	1.1	3.4
SS	1.6	15.5	17.2	-2.2	5.2	3.0	-2.4	3.9	1.5	9.7	2.4	12.0
GT	4.3	-3.1	1.2	0.7	0.4	1.1	3.3	-4.3	-1.0	0.9	0.3	1.1
Total Effect	7.5	-7.1	0.0	0.4	-4.4	-3.1	1.7	-0.6	0.9	18.3	-3.1	14.5

[1] The sector is omitted if the effect is close to zero or there is no information available.
[2] Total effect may not sum up to 100 per cent due to rounding.
[3] Overall total effect number comes from calculations for the actual aggregate earnings per worker.
[4] The discrepancy appears due to missing data for one or more sectors.

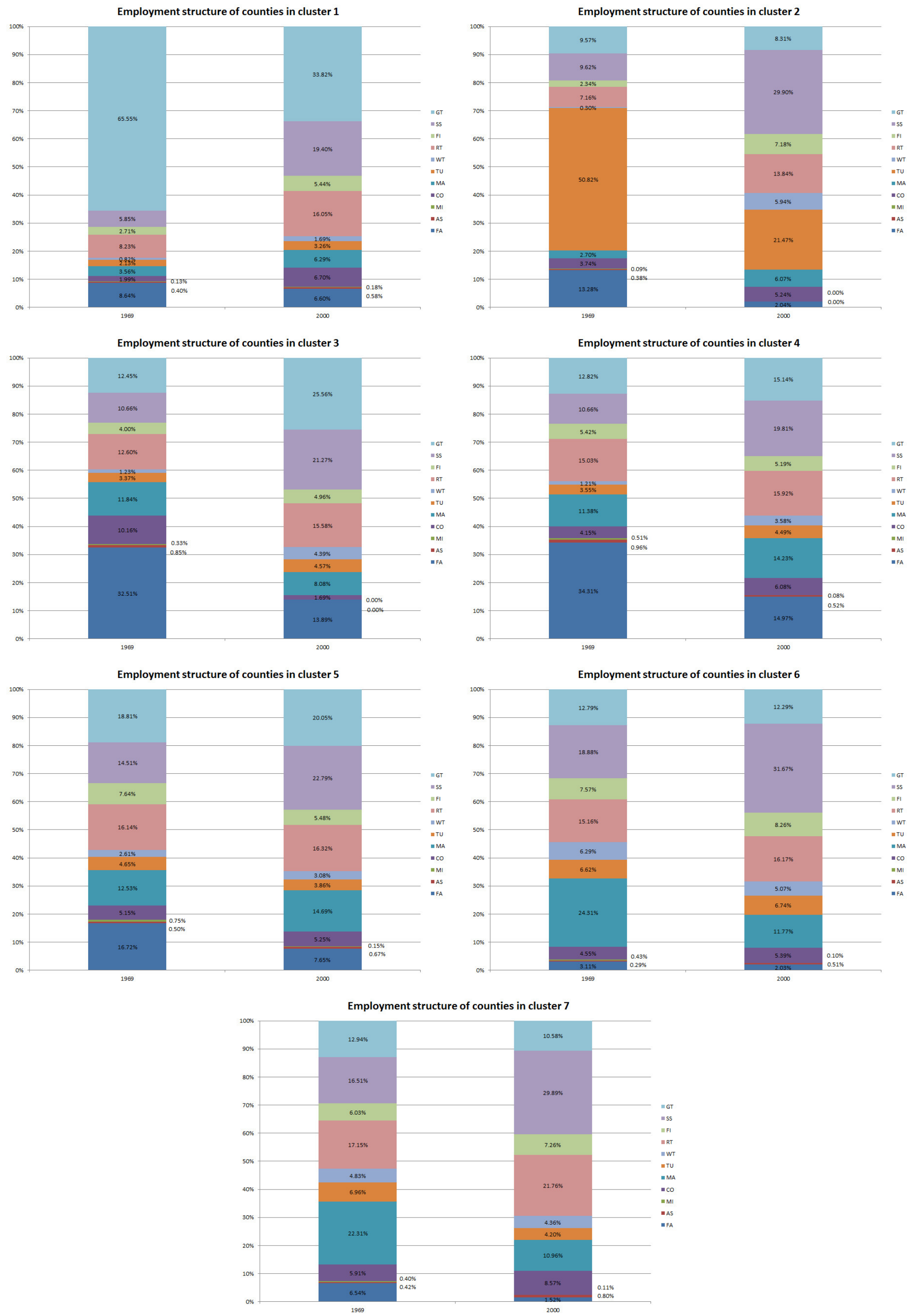

Figure 2.14: Employment structure of Missouri counties in 1969 and 2000 by clusters.

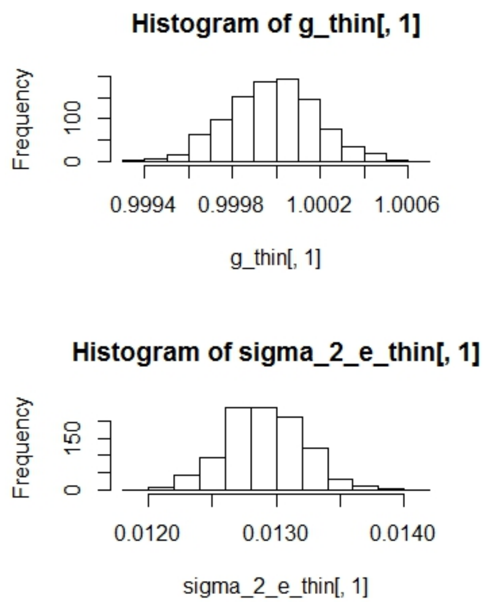

Figure 2.15: Histograms of the growth parameter g and error variance σ_ϵ^2 estimates for model 2.1.

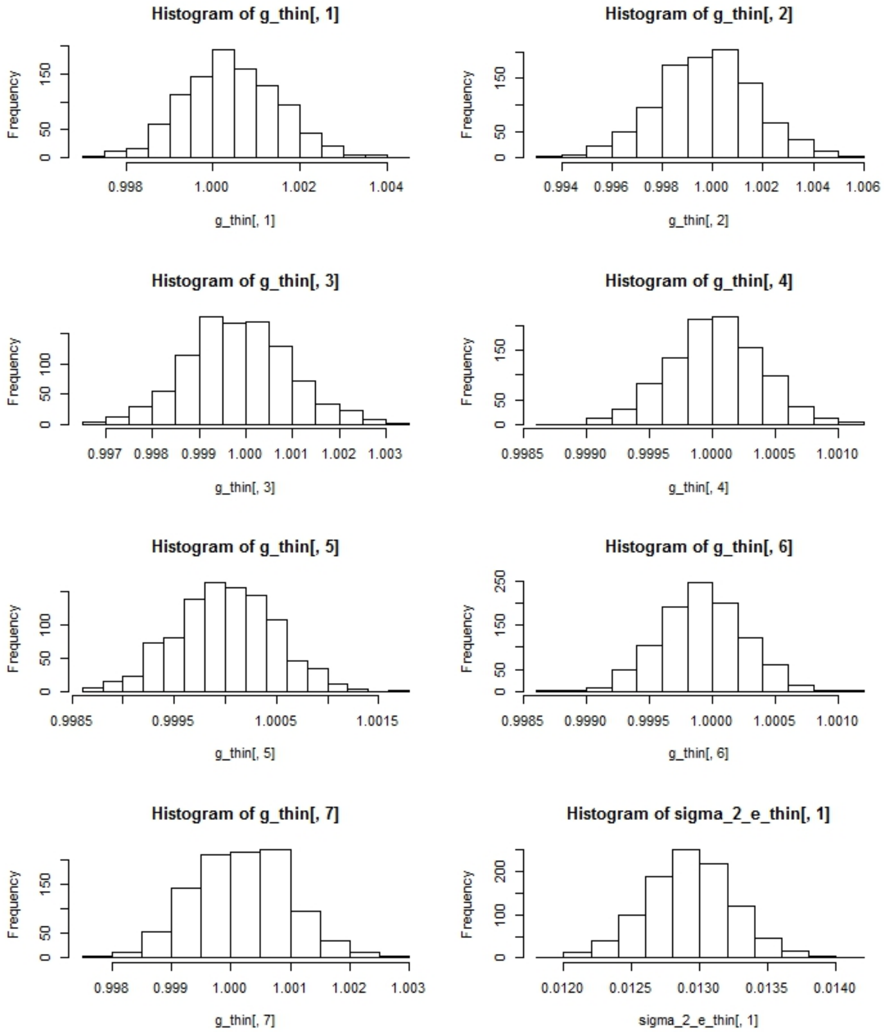

Figure 2.16: Histograms of the growth parameter coefficients g_j and error variance σ_ϵ^2 estimates for model 2.2.

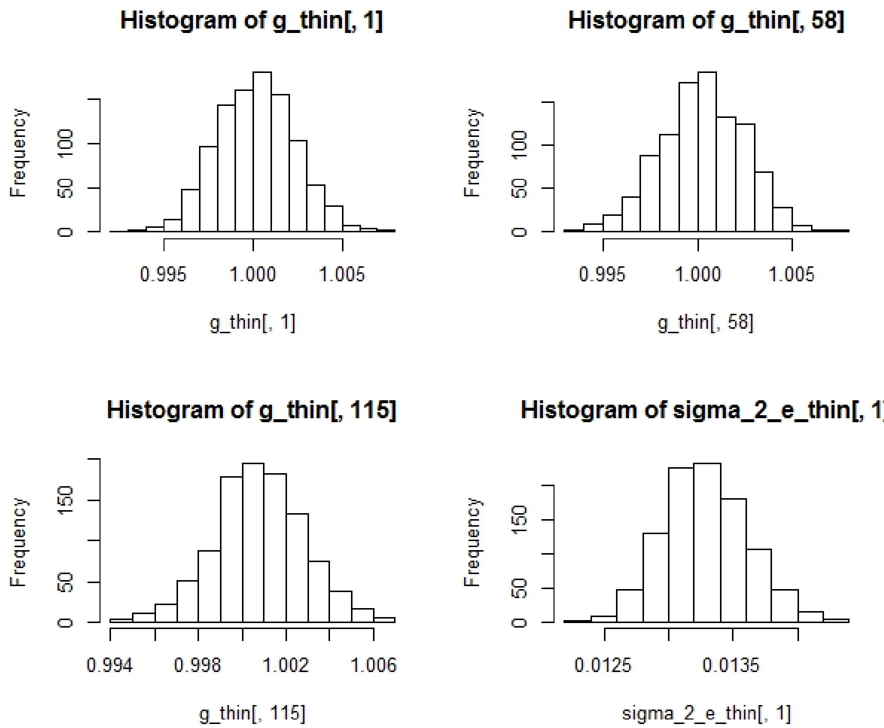

Figure 2.17: Histograms of some growth g_i parameter coefficients and error variance σ_ϵ^2 estimates for model 2.3.

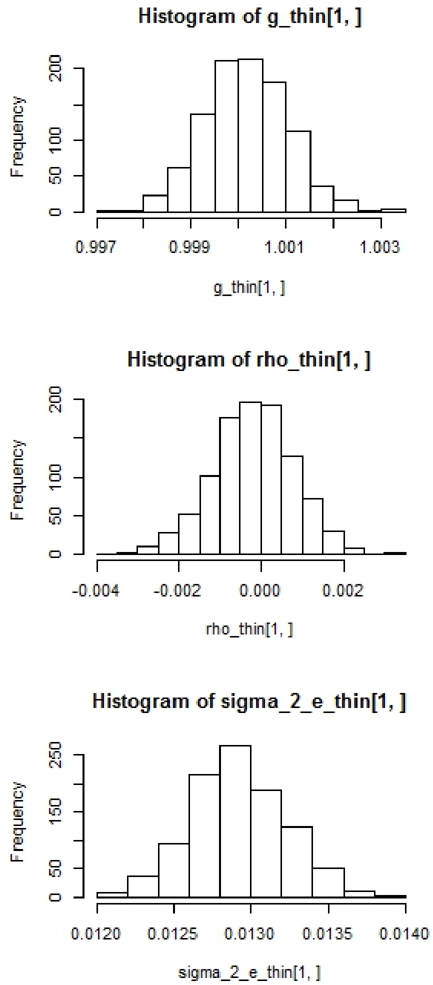

Figure 2.18: Histograms of the growth g and diffusion ρ parameters coefficients and error variance σ_ϵ^2 estimates for model 2.4.

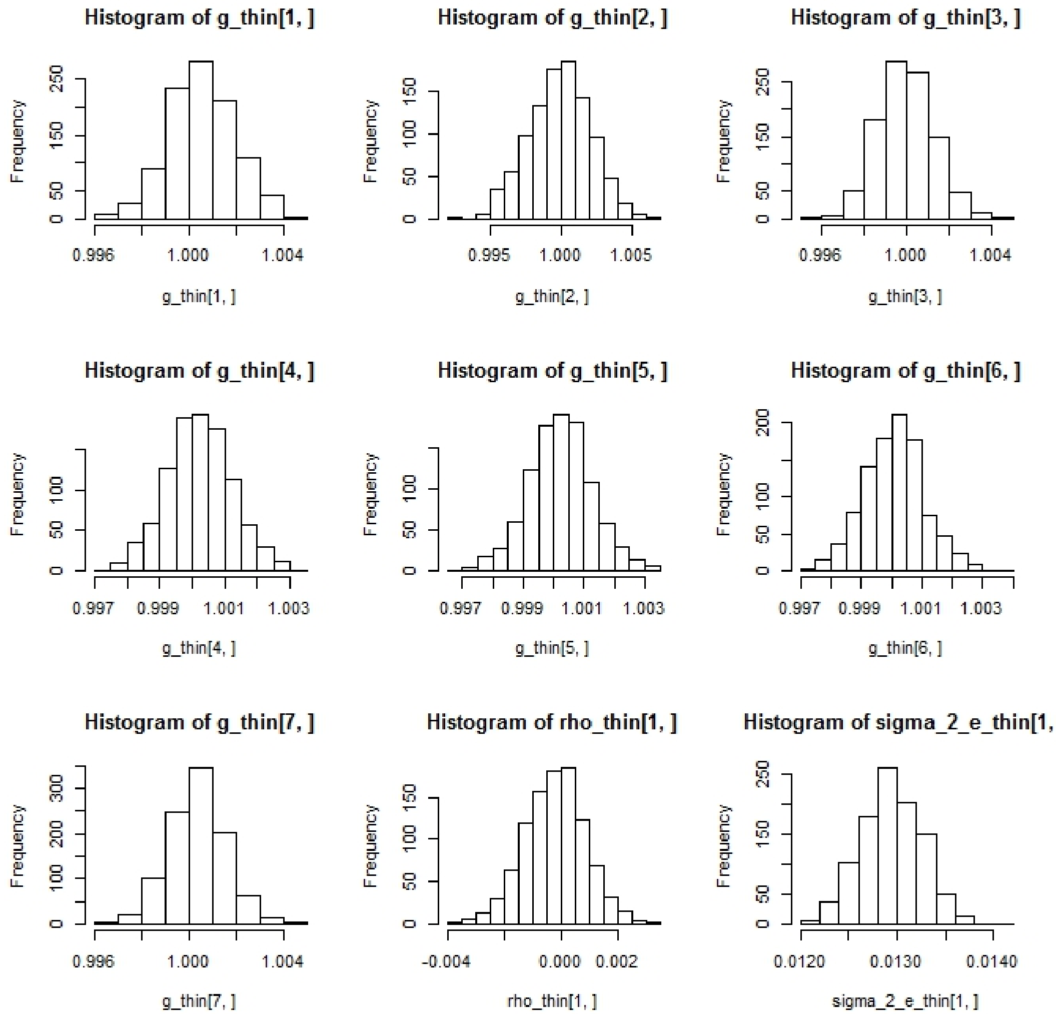

Figure 2.19: Histograms of the growth g_j and diffusion ρ parameters coefficients and error variance σ_ϵ^2 estimates for model 2.5.

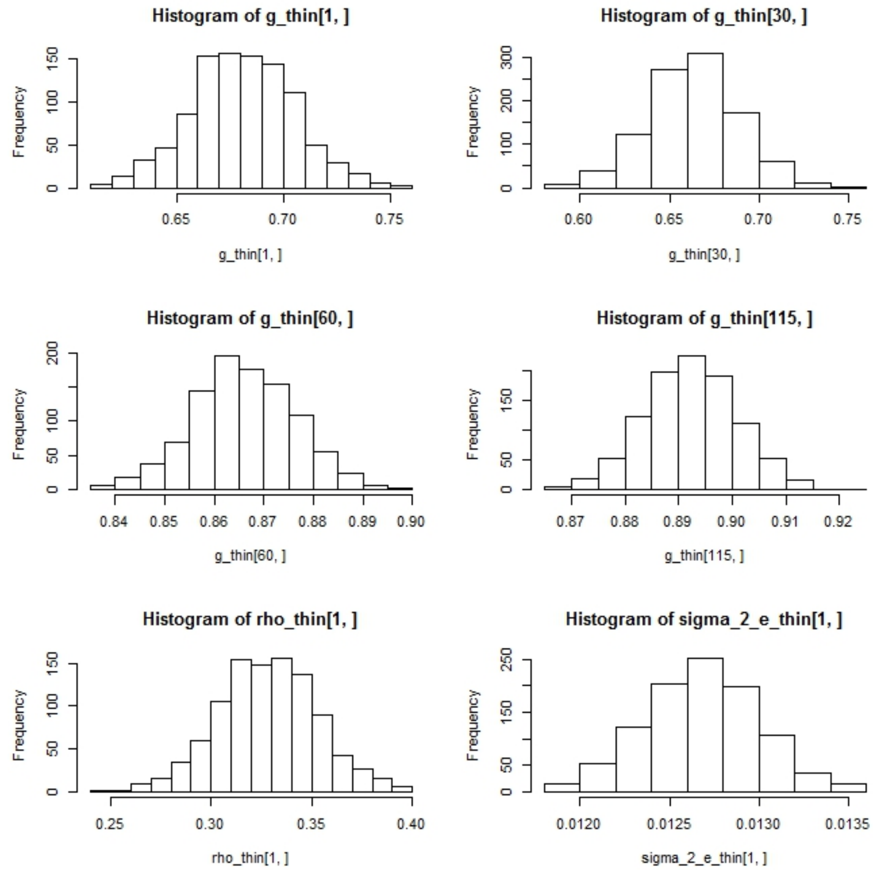

Figure 2.20: Histograms of some growth g_i and diffusion ρ parameters coefficients and error variance σ_ϵ^2 estimates for model 2.6.

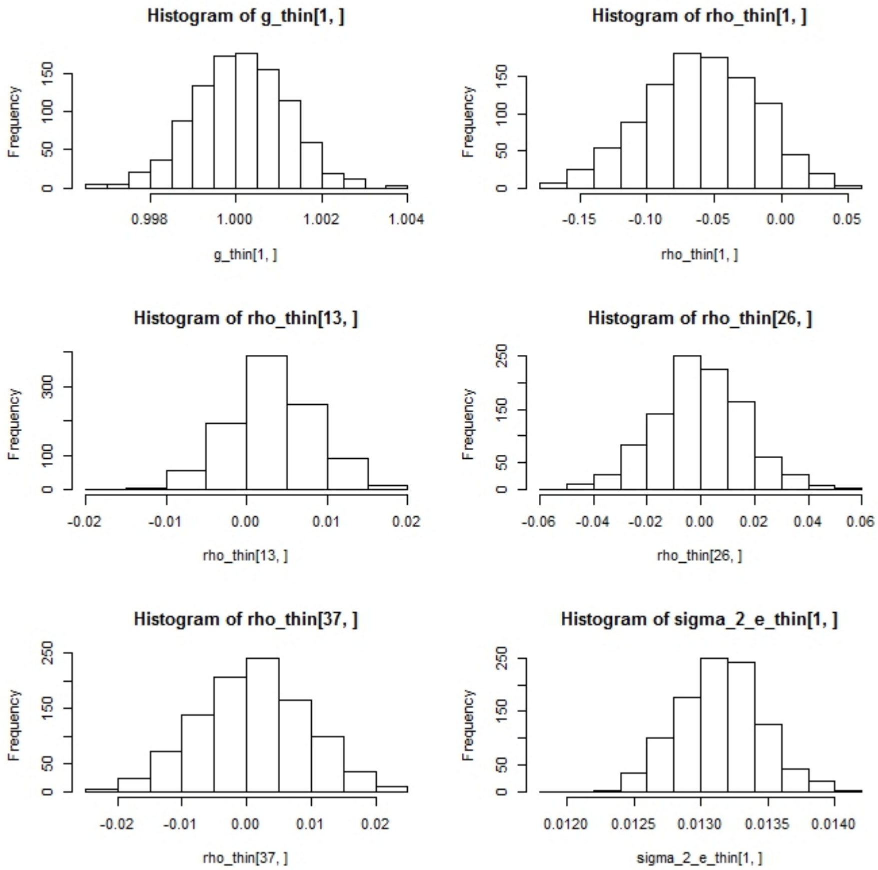

Figure 2.21: Histograms of the growth g and diffusion ρ_{jk} parameter coefficients and error variance σ_{ϵ}^2 estimates for model 2.7.

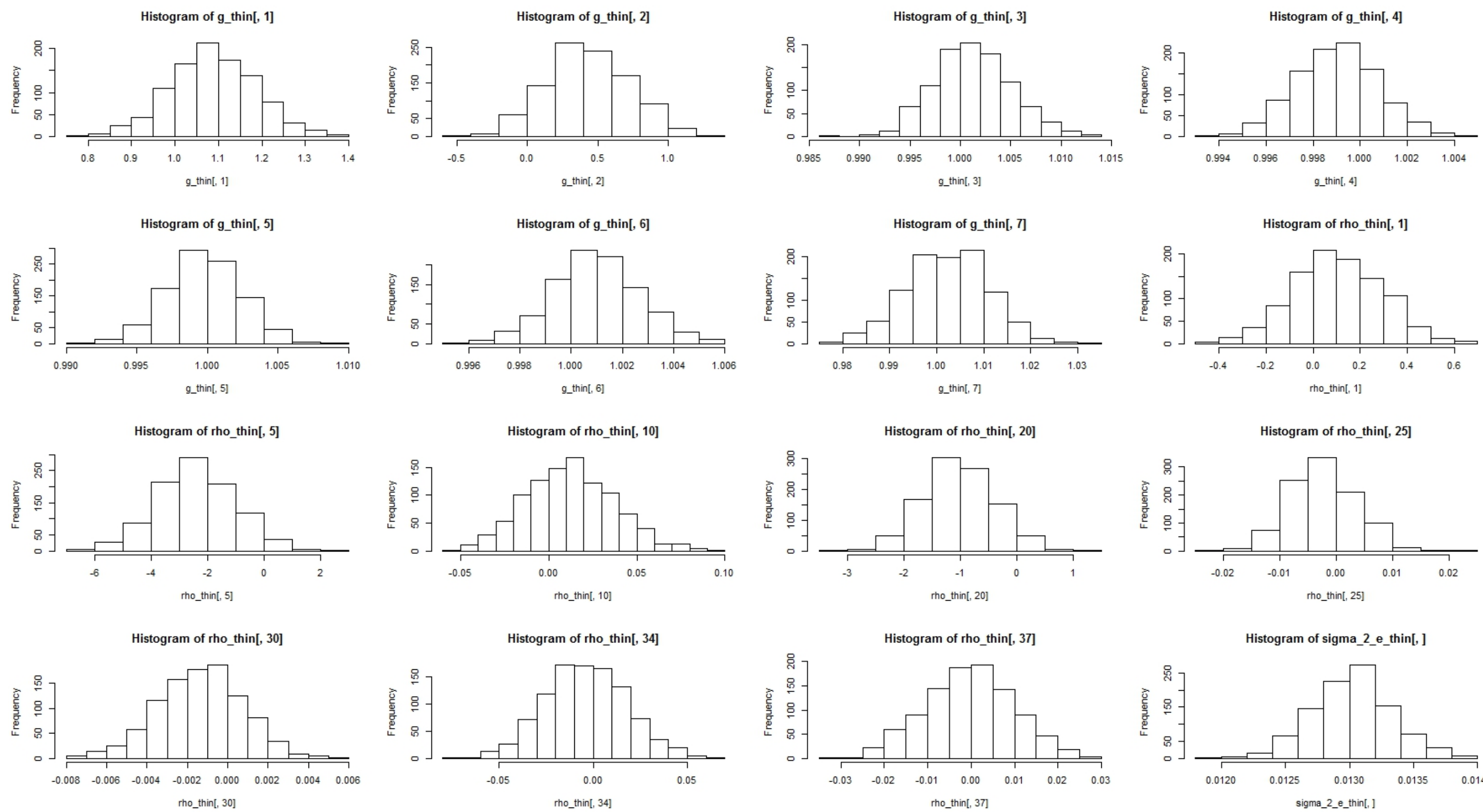

Figure 2.22: Histograms of the growth g_j and diffusion ρ_{jk} parameter coefficients and error variance σ_ϵ^2 estimates for model 2.8.

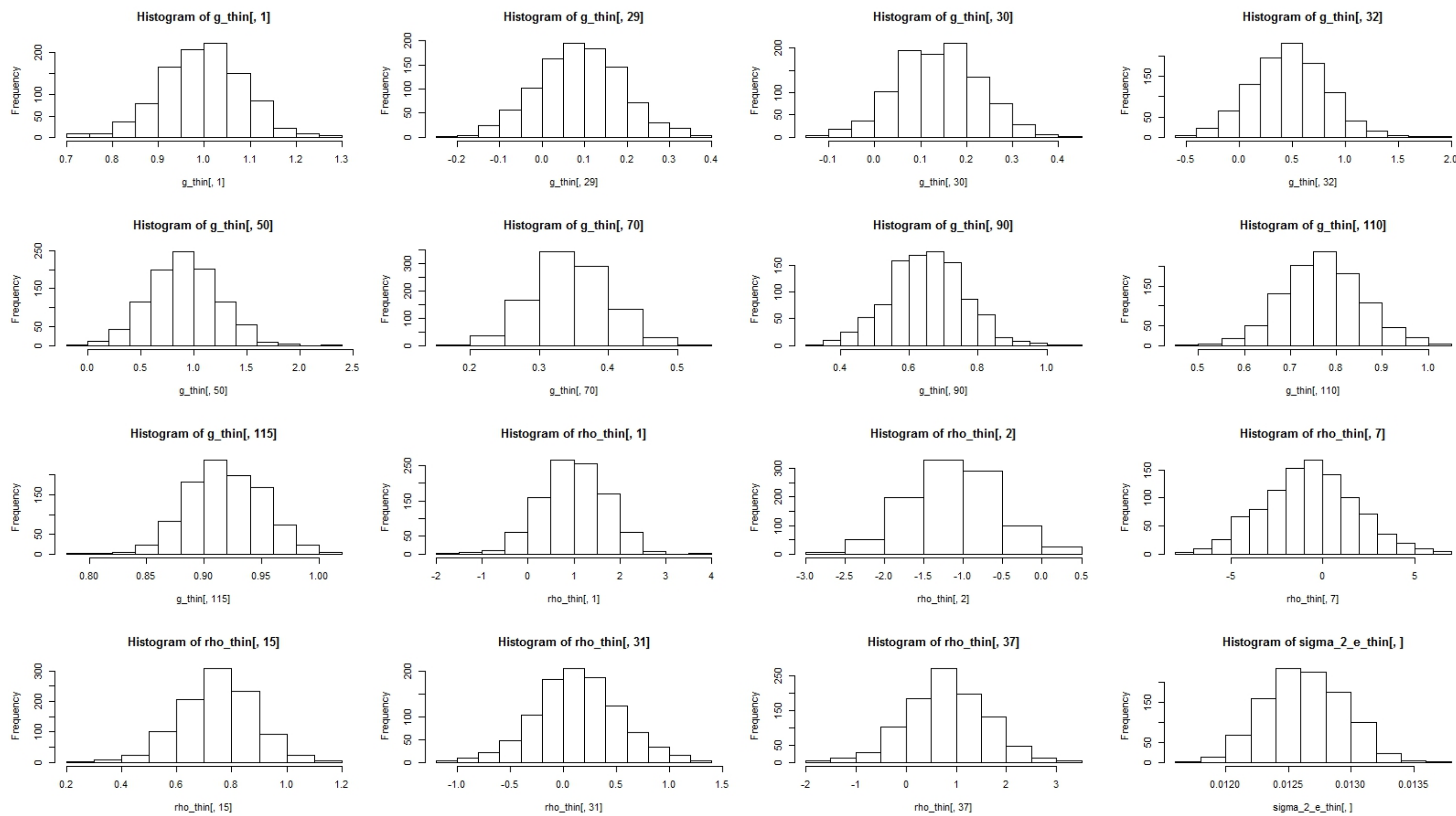

Figure 2.23: Histograms of some growth g_i and diffusion ρ_{jk} parameter coefficients and error variance σ_ϵ^2 estimates for model 2.9.

Table 2.8: MCMC estimation results for models with scalar temporal and spatio-temporal autoregressive coefficients.

Parameter	Model 2.1	Model 2.4	Model 2.5	Model 2.6	Model 2.7
g	0.9999	1.0002	cluster-	county-	1.0001
	(0.0002)	(0.0009)	specific	specific	(0.0010)
ρ	-	-0.0002	-0.0002	0.3279	cluster-
		(0.0010)	(0.0011)	(0.0246)	specific
σ_{ϵ}^{2}	0.0129	0.0129	0.0129	0.0127	0.0130
DIC	3413.15	3411.39	3411.78	3408.62	3413.35

Table 2.9: MCMC estimation results for models with cluster-specific spatio-temporal autoregressive coefficients.

Parameter	Model 2.2	Model 2.5	Model 2.8
g_1	1.0005	1.0005	1.0876
	(0.0011)	(0.0014)	(0.0975)
g_2	0.9998	1.0009	0.4361
	(0.0020)	(0.0021)	(0.2909)
g_3	0.9998	1.0019	1.0013
	(0.0011)	(0.0013)	(0.0038)
g_4	1.0000	1.0032	0.9990
	(0.0004)	(0.0010)	(0.0017)
g_5	1.0000	1.0042	0.9998
	(0.0003)	(0.0010)	(0.0026)
g_6	0.9999	1.0051	1.0010
	(0.0003)	(0.0010)	(0.0017)
g_7	1.0002	1.0064	1.0022
	(0.0008)	(0.0012)	(0.0086)
σ^2_ϵ	0.0129	0.0129	0.0130
DIC	3414.24	3411.78	3411.76

Table 2.10: MCMC estimations results of spatio-temporal correlation coefficients for model 2.7

		Cluster of neighbor						
		1	2	3	4	5	6	7
Cluster of center	1	-0.0613 (0.0432)	N/A	N/A	-0.3724 (0.2423)	0.0055 (0.0174)	0.7545 (0.4907)	-1.4852 (0.9714)
	2	N/A	N/A	N/A	N/A	-1.3735 (1.3892)	-0.1810 (2.4092)	1.4666 (2.3467)
	3	N/A	N/A	N/A	-0.0045 (0.0064)	0.0071 (0.0202)	0.0082 (0.0137)	N/A
	4	0.0009 (0.0045)	N/A	0.0032 (0.0052)	-0.0009 (0.0019)	-0.0001 (0.0025)	0.0005 (0.0019)	0.0003 (0.0048)
	5	0.0012 (0.0089)	0.9652 (0.6049)	-1.0399 (0.6514)	-0.0007 (0.0024)	0.0007 (0.0027)	-0.0002 (0.0016)	-0.0014 (0.0086)
	6	-0.0014 (0.0055)	-0.0004 (0.0168)	0.0021 (0.0124)	0.0002 (0.0019)	-0.0007 (0.0021)	-0.0005 (0.0015)	-0.0004 (0.0038)
	7	-0.0006 (0.0445)	-0.0006 (0.0204)	N/A	0.0009 (0.0082)	-0.0014 (0.0180)	-0.0004 (0.0030)	0.0013 (0.0084)

Table 2.11: MCMC estimations results of spatio-temporal correlation coefficients for model 2.8

		Cluster of neighbor						
		1	2	3	4	5	6	7
Cluster of center	1	0.1035 (0.1888)	N/A	N/A	-0.7455 (0.4840)	0.0947 (0.0998)	0.7952 (0.5002)	-2.3786* (1.4007)
	2	N/A	N/A	N/A	N/A	-2.4900 (1.4578)	-0.5416 (2.4344)	6.2934* (3.3962)
	3	N/A	N/A	N/A	-0.0068 (0.0102)	0.0121 (0.0250)	0.0063 (0.0144)	N/A
	4	0.0024 (0.0047)	N/A	0.0051 (0.0058)	0.0003 (0.0024)	0.0009 (0.0028)	0.0018 (0.0023)	0.0006 (0.0087)
	5	0.0010 (0.0087)	0.9572 (0.5803)	-1.0301 (0.6245)	-0.0026 (0.0039)	0.0013 (0.0037)	0.0003 (0.0031)	-0.0005 (0.0110)
	6	-0.0024 (0.0059)	-0.0021 (0.0167)	0.0003 (0.0123)	-0.0007 (0.0024)	-0.0015 (0.0024)	-0.0014 (0.0021)	-0.0013 (0.0041)
	7	0.0177 (0.0844)	0.0026 (0.0246)	N/A	-0.0039 (0.0217)	-0.0077 (0.0332)	-0.0029 (0.0106)	-0.0004 (0.0102)

Table 2.12: MCMC estimations results of spatio-temporal correlation coefficients for model 2.9. (Statistically significant at 10% level estimates are marked with a star.)

		Cluster of neighbor						
		1	2	3	4	5	6	7
Cluster of center	1	1.0037 (0.6912)	N/A	N/A	-1.1190* (0.5573)	0.6408 (0.7774)	0.60498 (0.5503)	-2.6482 (2.4318)
	2	N/A	N/A	N/A	N/A	-2.4764* (1.4361)	-0.6870 (2.4774)	6.4563* (3.5497)
	3	N/A	N/A	N/A	0.1684 (0.2775)	0.3916 (2.0997)	2.0232 (0.8809)	N/A
	4	1.0107* (0.4537)	N/A	0.2527 (0.2930)	0.2479* (0.0977)	0.7480* (0.1322)	1.0039* (0.1161)	1.0086* (0.4884)
	5	1.2990* (0.5501)	0.0957 (0.9896)	0.2055 (1.5751)	-0.5542* (0.1336)	0.9203* (0.1887)	0.3551* (0.1122)	1.9400* (0.7585)
	6	0.1390 (0.3319)	-0.2263 (1.1963)	0.1424 (0.5909)	-0.1568 (0.1110)	0.1253 (0.1580)	0.2496* (0.0977)	0.1399 (0.3942)
	7	0.4025 (1.3072)	-0.4940 (1.3515)	N/A	-0.3718 (0.5334)	-0.5187 (0.7972)	0.1108 (0.3879)	0.8161 (0.7905)

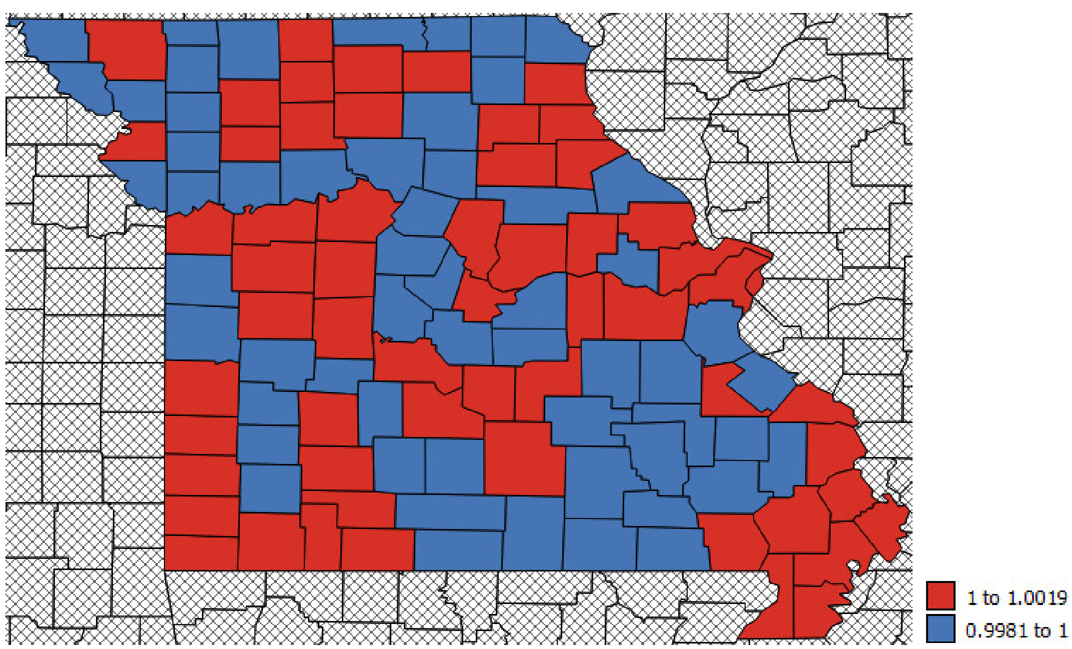

Figure 2.24: Map of posterior means of county-specific temporal autoregressive coefficients for model 2.3.

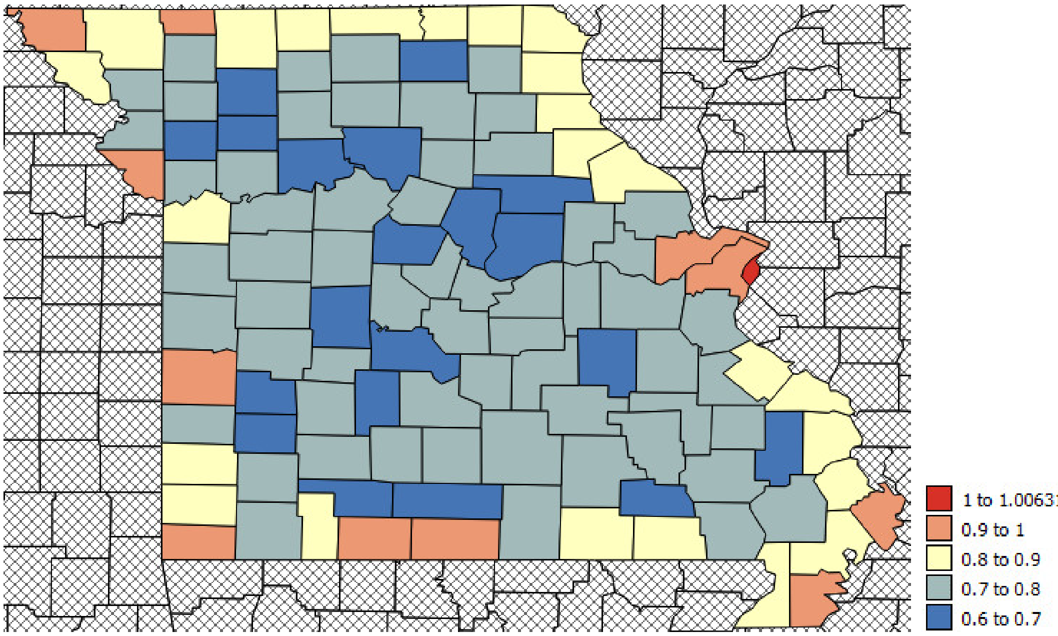

Figure 2.25: Map of posterior means of county-specific temporal autoregressive coefficients for model 2.6.

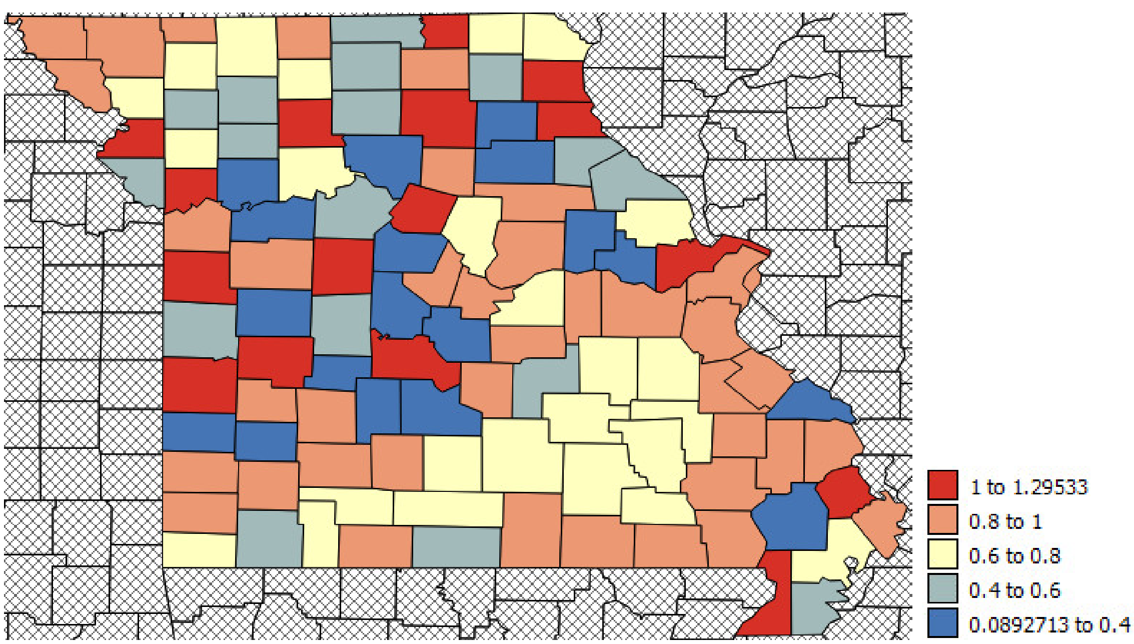

Figure 2.26: Map of posterior means of county-specific temporal autoregressive coefficients for model 2.9.

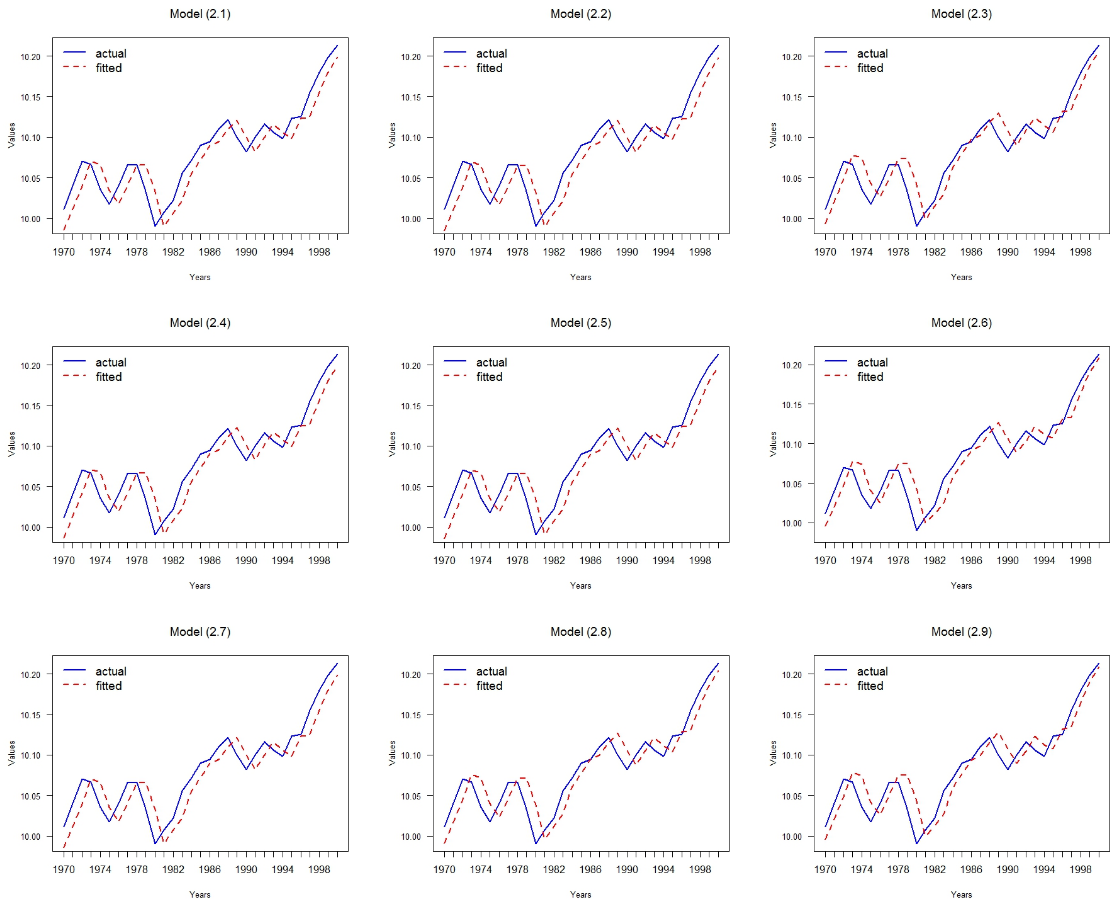

Figure 2.27: Actual and fitted values from all models for St. Louis City.

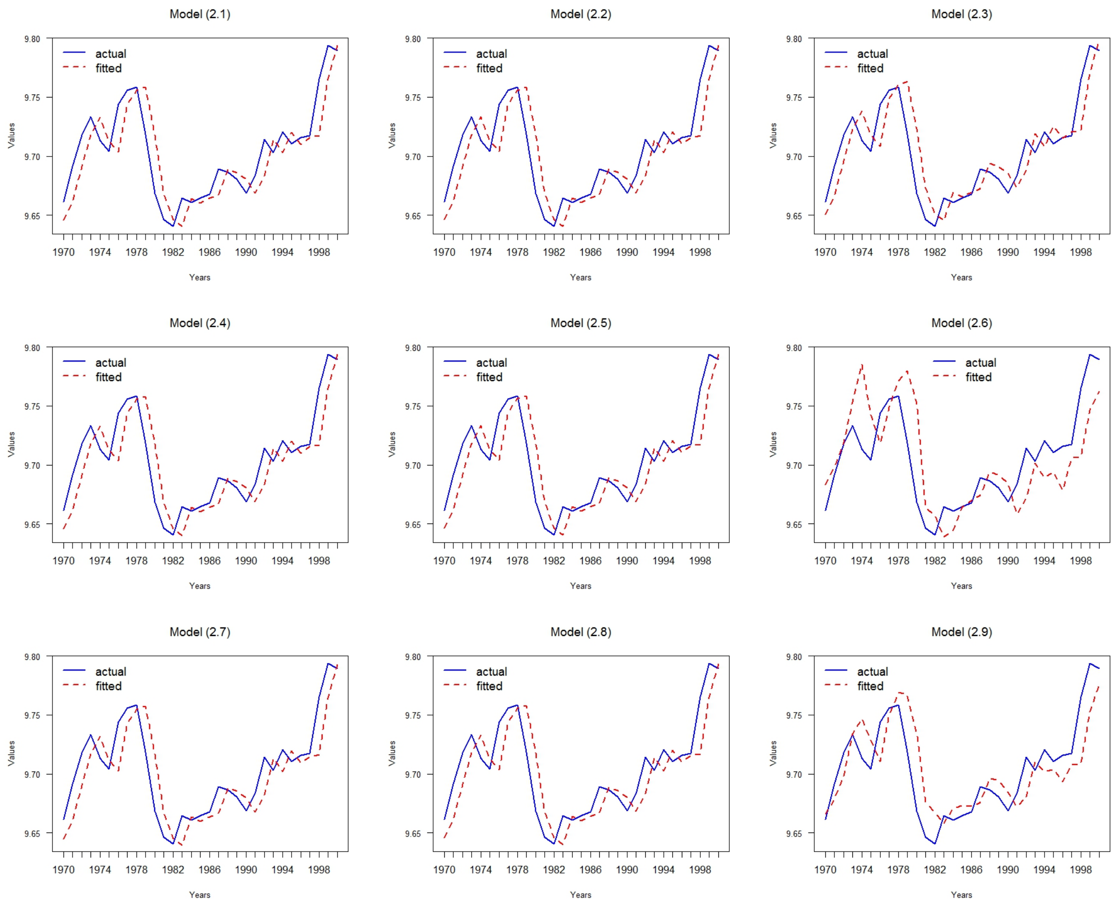

Figure 2.28: Actual and fitted values from all models for Boone County.

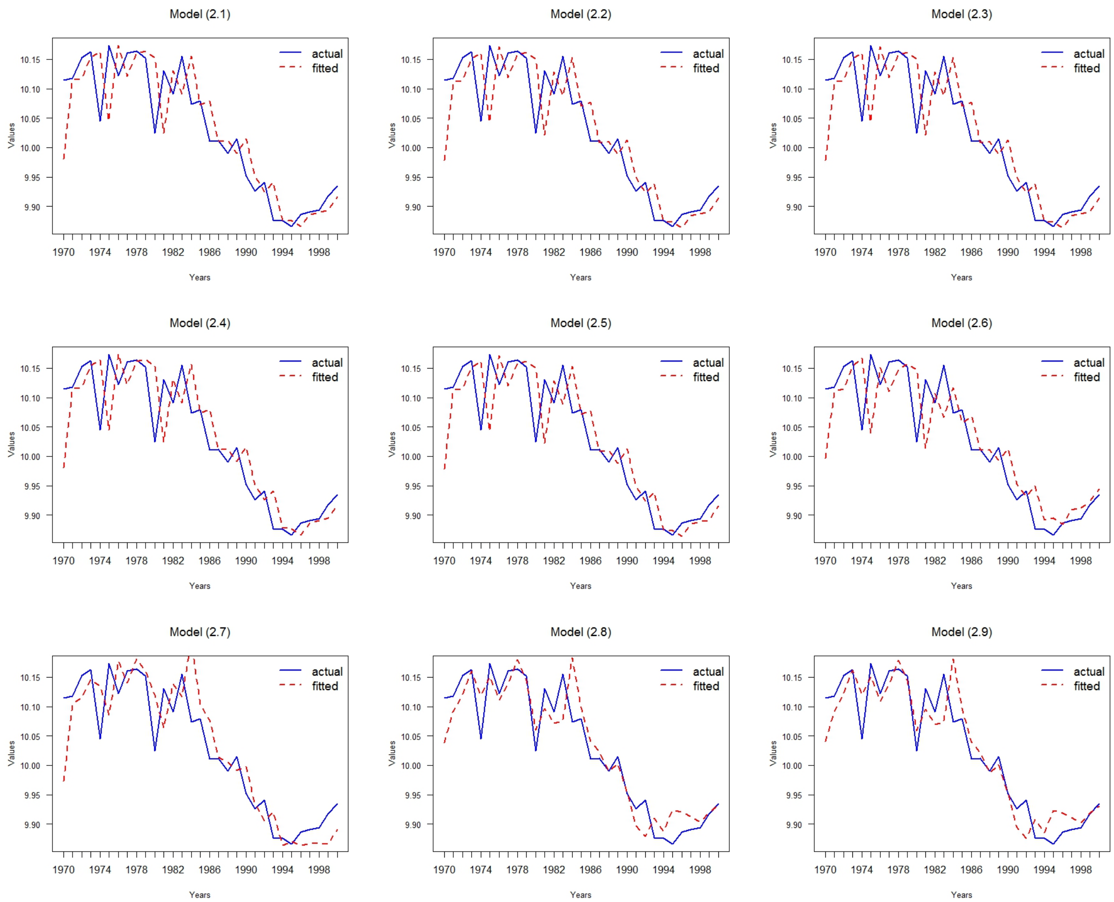

Figure 2.29: Actual and fitted values from all models for Platte County.

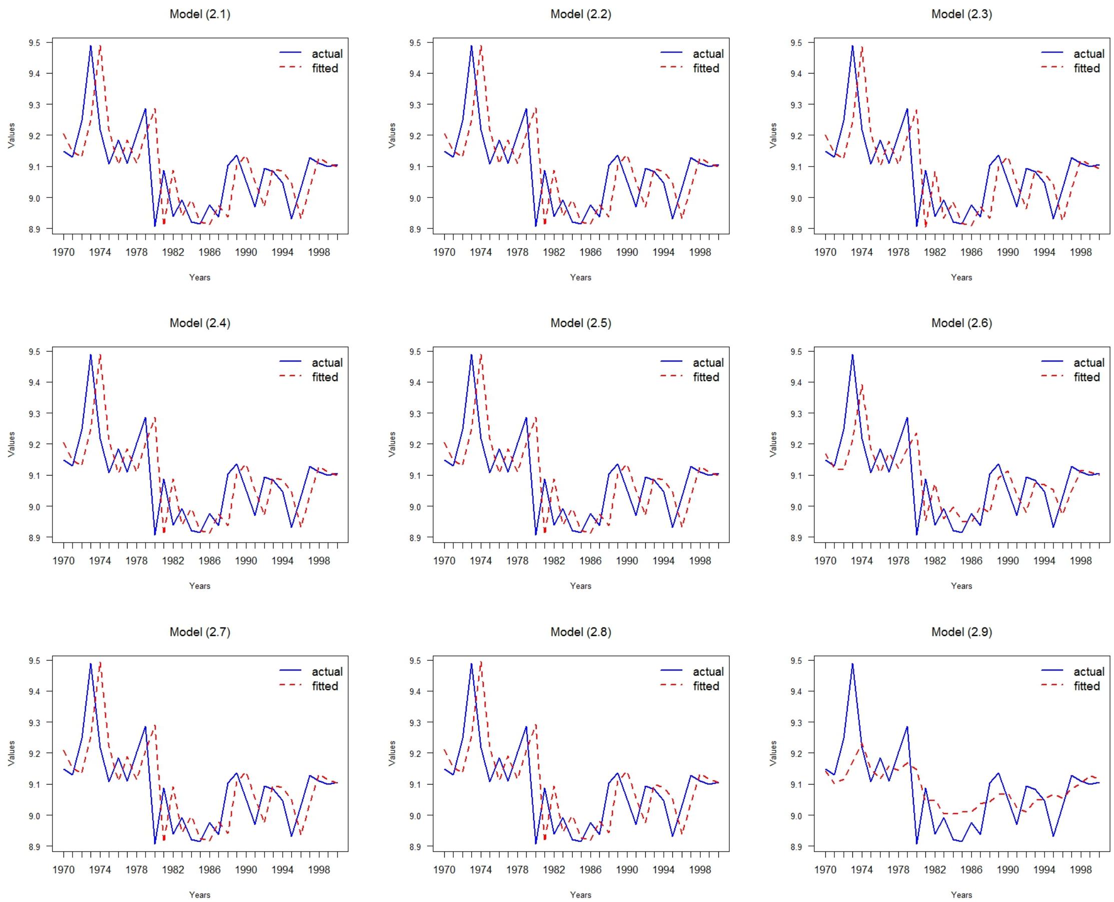

Figure 2.30: Actual and fitted values from all models for Dade County.

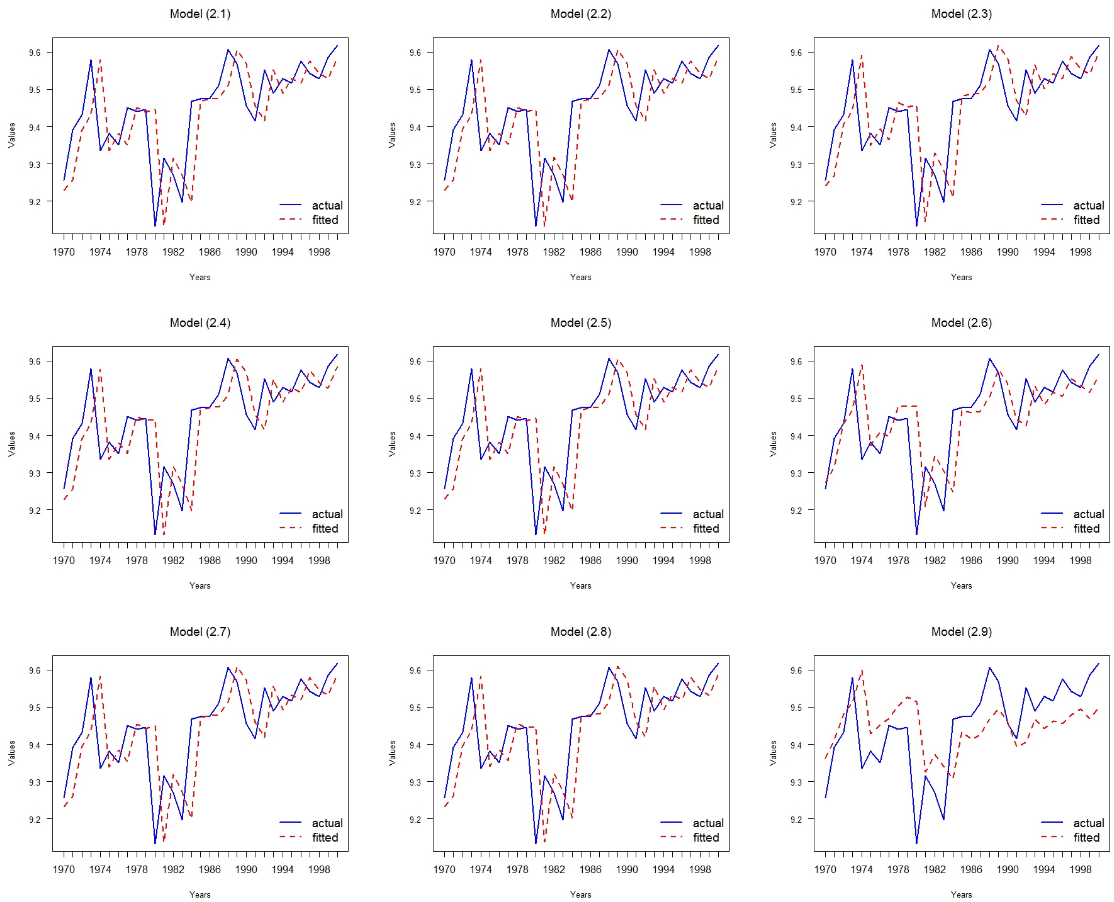

Figure 2.31: Actual and fitted values from all models for Stoddard County.

Table 2.13: Some results of estimation of the models and calculated DIC for model selection.

Model	σ_ϵ	σ_ϵ^2	$\bar{D}$	p_D	DIC
2.1	7.1×10^{-4}	0.0129	3413.15	0.01	3413.15
2.2	6.0×10^{-4}	0.0129	3414.23	0.01	3414.24
2.3	6.5×10^{-4}	0.0133	3421.35	1.37	3423.02
2.4	6.4×10^{-4}	0.0129	3411.22	0.17	3411.39
2.5	6.8×10^{-4}	0.0129	3411.14	0.64	3411.78
2.6	3.6×10^{-4}	0.0127	3408.09	0.53	3408.62
2.7	6.9×10^{-4}	0.0130	3413.29	0.06	3413.35
2.8	6.2×10^{-4}	0.0130	3411.73	0.03	3411.76
2.9	3.3×10^{-4}	0.0126	3261.80	3.96	3265.76

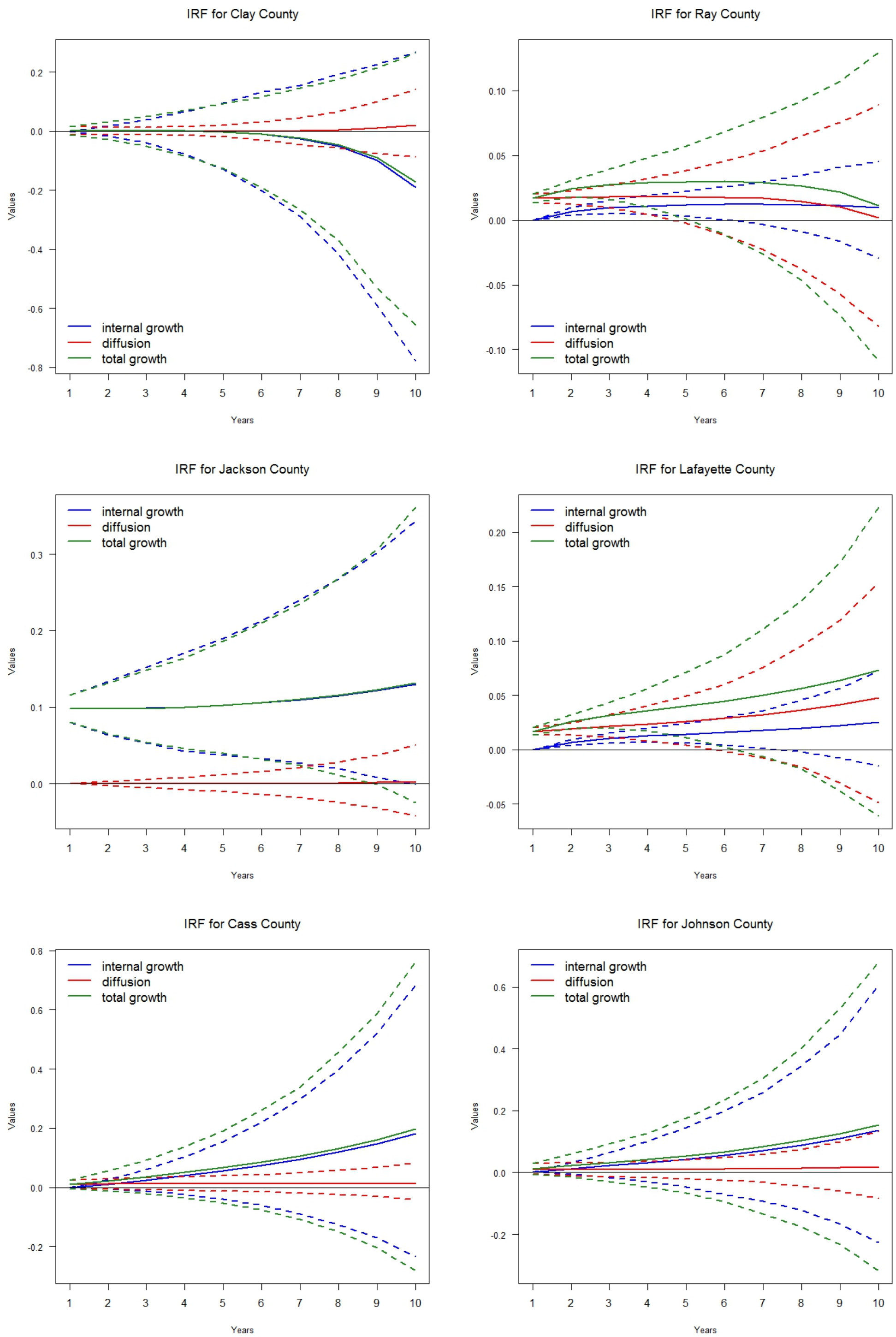

Figure 2.32: Impulse response functions for Jackson county and its first ring neighbors.

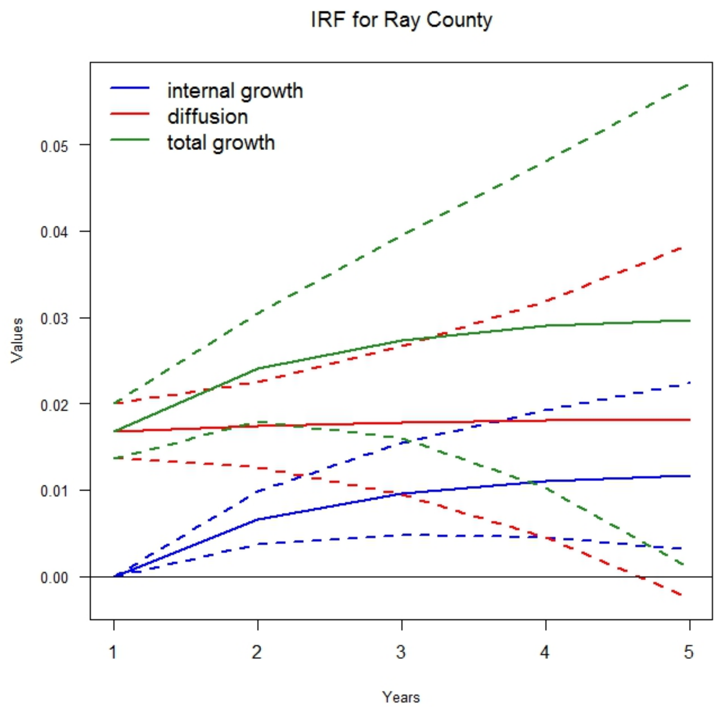

Figure 2.33: Impulse response functions for Ray county to a shock in Jackson county.

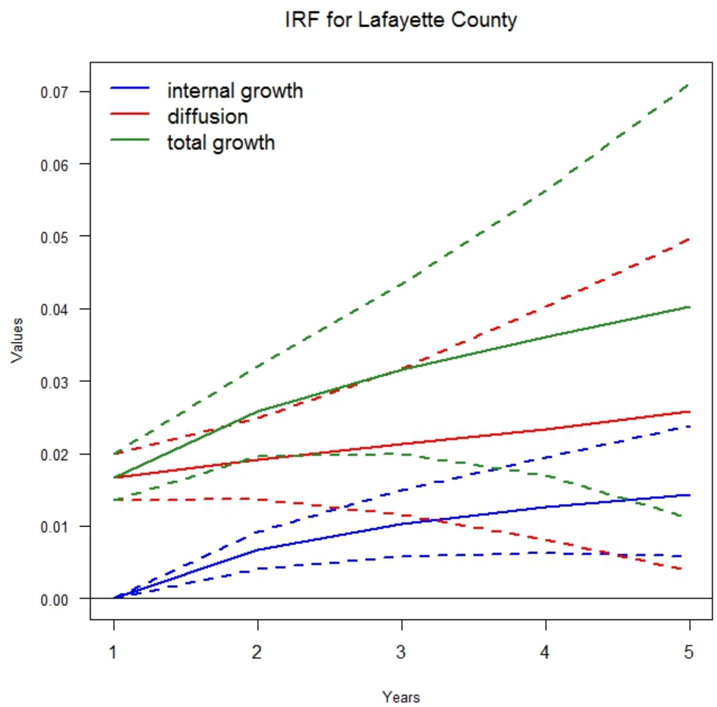

Figure 2.34: Impulse response functions for Lafayette county to a shock in Jackson county.

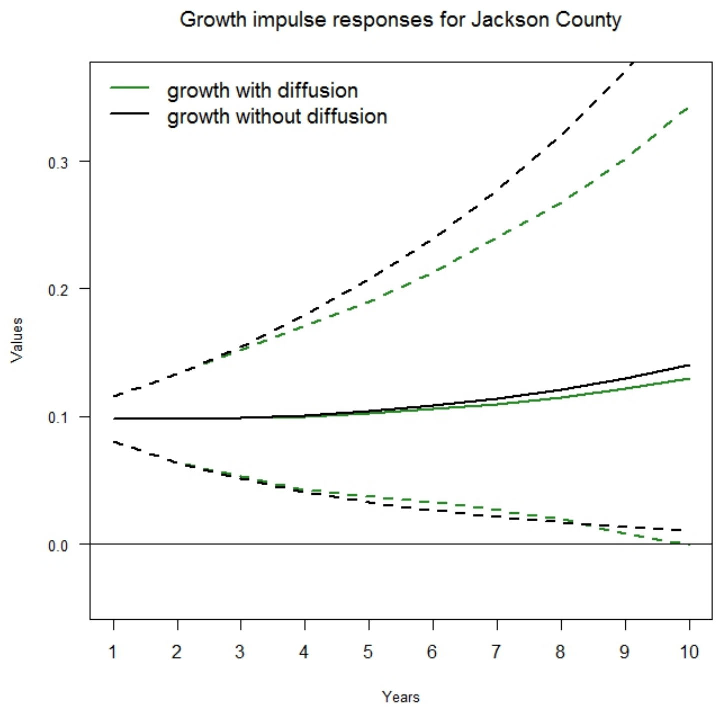

Figure 2.35: Growth impulse response functions for Jackson county with and without diffusion effect.

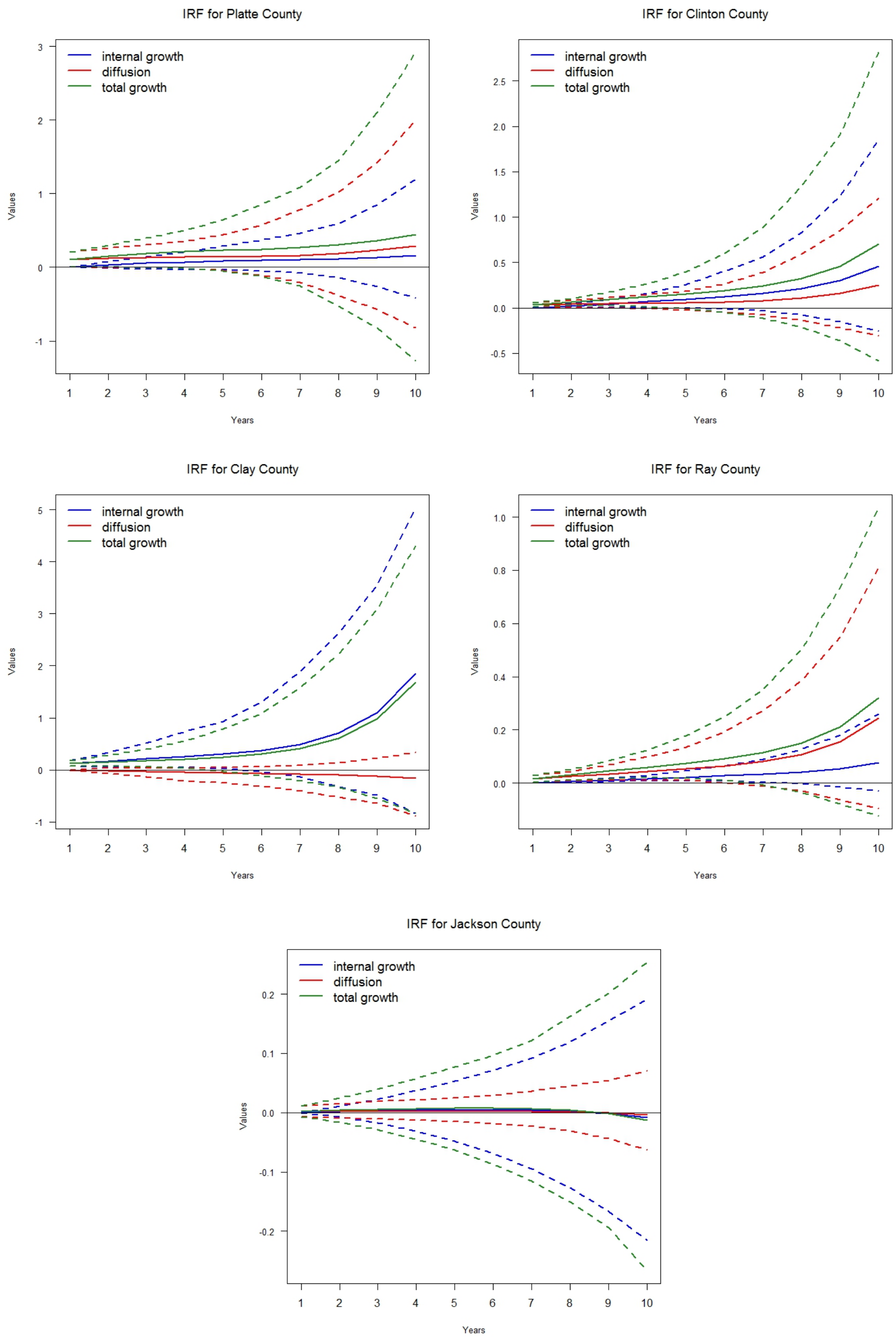

Figure 2.36: Impulse response functions for Clay county and its first ring neighbors.

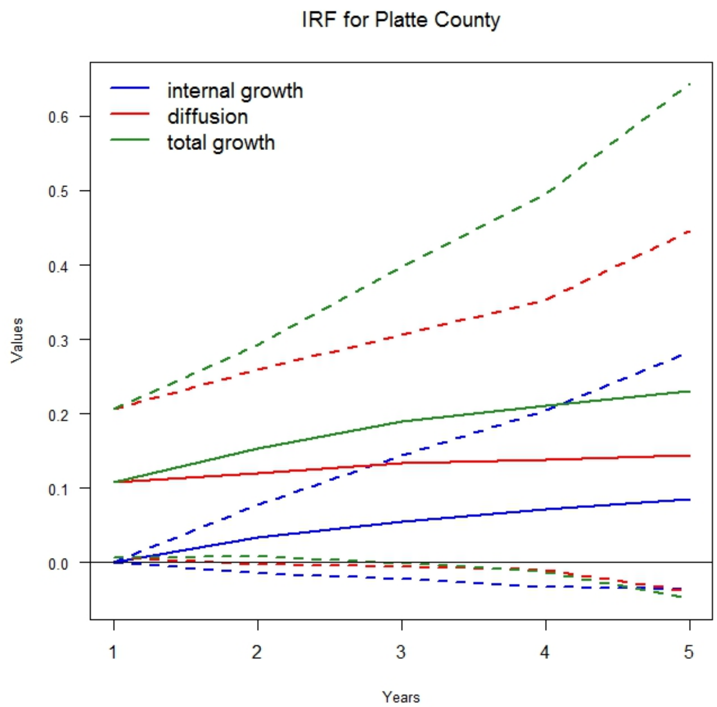

Figure 2.37: Impulse response functions for Platte county to a shock in Clay county.

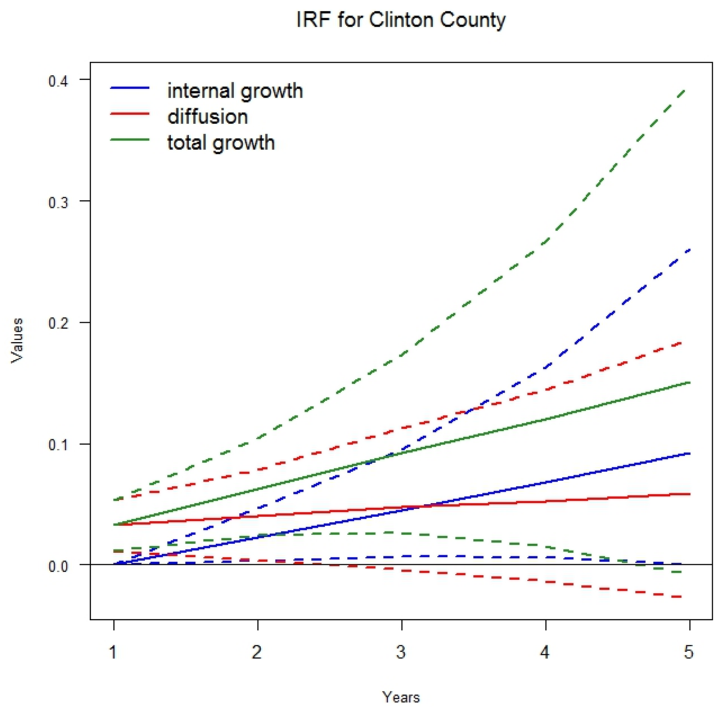

Figure 2.38: Impulse response functions for Clinton county to a shock in Clay county.

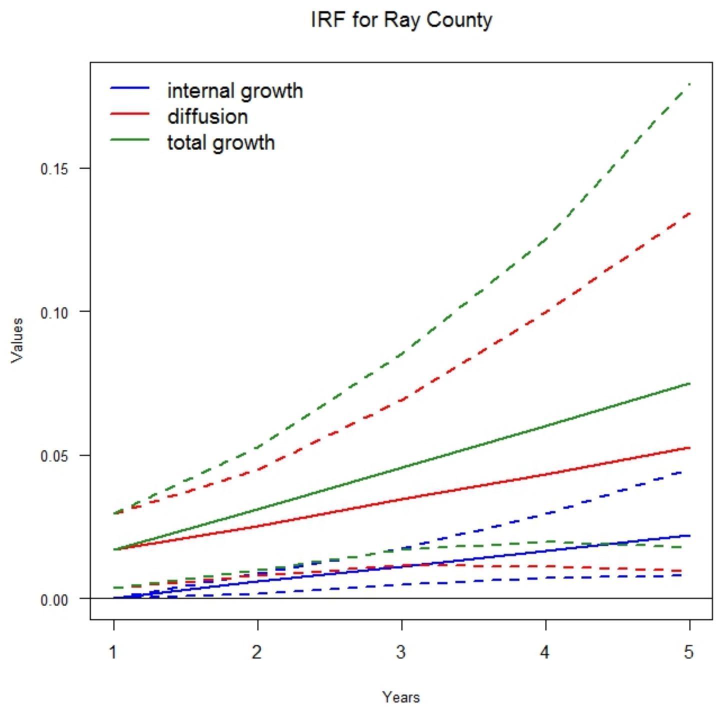

Figure 2.39: Impulse response functions for Ray county to a shock in Clay county.

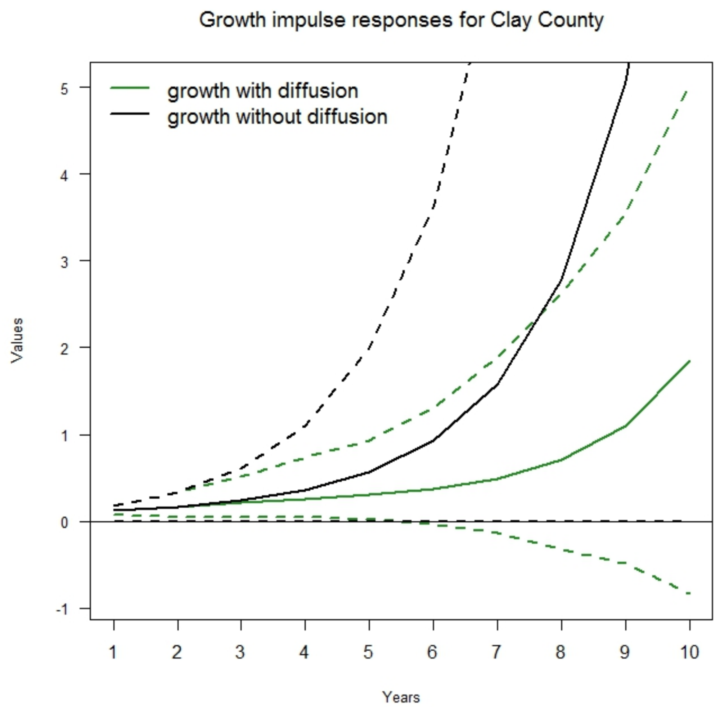

Figure 2.40: Growth impulse response functions for Clay county with and without diffusion effect.

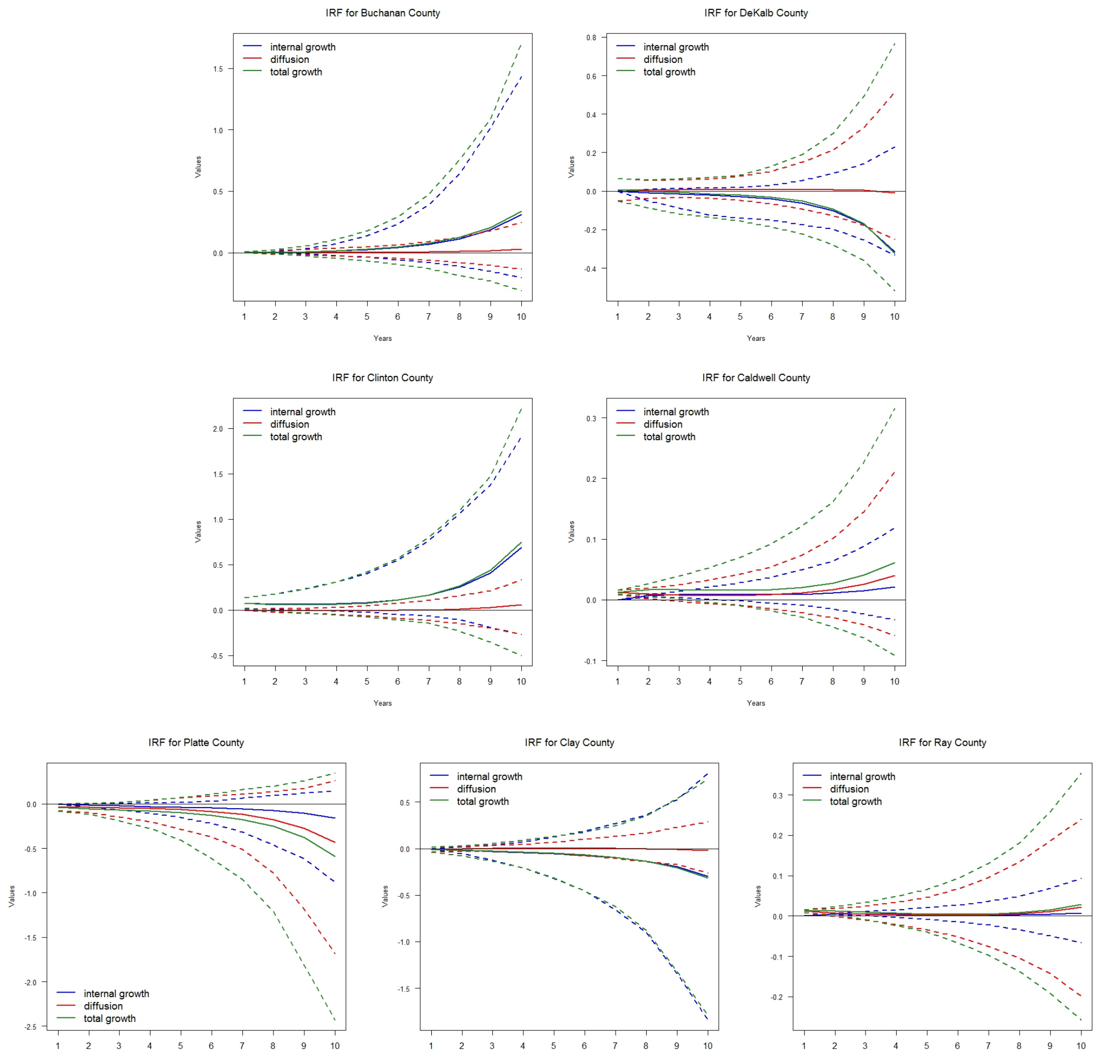

Figure 2.41: Impulse response functions for Clinton county and its first ring neighbors.

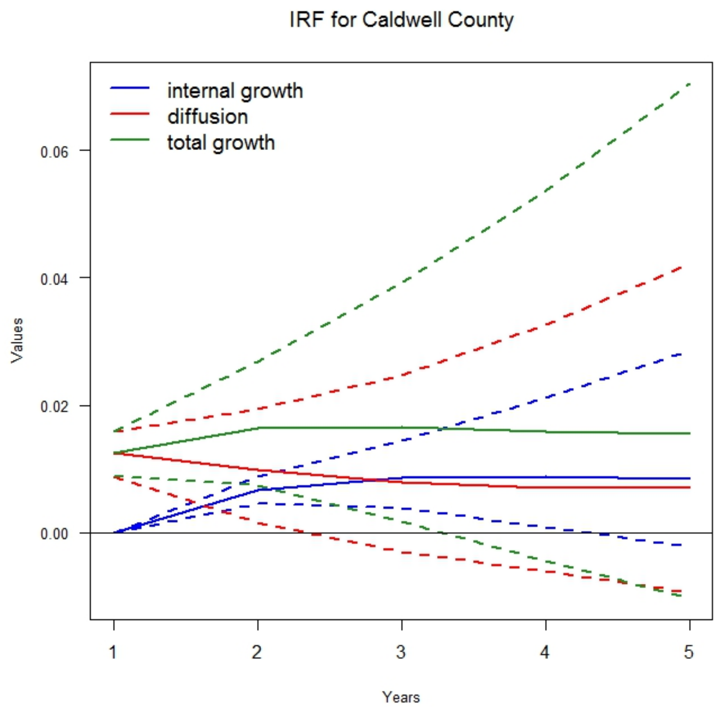

Figure 2.42: Impulse response functions for Caldwell county to a shock in Clinton county.

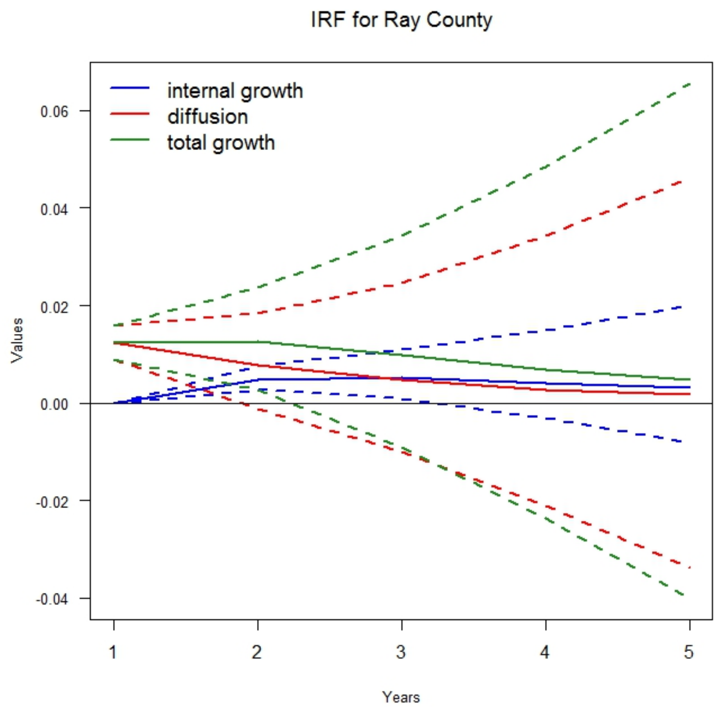

Figure 2.43: Impulse response functions for Ray county to a shock in Clinton county.

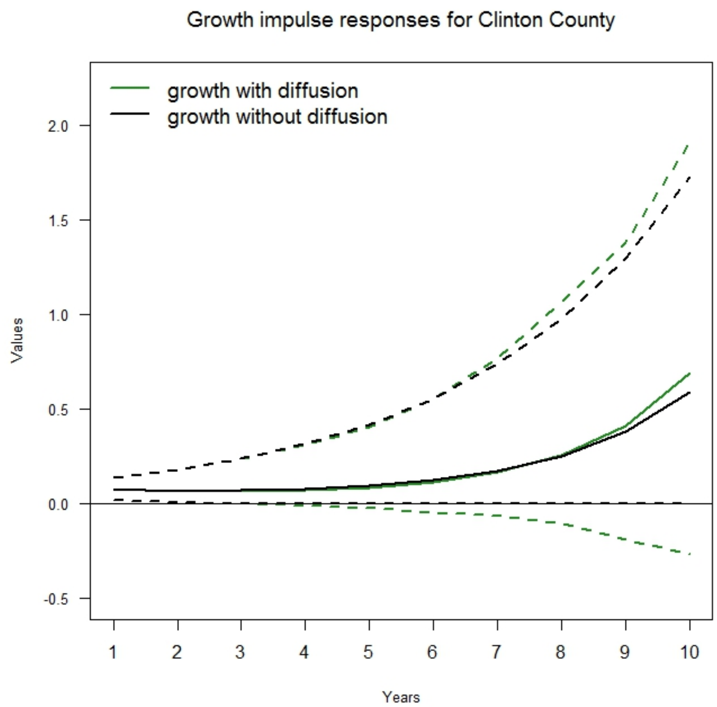

Figure 2.44: Growth impulse response functions for Clinton county with and without diffusion effect.

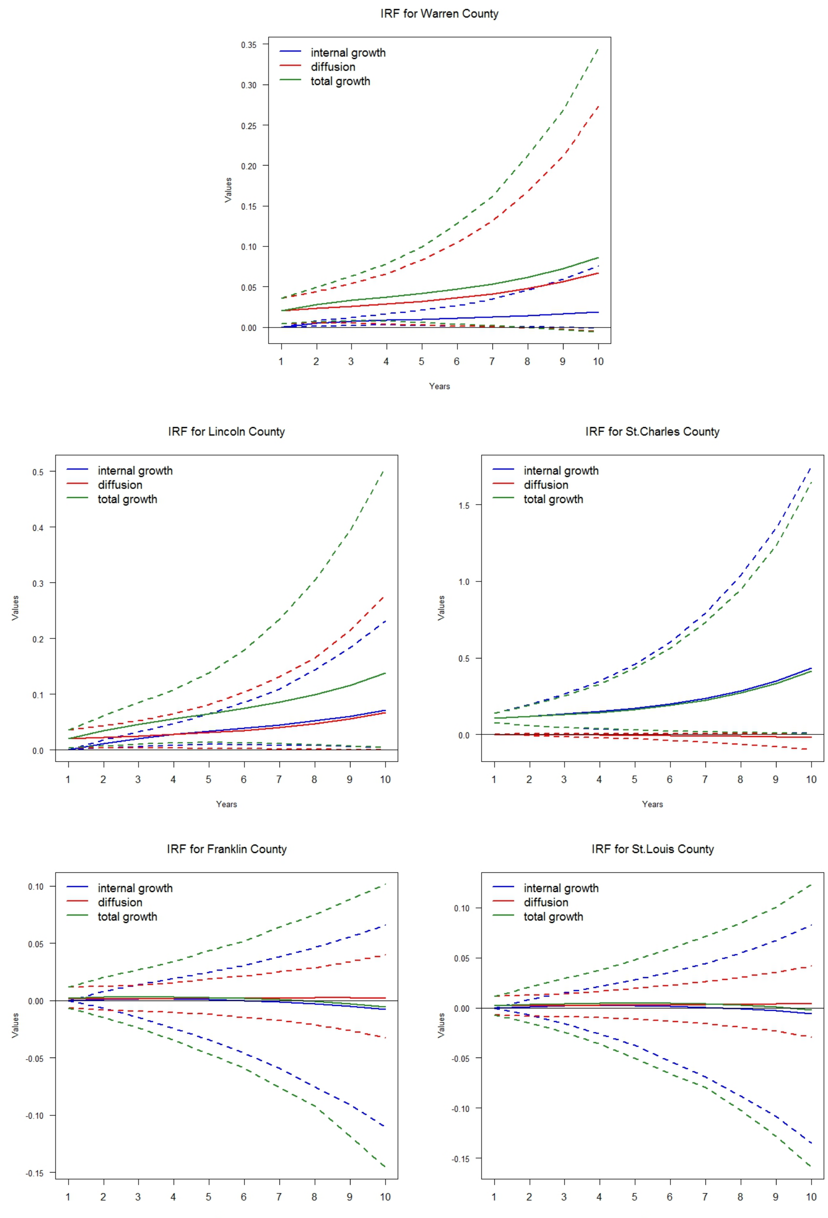

Figure 2.45: Impulse response functions for St.Charles county and its first ring neighbors.

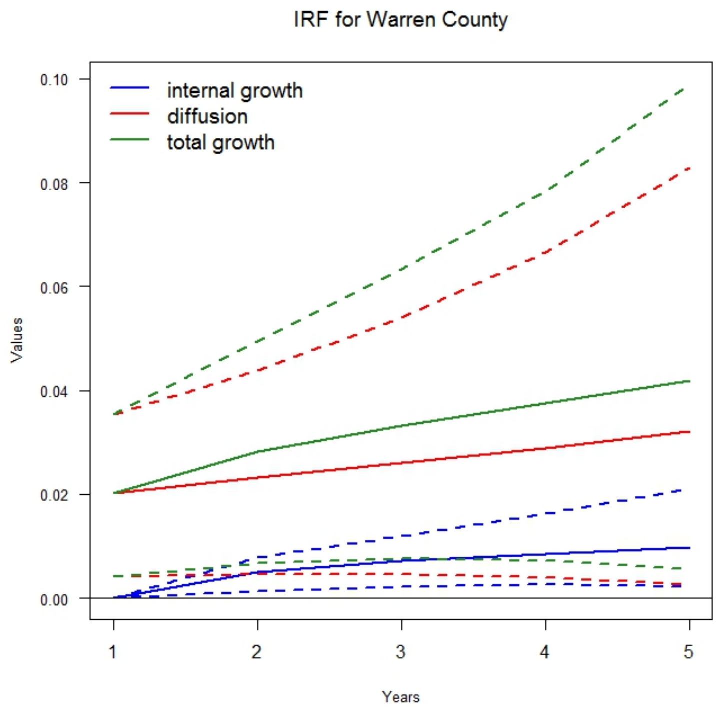

Figure 2.46: Impulse response functions for Warren county to a shock in St.Charles county.

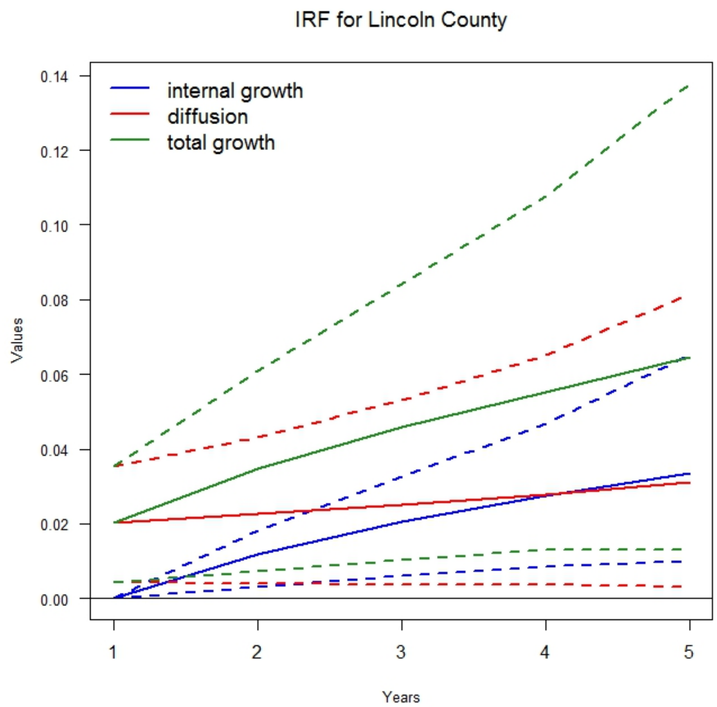

Figure 2.47: Impulse response functions for Lincoln county to a shock in St.Charles county.

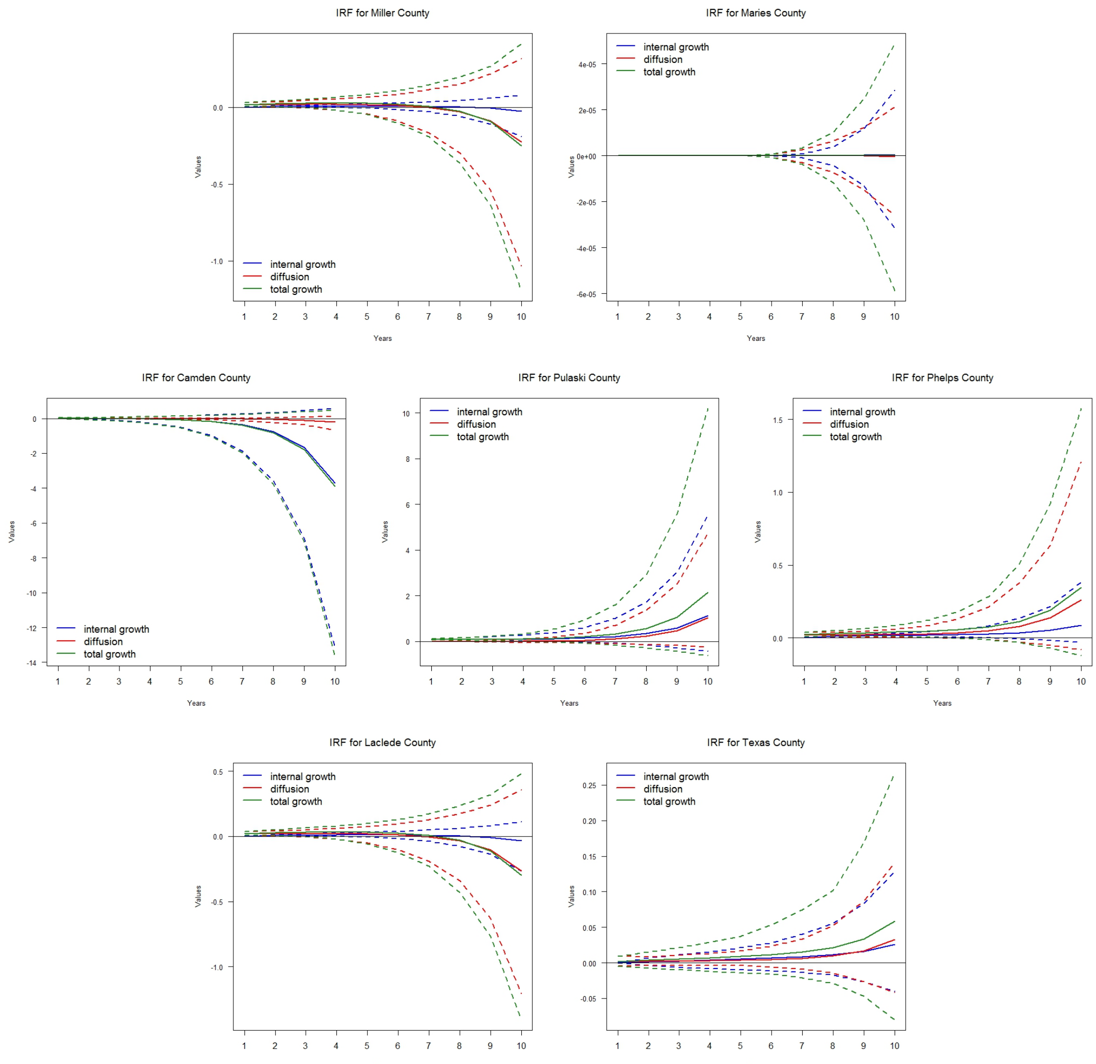

Figure 2.48: Impulse response functions for Pulaski county and its first ring neighbors.

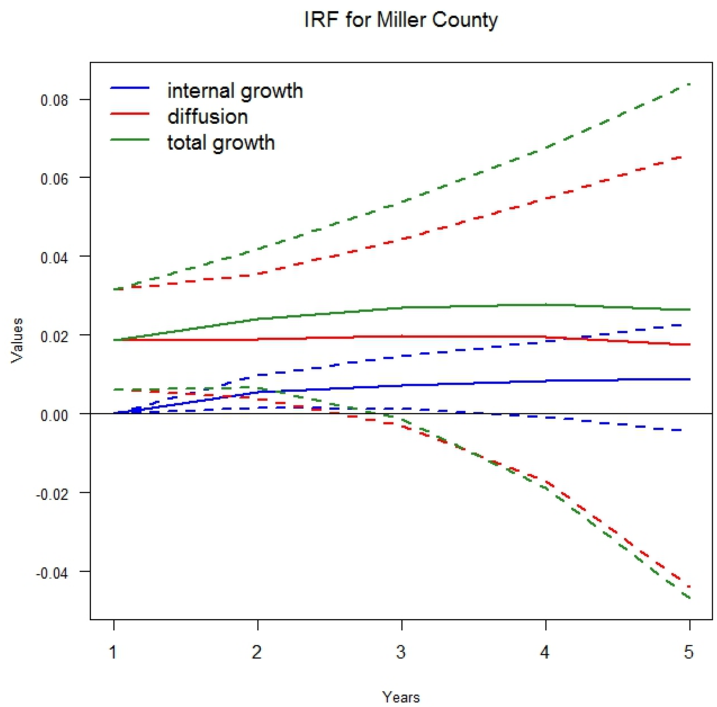

Figure 2.49: Impulse response functions for Miller county to a shock in Pulaski county.

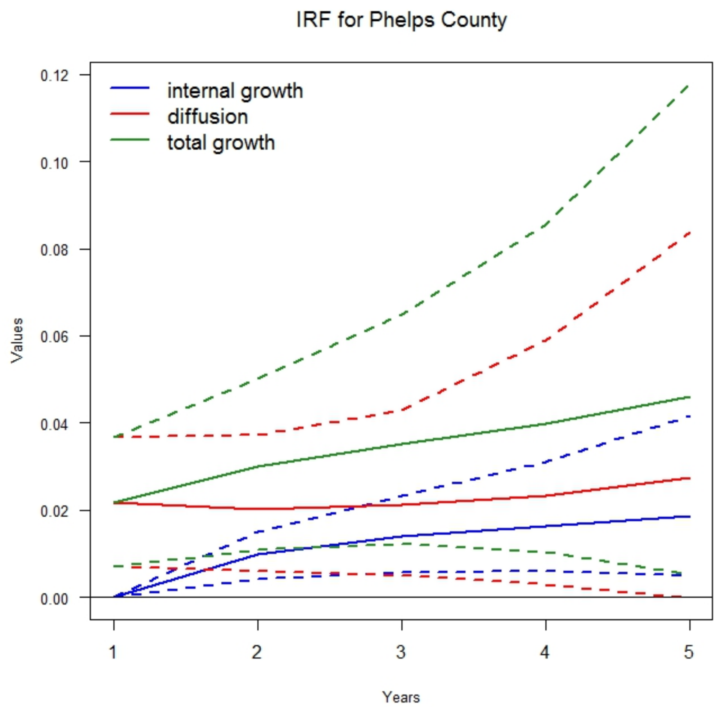

Figure 2.50: Impulse response functions for Phelps county to a shock in Pulaski county.

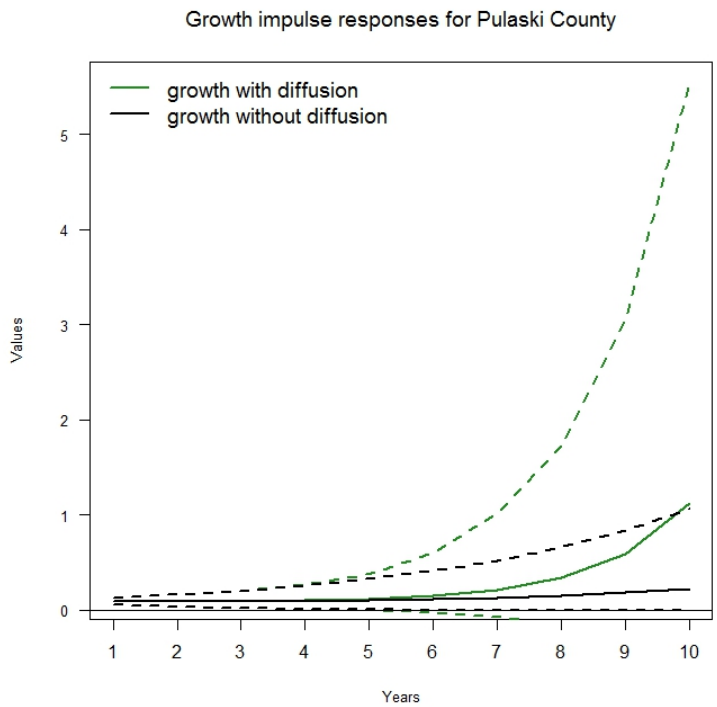

Figure 2.51: Growth impulse response functions for Pulaski county with and without diffusion effect.

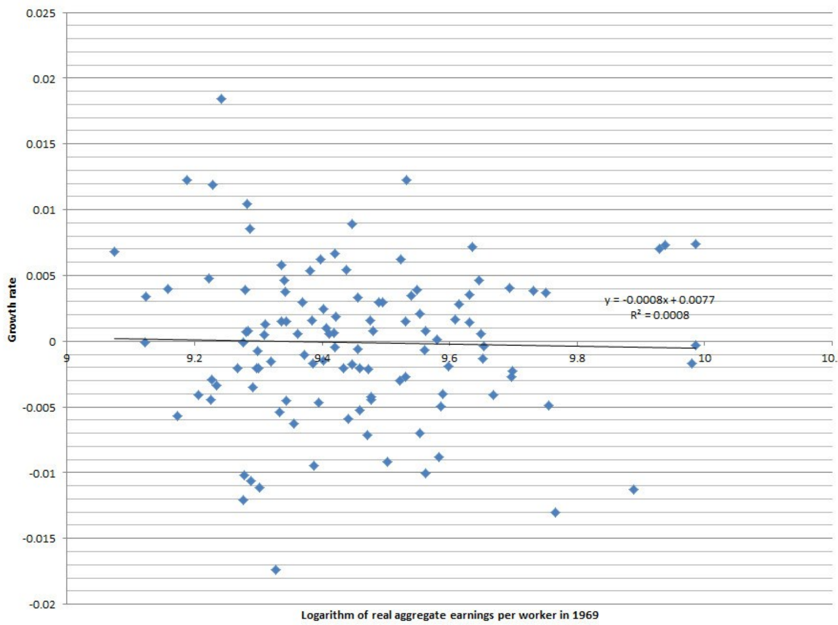

Figure 2.52: Convergence plot for aggregate earnings per worker in Missouri counties based on the estimates for model 2.3.

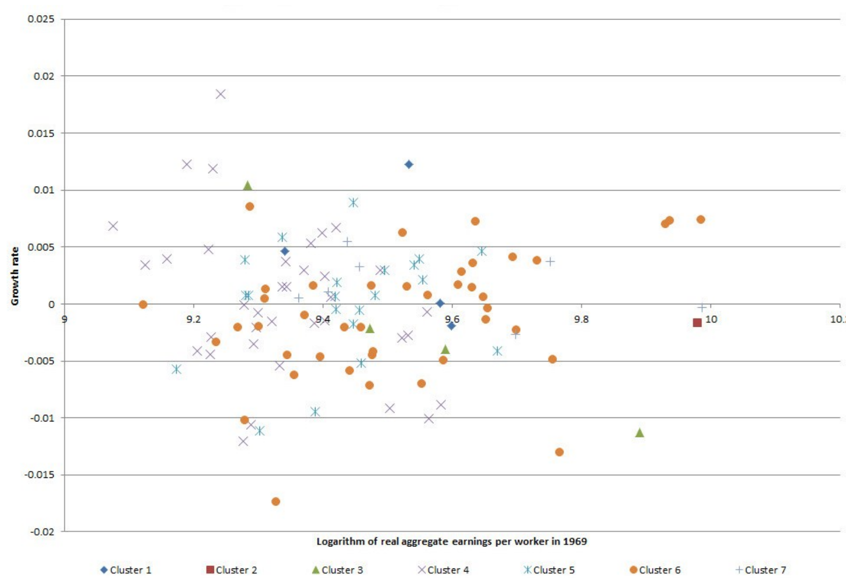

Figure 2.53: Convergence plot for aggregate earnings per worker in Missouri counties based on the estimates for model 2.3 by cluster.

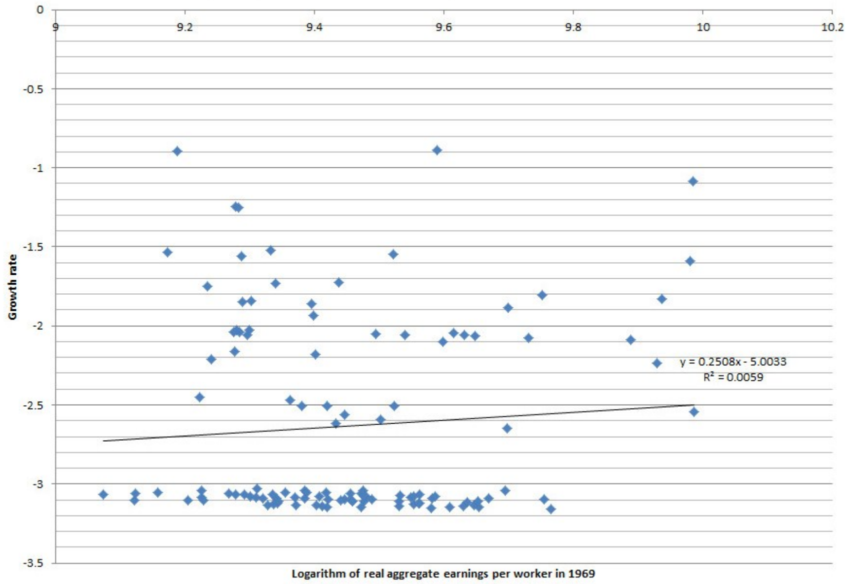

Figure 2.54: Convergence plot for aggregate earnings per worker in Missouri counties based on the estimates for model 2.6.

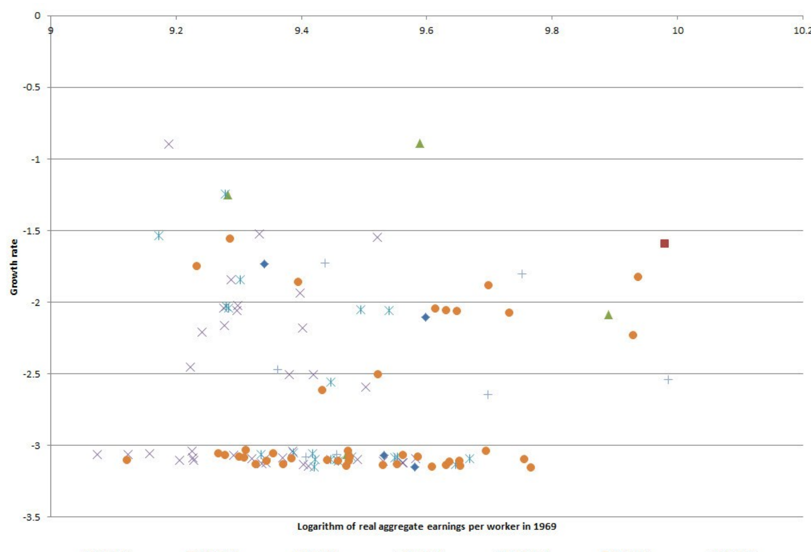

Figure 2.55: Convergence plot for aggregate earnings per worker in Missouri counties based on the estimates for model 2.6 by cluster.

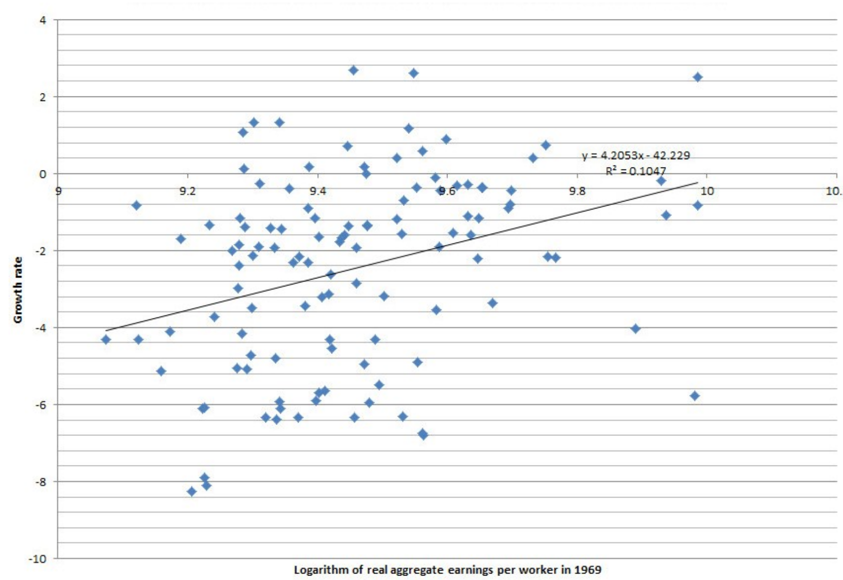

Figure 2.56: Convergence plot for aggregate earnings per worker in Missouri counties based on the estimates for model 2.9.

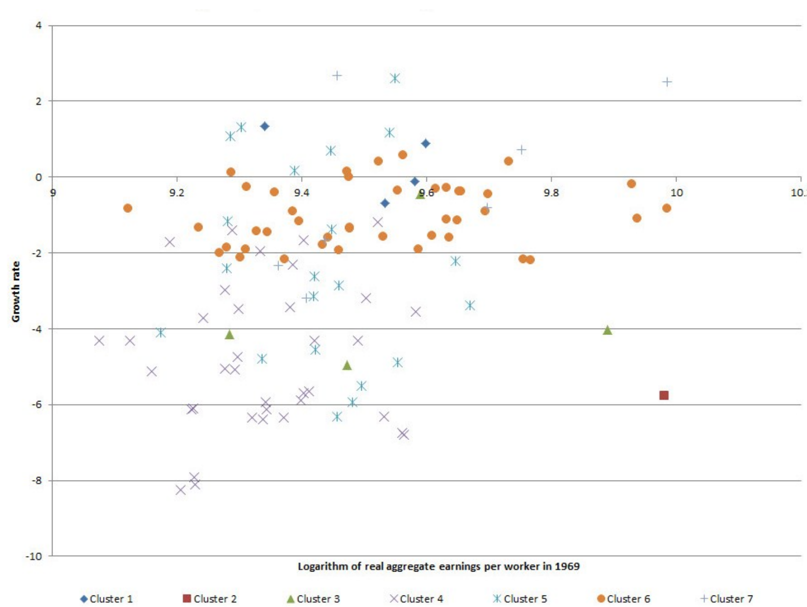

Figure 2.57: Convergence plot for aggregate earnings per worker in Missouri counties based on the estimates for model 2.9 by cluster.

Table 2.14: Means and 90% intervals for estimated values of county-specific AR(1) coefficients by clusters.

Cluster	Model 2.3		Model 2.6		Model 2.9	
	Mean	Interval	Mean	Interval	Mean	Interval
1	0.9994	(0.9472;1.0515)	0.7385	(0.6265;0.8505)	1.0363	(0.7212;1.3514)
2	0.9988	(0.9466;1.0509)	0.8413	(0.7937;0.8889)	0.4305	(-0.0478;0.9087)
3	0.9988	(0.9467;1.0509)	0.9063	(0.6496;0.9630)	0.6391	(0.1833;1.0949)
4	0.9990	(0.9469;1.0512)	0.7155	(0.5982;0.8328)	0.4868	(0.1238;0.8498)
5	0.9990	(0.9469;1.0511)	0.7186	(0.6021;0.8351)	0.7564	(0.2516;1.2612)
6	0.9989	(0.9468;1.0510)	0.7092	(0.5945;0.8239)	0.8898	(0.6913;1.0884)
7	0.9992	(0.9471;1.0513)	0.7903	(0.6875;0.8930)	0.9639	(0.3313;1.5937)

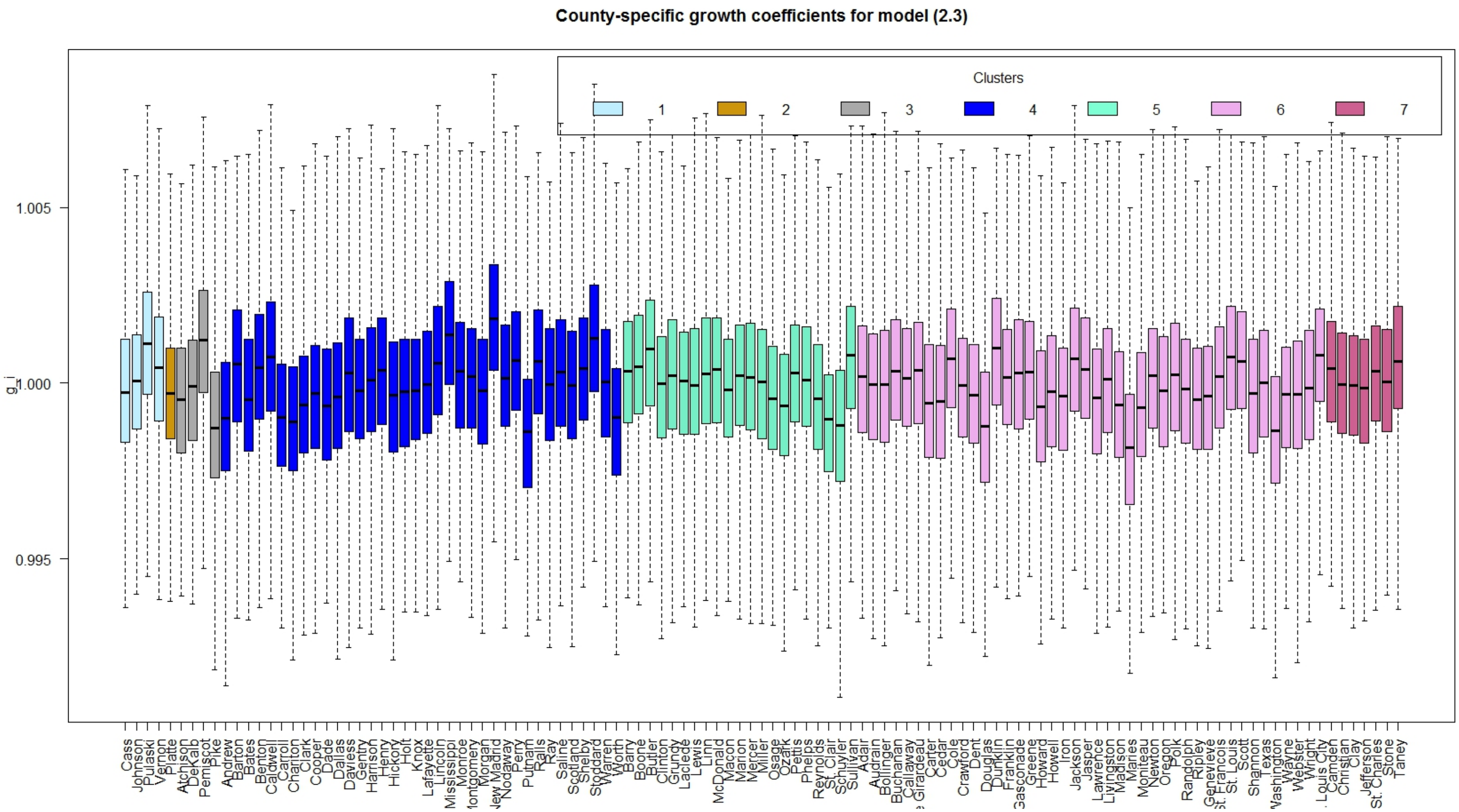

Figure 2.58: Boxplot for estimates of AR(1) coefficients from model 2.3.

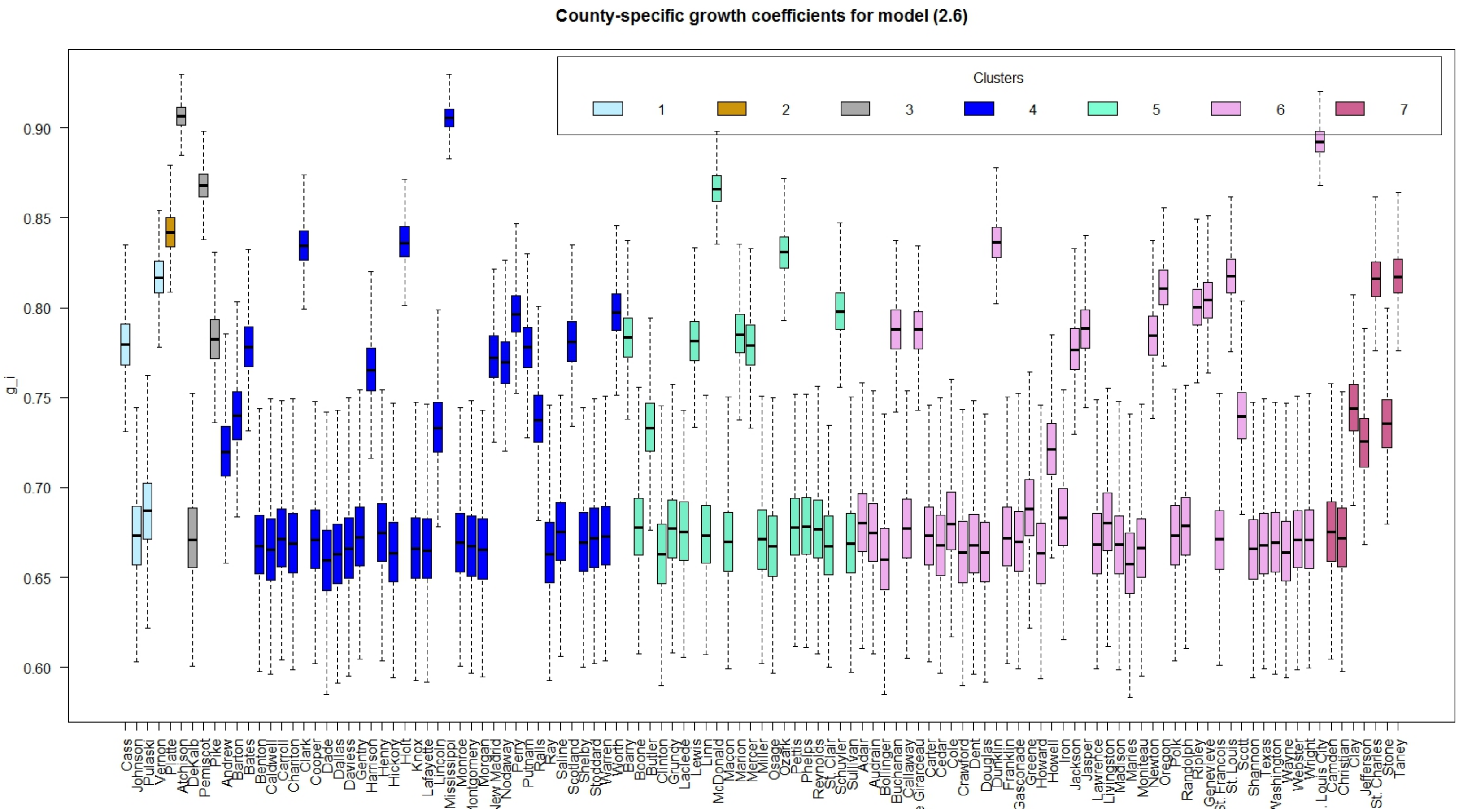

Figure 2.59: Boxplot for estimates of AR(1) coefficients from model 2.6.

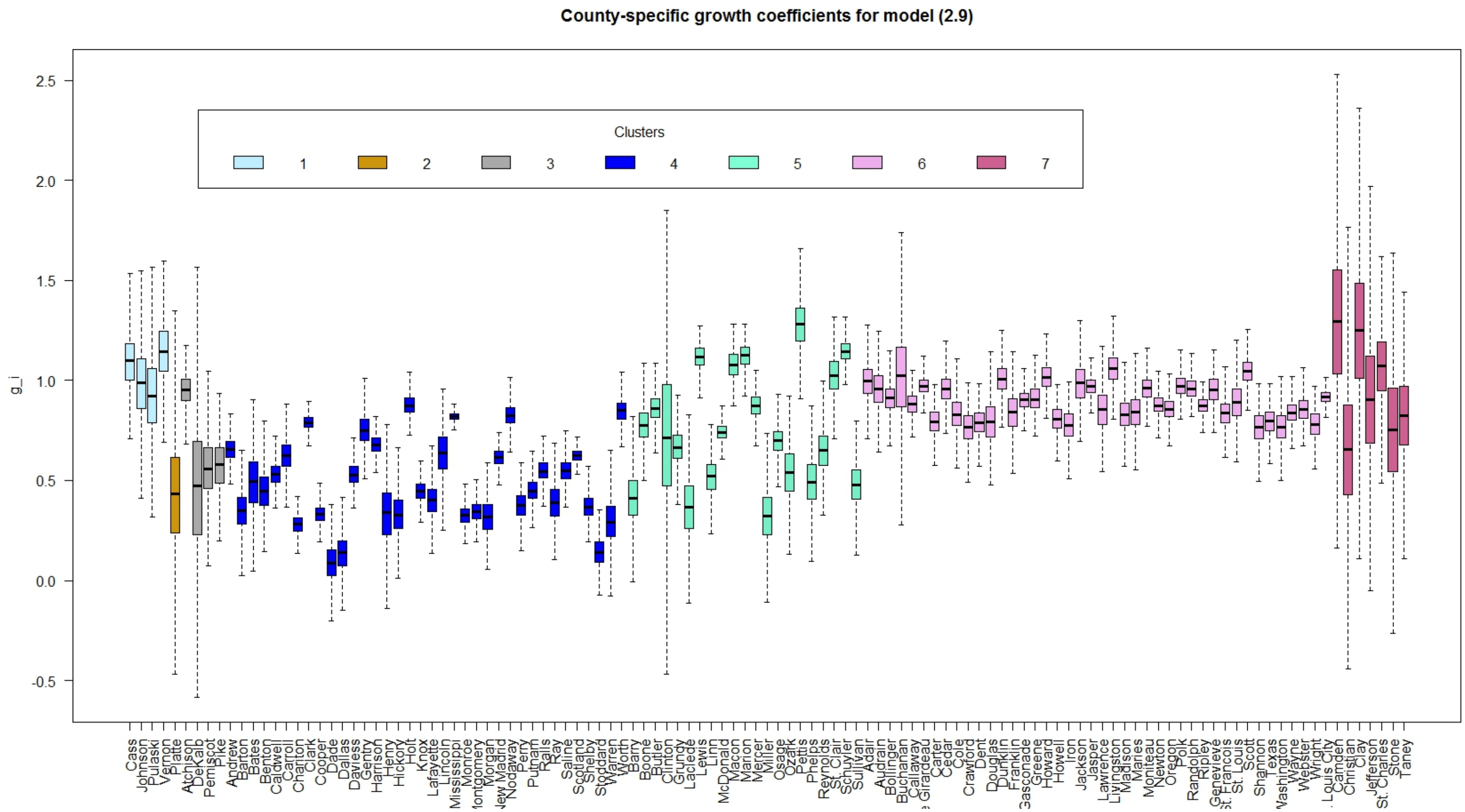

Figure 2.60: Boxplot for estimates of AR(1) coefficients from model 2.9.

Chapter 3

Sectoral earnings per worker and their space-time dynamics

In this chapter we look at sectoral earnings instead of aggregate earnings per worker. So we directly introduce sectoral composition of the economy into the model along with time and space. Unlike temporal and spatial dimensions, sectoral composition does not imply particular way that economic sectors affect each other. If these earnings are thought of as a proxy for the productivity of workers in the sector then the dynamics of these earnings might show diffusion of knowledge as a driving force of the convergence of earnings and incomes. The usable measure of the sectoral earnings per worker should satisfy two conditions; it should reflect the earnings of an average worker in the sector (to proxy the worker's productivity) and it should account for the number of workers in the sector (to reflect the intensity of interaction between sectors regardless of its actual mechanism). The discussion on the appropriate measure follows.

3.1 Data and stylized facts

We use the same sources of the data as in the second chapter. Sectoral earnings in 115 counties of the state of Missouri in 1969-2000 are coming from table CA05 and employment levels from table CA25 of BEA-REIS database. Nominal earnings are turned into real ones via application of CPI.

Table 2.4 presents growth accounting results for all counties in the state of Missouri. The second column of this table shows significant earnings growth effect for different sectors of the economy. The largest drop in the earnings per worker happened in farming sector (-4 percent) while the largest increase happened in manufacturing, services, and government sectors (4 percent in each).

At the same time, the growth of earnings per worker in different sectors does not follow the same pattern. As we can see from Figures 3.1 and 3.2 earnings per worker in service sector show one of the highest average rate of absolute convergence in 1969-2000 (3.27 percent) staying behind only wholesale trade sector (3.32 percent) while average rate of convergence in both manufacturing and government sectors are below 1 percent (0.73 percent and 0.92 percent, respectively).

We can interpret these number as an evidence of earnings in sectors not following the same pattern, so different mix of sectors in counties, especially in the ones that are located next to each other, may have an effect on the aggregate earnings per worker. In order to analyze these possible effects we use earnings in a county's sector as our variable of interest.

The data in BEA-REIS database available to the public have some features that make their usage possible for our analysis only after careful consideration. For example, farming sector contains significant number of negative earnings in some years that make it difficult to use log-normal distribution assumption which is suitable for other sectors. There is also significant number of missing data points in some other sectors (18.07 percent in agricultural services sector and 23.94 percent in mining) along with the absence of earnings in mining sector in 6.33 percent of county-years which complicates usage of these sectors as well. After elimination of the aforementioned farming, agricultural services, and mining sectors from the dataset we have 8 sectors that are suitable to work with: construction (CO), manufacturing (MA), transportation and public utilities (TU), wholesale trade (WT), retail trade (RT), finance and insurance (FI), services (SS), and government (GT) sectors. RT and GT sectors do not have missing data points.

We perform imputation of the missing data using Amelia R package by Honaker, King, and Blackwell (2011) [63] which assume that the data follow a multivariate normal distribution and use EM algorithm to find corrected estimates of the means and covariances for the distribution. After performing the imputation for each of the 6 sectoral total earnings separately, means and variances of the original (with missing data points) and complete (with imputed data points) datasets are reported in Table 3.1.

Slightly higher means for all sectors except service reflect the fact that the last few years of the period under consideration have the most of missing data points while for services sector early years have the most of the missing data points.

3.2 Choice of dependent variable and its characteristics

Earnings per worker in a sector of the county's economy can be considered in two dimensions – in time as a stochastic process and in space as a Markov random field. While the first dimension is clear in its direction the second one allows expanding the analysis in two different dimensions – across sectors and across counties. The intuition and the hypothesis behind this approach is such that if workers from one sector of the county's economy are located within that county they interact with workers from other sectors as well as with workers in their own sector. In this research we ignore possible mechanisms of this interaction while being aware that they exist. But the interaction does not stop within a county, for the workers interact with the workers from the same sector or other sectors of the economy through either relocating themselves to new places of residence or changing jobs. Since workers are carriers of the knowledge their mobility across space and across sectors of the economy affects productivity and earnings of other workers as well as their own. Thus, we can assume and test the existence of spatial and temporal relationships between the growth of workers' earnings in different sectors of the economy. If such relationships exist then we can test which of the sectors have the most significant effects on the growth of other sectors and, thus, the aggregate earnings of workers in the county.

We also emphasize that the intensity of this interaction and, thus, the magnitude of the resulting effects depend not only on the productivity of the workers employed in a particular sector in a particular county but also on the number of workers in that sector. Hence, as a variable of interest we would like to use a measure of productivity of a sector and not of an average worker in the sector. There are at least two potential variables that may serve this purpose – earnings share of the sector and sectoral portion of aggregate earnings per worker. While the first variable is well known as a ratio of total earnings in the sector to the total earnings in the economy the second one needs to be described more clearly. The sectoral portion of aggregate earnings per worker is calculated as a ratio of total earnings in the sector to the total number of worker in the economy (total employment in the county from table CA25 of BEA-REIS data). This variable can also be thought of as a product of sectoral earnings per worker and employment share of the sector. Using the same notations as in subsection 2.2.1 of the second chapter we can define the sectoral portion of aggregate earnings p_j in the following way:

$$p_j = \frac{E_j}{L_j}\frac{L_j}{L} = e_j s_j.$$

We prefer the second variable to be used in our model for the following reasons. While the employment share is bounded between 0 and 1 the sectoral portion of aggregate earnings is not, for it is a monetary measure. The earnings share merely reflects the 'size' of the sector since it depends on both productivity of workers and the number of workers. To the contrary, the sectoral portion of aggregate earnings depends not on the number of workers in the sector but on the number of all workers in the economy. The earnings share depends equally on the number of the workers in the sector and the average productivity of a worker in the sector while sectoral portion of aggregate earnings depends directly on the average productivity of a worker and only indirectly on the number of workers in the sector. Also the sectoral portion of aggregate earnings shows what part of the aggregate earnings is earned in the sector. For example, if the aggregate earnings of a worker in a county are \$20,000 made of

\$4000 earned in 5 sectors then the \$4000 may be thought as a sectoral portion of the aggregate earnings per worker.

Since we model the dynamics of the sectoral earnings we need to make an assumption about the data-generating process. For this purpose we use plots of autocorrelation (ACF) and partial autocorrelation (PACF) functions. These plots for all 8 sectors used for the analysis for some of Missouri counties are represented on Figures 3.3 for Boone County, 3.4 for Dade County, 3.5 for Platte County, 3.6 for Stoddard County, and 3.7 for St. Louis City. These plots suggest that most of the time series can be assumed to follow an AR(1) process.

The spatio-temporal term is included into the model if we assume that there is correlation between a value of the dependent variable in a county in the previous and a value of the dependent variable in a neighboring county in the current year, i.e., there is a pattern in growth of the dependent variable in a geographical space of counties. For the purpose of testing the randomness of the spatio-temporal growth of the dependent variable we ran global Moran's I test for all 8 sectors and report results in Table 3.2. Statistically significant and large positive numbers in the table mean that nearby counties have similar levels of dependent variable while negative – dissimilar ones. The numbers in parenthesis mean that the null hypothesis of spatio-temporal randomness is not rejected.

The results of Moran's I bivariate test for global spatio-temporal randomness for the dependent variable (see Table 3.2) show that sectoral portions of aggregate earnings for all sectors have some degree of clustering of similar values.

3.3 Model specification

Proper estimation of the inter-sector and inter-county effects is possible only when these effects are also inter-temporal. If they are simultaneous then proper identification and estimation of the respective parameters is possible only for inter-county effects (as is the case in spatial econometrics, when geographical spatial structure is known) but difficult if not impossible for inter-sector effects because there is no supporting theoretical model that describe the way the sectors interact with each other and affect each other within the same time period. In this case to account for these effects we exploit mixed linear model with random effects. This model allows us to estimate separate inter-county and inter-sector effects and compare their magnitude, thus, making conclusion about the strength of prevailing interaction. We should also recognize that modeling spatial contemporaneous effect is feasible in our setting but having inter-sector and inter-county effects modeled in different ways does not allow comparison of their magnitudes and should not be exploited.

In this model the dependent variable is a yearly log-real sectoral portion of aggregate earnings in a sector in a county Z_{ijt}. The calculated logarithms of sectoral portions of the aggregate earnings in county $i, i = 1, ..., n$, sector $j, j = 1, ..., m$ at time $t, t = 1, ..., T+1$ $(T = 31)$ Z_{ijt} form a third-order $n \times m \times (T+1)$ tensor $\widetilde{\boldsymbol{Z}}$ that is suitable for representation of three-dimensional panel data. The model includes intra- and inter-sector-specific coefficients for the growth term α_{jk} and ρ_{jk}. These coefficients show the effect that the log-sectoral portion of aggregate earnings in a sector j at time $t-1$ has on the log-sectoral portion of aggregate earnings in a sector k at time t $(j, k = 1, ..., m)$ in the same and in the neighboring counties. We also model fixed effects for both counties μ_i and sectors β_j, for we cannot assume strict exogeneity between the explanatory variables and the composite error term which is necessary for modeling random effects. So the model for the log-sectoral portion of aggregate earnings in county i, sector j at year t has the following form:

$$Z_{ijt} = \sum_{k=1}^{m} \alpha_{jk} Z_{ik,t-1} + \sum_{k=1}^{m} \rho_{jk} \sum_{l \in N_i} w_{il} Z_{lk,t-1} + \mu_i + \beta_j + \epsilon_{ijt}, \tag{3.1}$$

where $\epsilon_{ijt} \sim N(0, \sigma_\epsilon^2), t = 1, ..., T$ is the error term. The same for all counties in sector j at time t:

$$\boldsymbol{Z}_{jt} = \boldsymbol{Z}_{t-1}\tilde{\boldsymbol{\alpha}} + \boldsymbol{Z^W}_{t-1}\tilde{\boldsymbol{\rho}} + \boldsymbol{I_n}\boldsymbol{\mu} + \boldsymbol{1_n}\beta_j + \boldsymbol{\epsilon}_{jt}, \tag{3.2}$$

where $\boldsymbol{Z}_{jt}$ is an $n \times 1$ column vector, $\boldsymbol{Z}_{t-1}$ and $\boldsymbol{Z^W}_{t-1}$ are $n \times m$ matrices, $\tilde{\boldsymbol{\alpha}}$ and $\tilde{\boldsymbol{\rho}}$ are $m \times 1$ column vectors, $\boldsymbol{I_n}$ is an $n \times n$ identity matrix, and $\boldsymbol{1_n}$ is an $n \times 1$ unity vector. The same for all counties and all sectors at time t:

$$vec_j(\boldsymbol{Z}_t) = \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}\boldsymbol{\alpha} + \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W\boldsymbol{\rho} + (\boldsymbol{1_m} \otimes \boldsymbol{I_n})\boldsymbol{\mu} + (\boldsymbol{I_m} \otimes \boldsymbol{1_n})\boldsymbol{\beta} + \boldsymbol{\epsilon}_t, \tag{3.3}$$

where vec_j denotes vectorization of a matrix by sector represented with columns, $\boldsymbol{\alpha}$ and $\boldsymbol{\rho}$ are $m^2 \times 1$ column vectors.

Conjugate prior distributions for the parameters-vectors in the models are the following:

$$\epsilon \sim N(0, \sigma_\epsilon^2)$$

$$\boldsymbol{\rho} \sim N(\boldsymbol{\rho_0}, \sigma_\rho^2 \boldsymbol{I}_{m^2})$$

$$\boldsymbol{\alpha} \sim N(\boldsymbol{\alpha_0}, \sigma_\alpha^2 \boldsymbol{I}_{m^2})$$

$$\sigma_\epsilon^2 \sim IG(\tilde{q}_\epsilon, \tilde{r}_\epsilon)$$

$$\boldsymbol{\mu} \sim N(\boldsymbol{\mu_0}, \sigma_\mu^2 \boldsymbol{I_n})$$

$$\boldsymbol{\beta} \sim N(\boldsymbol{\beta_0}, \sigma_\beta^2 \boldsymbol{I_m})$$

Hyperparameters for the prior distributions are the following:

$$\sigma_\rho^2 \sim IG(\tilde{q_\rho}, \tilde{r_\rho})$$

$$\sigma_\alpha^2 \sim IG(\tilde{q_\alpha}, \tilde{r_\alpha})$$

$$\sigma_\mu^2 \sim IG(\tilde{q_\mu}, \tilde{r_\mu})$$

$$\sigma_\beta^2 \sim IG(\tilde{q_\beta}, \tilde{r_\beta})$$

The following are the full-conditional distributions for parameters of interest:

$$\boldsymbol{\rho} \sim N(\boldsymbol{v_\rho a_\rho}, \boldsymbol{v_\rho})$$

$$\boldsymbol{v_\rho} = [\frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}(\boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W)'\boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W + \frac{\boldsymbol{I}_{m^2}}{\sigma_\rho^2}]^{-1}$$

$$\boldsymbol{a_\rho} = \frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}(\boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W)'(vec_j(\boldsymbol{Z}_t) - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}\boldsymbol{\alpha} - (\boldsymbol{1_m} \otimes \boldsymbol{I_n})\boldsymbol{\mu} - (\boldsymbol{I_m} \otimes \boldsymbol{1_n})\boldsymbol{\beta}) + \frac{\boldsymbol{\rho_0}}{\sigma_\rho^2}$$

$$\boldsymbol{\alpha} \sim N(\boldsymbol{v_\alpha a_\alpha}, \boldsymbol{v_\alpha})$$

$$\boldsymbol{v_\alpha} = [\frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}(\boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1})'\boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1} + \frac{\boldsymbol{I}_{m^2}}{\sigma_\alpha^2}]^{-1}$$

$$\boldsymbol{a_\alpha} = \frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}(\boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1})'(vec_j(\boldsymbol{Z}_t) - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W\boldsymbol{\rho} - (\boldsymbol{1_m} \otimes \boldsymbol{I_n})\boldsymbol{\mu} - (\boldsymbol{I_m} \otimes \boldsymbol{1_n})\boldsymbol{\beta}) + \frac{\boldsymbol{\alpha_0}}{\sigma_\alpha^2}$$

$$\boldsymbol{\mu} \sim N(\boldsymbol{v_\mu a_\mu}, \boldsymbol{v_\mu})$$

$$\boldsymbol{v_\mu} = [\frac{(T-1)m\boldsymbol{I_n}}{\sigma_\epsilon^2} + \frac{\boldsymbol{I_n}}{\sigma_\mu^2}]^{-1}$$

$$\boldsymbol{a_\mu} = \frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}(\boldsymbol{1_m}' \otimes \boldsymbol{I_n})(vec_j(\boldsymbol{Z}_t) - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}\boldsymbol{\alpha} - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W\boldsymbol{\rho} - (\boldsymbol{I_m} \otimes \boldsymbol{1_n})\boldsymbol{\beta}) + \frac{\boldsymbol{\mu_0}}{\sigma_\mu^2}$$

$$\boldsymbol{\beta} \sim N(\boldsymbol{v_\beta a_\beta}, \boldsymbol{v_\beta})$$

$$\boldsymbol{v_\beta} = [\frac{(T-1)n\boldsymbol{I_m}}{\sigma_\epsilon^2} + \frac{\boldsymbol{I_m}}{\sigma_\beta^2}]^{-1}$$

$$\boldsymbol{a_\mu} = \frac{1}{\sigma_\epsilon^2}\sum_{t=2}^{T}(\boldsymbol{I_m} \otimes \boldsymbol{1_n}')(vec_j(\boldsymbol{Z}_t) - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}\boldsymbol{\alpha} - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W\boldsymbol{\rho} - (\boldsymbol{1_m} \otimes \boldsymbol{I_n})\boldsymbol{\mu}) + \frac{\boldsymbol{\beta_0}}{\sigma_\beta^2}$$

$$\sigma_\epsilon^2 \sim IG(\frac{nm(T-1)}{2} + \tilde{q}_\epsilon, \frac{1}{\tilde{r}_\epsilon} + \frac{1}{2}\sum_{t=2}^{T}\tilde{\boldsymbol{\epsilon}}'\tilde{\boldsymbol{\epsilon}})$$

$$\tilde{\boldsymbol{\epsilon}} = vec_j(\boldsymbol{Z}_t) - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}\boldsymbol{\alpha} - \boldsymbol{I_m} \otimes \boldsymbol{Z}_{t-1}^W\boldsymbol{\rho} - (\boldsymbol{1_m} \otimes \boldsymbol{I_n})\boldsymbol{\mu} - (\boldsymbol{I_m} \otimes \boldsymbol{1_n})\boldsymbol{\beta}$$

3.4 Estimation results

We ran two short pilot simulations (2000 Gibbs iterations each) to assess convergence of the sequences of posterior drawings according to the procedure described in the previous chapter. Each pair of sequences converged to the same mean and similar variances so that the convergence monitor $\hat{R}$ was stayed in the range 0.999-1.003.

We then ran a single long (15000 iterations) chain, conservatively discarded first 5000 iterations as 'burn in' period, thinned the remaining 10000 iterations by picking every 10^th value, and derived posterior means and variances for the parameters of interest.

The temporal lag (growth term) measures correlation between log-sectoral portion of aggregate earnings in a sector in a current year and log-sectoral portion of aggregate earnings in another (or the same) sector in a previous year in the same county. The spatio-temporal lag (diffusion term) measures correlation between log-sectoral portion of aggregate earnings in a sector in a county in a current year and log-sectoral portion of aggregate earnings in another (or the same) sector in counties within the county's neighborhood in the previous year. Both terms consist of 64 parameters since these pairwise correlations between earnings within a pair of sectors may not be symmetric. Histograms of some of the parameters' thinned posterior distributions are presented on Figures 3.8, 3.9, 3.10 and 3.11.

The temporal lag estimation results are presented in Table 3.3 and the spatio-temporal lag estimates in Table 3.4. These results show that temporal correlation of the log-sectoral portion of aggregate earnings in particular sectors within the same county across time is positive for all sectors while the temporal correlation across sectors is either positive or negative. There are several patterns that the estimation results demonstrate. Firstly, sectoral portions of aggregate earnings in all sectors except wholesale trade show strong intrasectoral temporal correlation with the magnitude of coefficients ranging from 0.56 (services sector) to 0.95 (government sector). Secondly, as it can be seen in the columns of Table 3.3, manufacturing sector's portion of aggregate earnings in the previous year negatively affects all other sectors' portion of aggregate earnings with coefficients ranging in absolute value from 0.023 to 0.048

while all other sectors' portions of aggregate earnings related with other sectors' portion of aggregate earnings either positively or negatively or insignificantly. Thirdly, as it can be seen in the rows of the same table, government sector is the only sector which portion of aggregated earnings in the current year is negatively related to the earnings in all other sectors in the previous year. For all other sectors this relation is either positive or negative or insignificant. Fourthly, the spatio-temporal relations are weaker than temporal ones as Table 3.4 shows but even for them the intrasectoral relations which represented by the diagonal elements of the table are all positive. The columns of this table show that only manufacturing sector's portion of aggregate earnings in the neighboring counties in the previous year related negatively with all other sectors' portions of aggregate earnings in the center county in the current year. Finance and insurance and government sectors' portions of aggregate earnings have the same relations positive while for the rest of the sectors they are either positive or negative or insignificant.

The county fixed effects are estimated while the coefficient for one of them (Pulaski county) is omitted because preliminary estimation showed it to be the smallest one by the magnitude. For the rest of the counties the estimates of these coefficient are reported in Table 3.5 and the map of these coefficients is presented on Figure 3.12. These coefficients show that St. Louis city has highest levels of all sectoral portion of aggregate earnings among Missouri counties which can be explained by the fact that the aggregate earnings themselves are highest for this city.

The sector fixed effects' estimates are reported in Table 3.6. They show that manufacturing sector has the highest and significant effect.

3.5 Interpretation of results and conclusions

3.5.1 Impulse response functions

In order to see how these different relations work together and affect growth of the sectoral portion of aggregate earnings we construct impulse-response functions for two type of shocks – sector shocks and county shocks. While the former is placed in a county at a sector and affects other sectors via intersectoral temporal and spatio-temporal connections the latter affect all sectors at the same time and can be thought of as convoluted sector shocks impulse responses. The sector shock impulse response functions are calculated for Boone county and their graphs are represented below. Graphs for other counties will have slightly different diffusion pattern if they have different number of neighbors.

When analyzing the impulse response functions we should keep in mind that the diffusion effect across counties propagates throughout neighborhoods in circles, i.e., the neighbors of the center (where the shock is applied) propagate the shock to their own neighbors in all directions – to the outside, the next ring's neighbors, and to the inside, the center if they belong to its first ring neighbors. At the same time, the magnitude of the effects across sectors depends not only on the coefficient of temporal correlation between two sectors (since the IRFs are built for the pairwise effects across sectors) but also on the coefficients of temporal correlations between all other sectors, for eventually all sectors are affected with the derivatives of the initial shock.

The first set of impulse response functions shows the effects of the shock to a sectoral portion of agggregate earnings per worker in a county on the other sectoral portions of aggregate earnings per worker in the same county. The effects of the same shock on the sectoral portions of aggregate earnings in the neighboring county follow. The shock size is set one standard deviation, i.e. 0.3 according to the model estimate.

Impulse response functions for the portions of aggregate earnings per worker in different sectors to a shock in construction sector are presented on Figure 3.13. For this sector's average sectoral portion of aggregate earnings being equal $715.23 the applied shock translates into $215.23 rise in the earnings. These graphs show that a shock to construction's portion of aggregate earnings produces different types of effects on the other sectors' portions of aggregate earnings – its own portion of aggregate earnings steadily declines over time from initial 20.8 percent increase to 1 percent by year 10 after which it becomes statistically insignificant (see Figure 3.14). Manufacturing's portion initially increases by 1.7 percent by year 5 and then steadily decreases becoming statistically insignificant by year 12 (see Figure 3.15). Among other sectors which impulse responses are statistically significant during some of the forecast period and show the same patterns – initial rise and following decline – retail trade's portion of aggregate earnings declines the least – by 2.1 percent at year 5 while wholesale trade's portion declines by 2.5 percent at year 4 and, government's portion declines the most – 2.7 percent at year 16.

Impulse responses in different sectors to a shock in manufacturing sector are presented on Figure 3.16. For this sector's average sectoral portion of aggregate earnings being equal $1826.94 the applied shock translates into $639.17 rise in the earnings. According to these graphs the shock to manufacturing's portion of aggregate earnings produces similar effect on all sectors' portions of aggregate earnings except its own. All impulse responses are statistically significant for a whole forecast period (except for the last two years for government sector). While all sectors' portions of aggregate earnings decline after the shock and then fluctuate within a narrow range, manufacturing portion steadily goes down over time after initial increase by 24 percent. The magnitude of decrease for former sectors stays between less than 3.3 percent in construction sector (see Figure 3.17) to about 5.4 percent in finance and insurance sector (see Figure 3.18).

Impulse responses in different sectors to a shock in transportation and public utilities sector are presented on Figure 3.19. For this sector's average sectoral portion of aggregate earnings being equal \$899.11 the applied shock translates into \$314.56 rise in the earnings. The shock to this sector portion of aggregate earnings produces positive effect on its own portion of aggregate earnings that rises by 25.4 percent during the first year after the shock and then steadily declines for the rest of the forecast period. The effect on manufacturing and wholesale trade sectors is insignificant for the most of or whole period. For the rest of the sectors the effect is negative with the smallest decline in services sectors (3.6 percent) and the biggest in finance and insurance sector – 5.5 percent.

Impulse responses to a shock to wholesale sector's portion of aggregate earnings (one standard deviation for this sector's average portion of aggregate earnings of \$477.37 equals \$167.01) show (see Figure 3.20) that this shock produces insignificant effect on finance and insurance sector. Its own portion of aggregate earnings starts with 20.6 percent increase after the shock and declines steadily over forecast period. Manufacturing sector is the only one that experiences small positive effect during years 7 through 17 in the size of close to 1 percent (see Figure 3.21). All other sectors portions of aggregate earnings decline after the shock as little as 0.4-0.8 percent in construction and services and as much as 1.4-1.5 percent in transportation and public utilities, retail trade, and government.

A shock to retail trade's portion of aggregate earnings (one standard deviation for this sector's average portion of aggregate earnings of \$1447.66 equals \$506.47) shown on Figure 3.22 produces insignificant effect on finance and insurance sector and transportation and public utilities sector. Retail trade's own portion of aggregate earnings starts with 27.4 percent increase after the shock and declines steadily over forecast period. Manufacturing and government sectors' portions of aggregate earnings fall by 4.8 percent and 9.3 percent, respectively, but eventually become statistically insignificant. The other three sectors – construction, services, and wholesale trade – experience rise in their portions of aggregate earnings by 5.7 percent, 6.2 percent, and 9 percent, respectively.

Impulse response functions in different sectors to a shock in finance and insurance sector are presented on Figure 3.23. For this sector's average portion of aggregate earnings of \$418.55 the size of the shock equals \$146.43. The graphs show that shock to this sector's portion of aggregate earnings produces insignificant effect on construction, transportation and public utilities, and manufacturing (for most of the time) sectors. For services and wholesale trade sectors the portions of aggregate earnings grow to 3.7 percent and 3.3 percent, respectively, for 10-11 year after the shock and then become statistically insignificant. The portions of aggregate earnings for government and retail trade sectors experience the opposite effect – they fall by 3.1 percent and 2.5 percent, respectively, during first 10 years and then become statistically insignificant. The finance and insurance own portion of aggregate earnings rises to 24.3 percent right after shock and steadily declines afterwards.

Impulse response functions to a shock in services sector are presented on Figure

3.24. For this sector's average portion of aggregate earnings of $1831.70 the shock equals $640.84. These graphs show that this shock initially raises its own sector's portion of aggregate earnings by 1.5 percent that falls afterwards. Also this shock produces either delayed positive effect on some sectors – finance and insurance by 2.5 percent and construction by 1.8 percent – or temporary negative effect in the rest of the sectors with the decline ranging from 1.6 percent in retail trade and transportation and public utilities sectors to 2.3-2.4 percent in government and manufacturing.

Impulse response functions to a shock in government sector (see Figure 3.33) show steadily positive effect in the same sector that fluctuates around 28 percent. In half of the sectors – construction, transportation and public utilities, wholesale trade, and retail trade – this shock does not produce significant effect. In manufacturing the portion of aggregate earnings per worker initially falls by 8.3 percent but later rises to -2.1 percent. In finance and insurance sector and services sector the growth of their portions of aggregate earnings is delayed but raises the former's portion by 12.1 percent and the latter's by 6.9 percent by the end of the forecast period. For this sector's average portion of aggregate earnings of $2151.67 the shock equals $752.78.

The overall results of the shocks to different sectors' portions of aggregate earnings in the center county show that these shocks raise their own portions of aggregate earnings but in government, manufacturing, and retail trade sectors this rise is long-lasting while in other sectors the growth rates eventually go back to zero. The government sector's portion of aggregate earnings has the least effect on the other sectors' portions. Transportation and public utilities and manufacturing sectors' portions of aggregate earnings have mostly negative effect on other sectors' portions while retail trade, services, and finance and insurance sectors' portion have mostly positive effect. In terms of the effects that the sectors' portions of aggregate earnings experience after shocks transportation and public utilities's portion is the least affected by other sectors while government and retail trade sectors' portions are mostly affected negatively, i.e., their portions fall after shocks. For the rest of the sectors' portions of aggregate earnings the shocks' effects are a mix of rises, falls, and no changes. The diffusion effect is much smaller in size in comparison to the growth and total effects and ranges from -1.3 percent of the response of finance and insurance sector to a shock in manufacturing sector to 3 percent of the response of the same sector to a shock to government sector.

In order to see how these responses are relative to each other we incorporate sector fixed effects (see Table 3.6) into the graphs drawn on the same scale. These graphs are presented on Figures 3.33 through 3.32. The green lines represent total effect with a 90-percent confidence region while the black ones – total effect with the sector fixed effect added to it. These graphs should be interpreted keeping in mind that the actual fixed effects are added to the log-levels of sectoral portions of aggregate earnings per worker while on these graphs they are added to the impulse response function coefficients. So the confidence regions for most (if not all) sectors do not include zero, i.e., stay statistically significant if used for the log-levels of the dependent variable. But even in this particular case adding fixed effects allows concluding that retail trade, government, and manufacturing sectors when experience positive exogenous shock affect sectoral portions of aggregate earnings in other sectors the most. After a shock to the government sector all sectors except manufacturing experience rise of their portions of aggregate earnings. After a shock to manufacturing sector all other sectors except manufacturing itself experience fall in their portions of aggregate earnings. After a shock to retail trade sector the effects on other sectors' portions of aggregate earnings are such that manufacturing, transportation and public utilities, and government sectors' portions fall without recovery for the last one while the other sectors' portion experience rise. A shock to the rest of the sectors does not produce any significant effects on sectoral portions of aggregate earnings either in the same sectors or the other sectors.

Since our model includes spatio-temporal term it is useful to take a look at the effect that shocks to sectoral portions of aggregate earnings in a center county have on sectoral portions of aggregate earnings in a neighboring county. As an example we choose Cole county. The impulse response functions of sectoral portions of aggregate earnings in Cole county to sectoral shocks in Boone county are represented on Figures 3.34 through 3.49. These graphs show that shocks to sectoral portions of aggregate earnings in one county have effects on sectoral portions of aggregate earnings in neighboring counties. They show that a shock to government portion of aggregate earnings in Boone county affects positively all sectors' portions of aggregate earnings in Cole county with the highest rise in finance and insurance and wholesale trade sectors (more than 11 percent by the end of the forecast period) and the lowest in manufacturing (3.3 percent). The shock to finance and insurance sector also produces positive effects on half of the sectors in neighboring counties. The size of the effects varies between 1 percent in wholesale trade sector to 2 percent in the same finance and insurance sector. Another sector a shock to which produces positive effects on sectors in the neighboring county is retail trade. The rise of sectoral portion of aggregate earnings varies from 2 percent in construction sector to 3.5 percent in the same retail trade sector. The shock to manufacturing sector in Boone county produces negative effects on all other sectors in Cole county with the smallest decline in transportation and public utilities sector (-2.5 percent) and the biggest in finance and insurance sector (-4.8 percent). The shock to transportation and public utilities sector produces negative effects in all sectors except manufacturing sector (+1.4 percent) in the neighboring county. The decline of the sectoral portions of aggregate earnings per worker in neighboring county varies between -2.6 percent in the same sector and -5 percent in finance and insurance sector. Another sector shock to which affects negatively other sectors is wholesale trade with the smallest fall of sectoral portion of aggregate earnings in the same sector (-1 percent at the end of the forecast period) and the largest in services sector (-8.3 percent). It is worth mentioning that, to the contrary to the effects in the same center county, in the neighboring county not all sectors get affected positively after shock being applied to them. These sectors are transportation and public utilities and wholesale trade.

Again, in order to assess impact of these shocks on sectoral portions of aggregate earnings we take a look at the impulse response functions with added sector fixed effects to them presented on a common to all sectors scale. These graphs are presented on Figures 3.41 through 3.48. These graphs show that a shock to government sector in Boone county positively affects all sectors in Cole county which is similar to the effect of this shock to sectors in Boone county. A shock to manufacturing sector in Boone county affects negatively all sectors in Cole county except manufacturing itself for which the effect is negligible. These effect also resemble the effect of a shock to manufacturing county to the sectors in Boone county. A shock to retail trade sector in Boone county raises sectoral portions of aggregate earnings in all sectors except manufacturing in Cole county while a shock to transportation and public utilities sector decreases sectoral portions of aggregate earnings in all sectors in Cole county except manufacturing.

The impulse response functions to a county shock are represented on Figure 3.50 for the county where the shock happens (Boone county) and on Figure 3.51 for its neighbor (Cole county). The size of the shock is a sum of the sector shocks mentioned above – \$3417.50. These graphs show that when all sectors are affected at the same time the sectoral portions of aggregate earnings in all sectors except manufacturing experience positive effect of higher growth rates ranging from 3 to 7 percent in the long-run. As for the neighboring county, its sectors respond to the shock to the center in a similar way – with a growth of 3 to 6 percent while the temporary rise in growth of manufacturing's portion of aggregate earnings disappears in about 7 years.

3.5.2 Convergence of sectoral earnings per worker

Since in the model we used sectoral portion of aggregate earnings as our dependent variable which was defined as a product of sectoral earnings per worker and employment share of a sector, we can exploit this definition to assess convergence of 'net' sectoral earnings per worker, using 'net' growth rates of sectoral portion of aggregate earnings from the model analogously the way we did it in subsection 2.6.3 of the second chapter. Since

$$p_j = e_j s_j,$$

we can derive the following formula for the percentage change in sectoral portion of aggregate earnings as

$$\%\Delta p_j = \%\Delta e_j + \%\Delta s_j$$

and calculate percentage change in sectoral earnings per worker as

$$\%\Delta e_j = \%\Delta p_j - \%\Delta s_j.$$

$\%\Delta p_j = (\alpha_j - 1)Z_{j,t-1}$ where α_j is a diagonal element of the matrix of temporal lag parameters estimates from Table 3.3.

The resulting absolute convergence plots for 'net' sectoral earnings per worker are presented on Figures 3.52 and 3.53. These graphs show that 'net', i.e., obtained after removing spillover effects, sectoral earnings per worker converge in wholesale trade, retail trade, finance and insurance, and services sectors while they diverge in all other sectors – construction, manufacturing, transportation and public utilities, and government. Presented earlier absolute convergence plots of 'gross' sectoral earnings per worker showed weak convergence of earnings per worker in manufacturing and government sectors and much stronger convergence in other sectors. These findings show that if intersectoral spillover effects are accounted for then in economic sectors that produce goods rather than services (except for government sector) workers' productivity does not converge, i.e., in counties with lower initial workers' productivity it does not grow faster than in counties with higher initial workers' productivity.

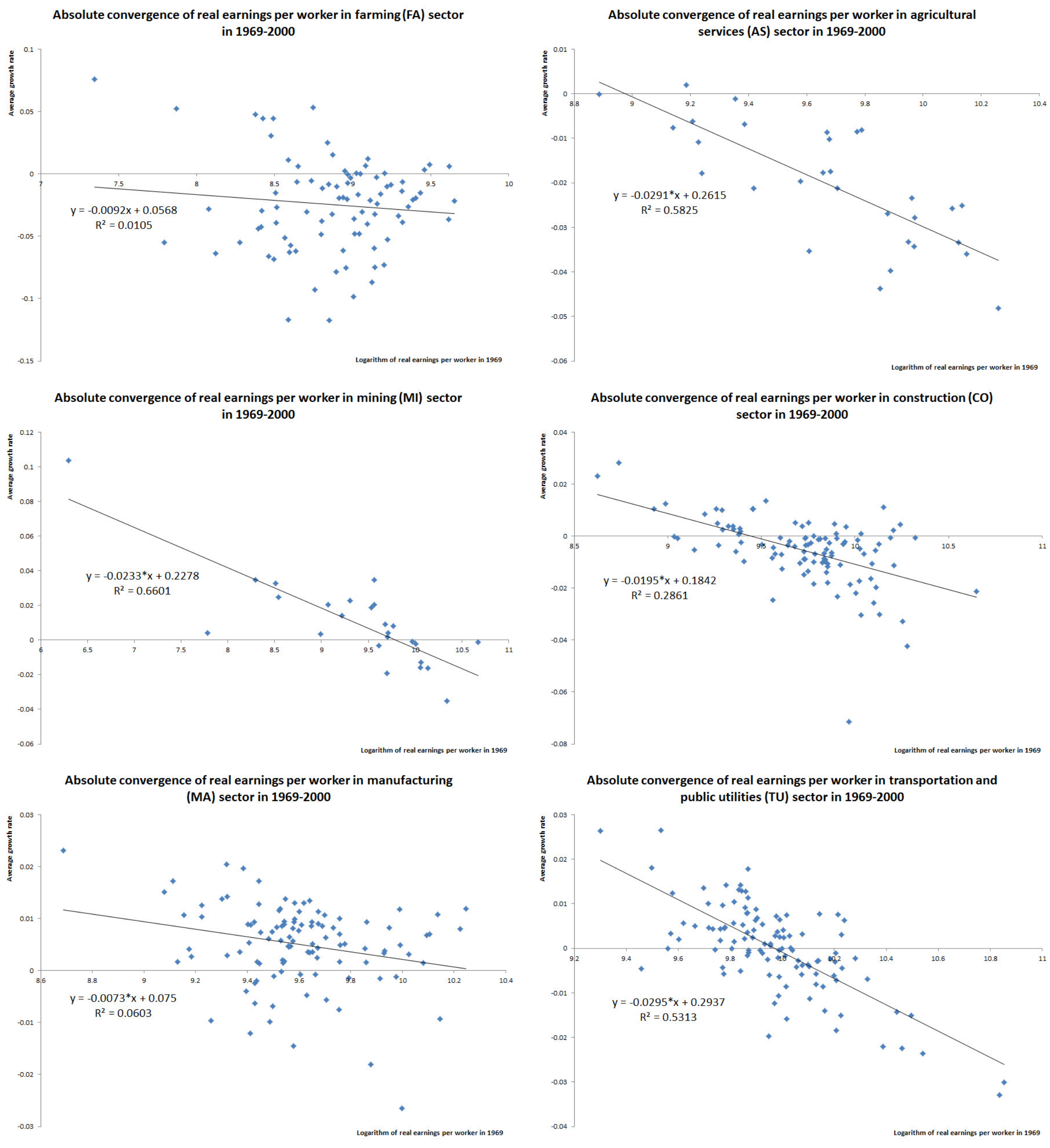

Figure 3.1: Convergence plots of earnings per worker in sectors of economy for Missouri counties in 1969-2000.

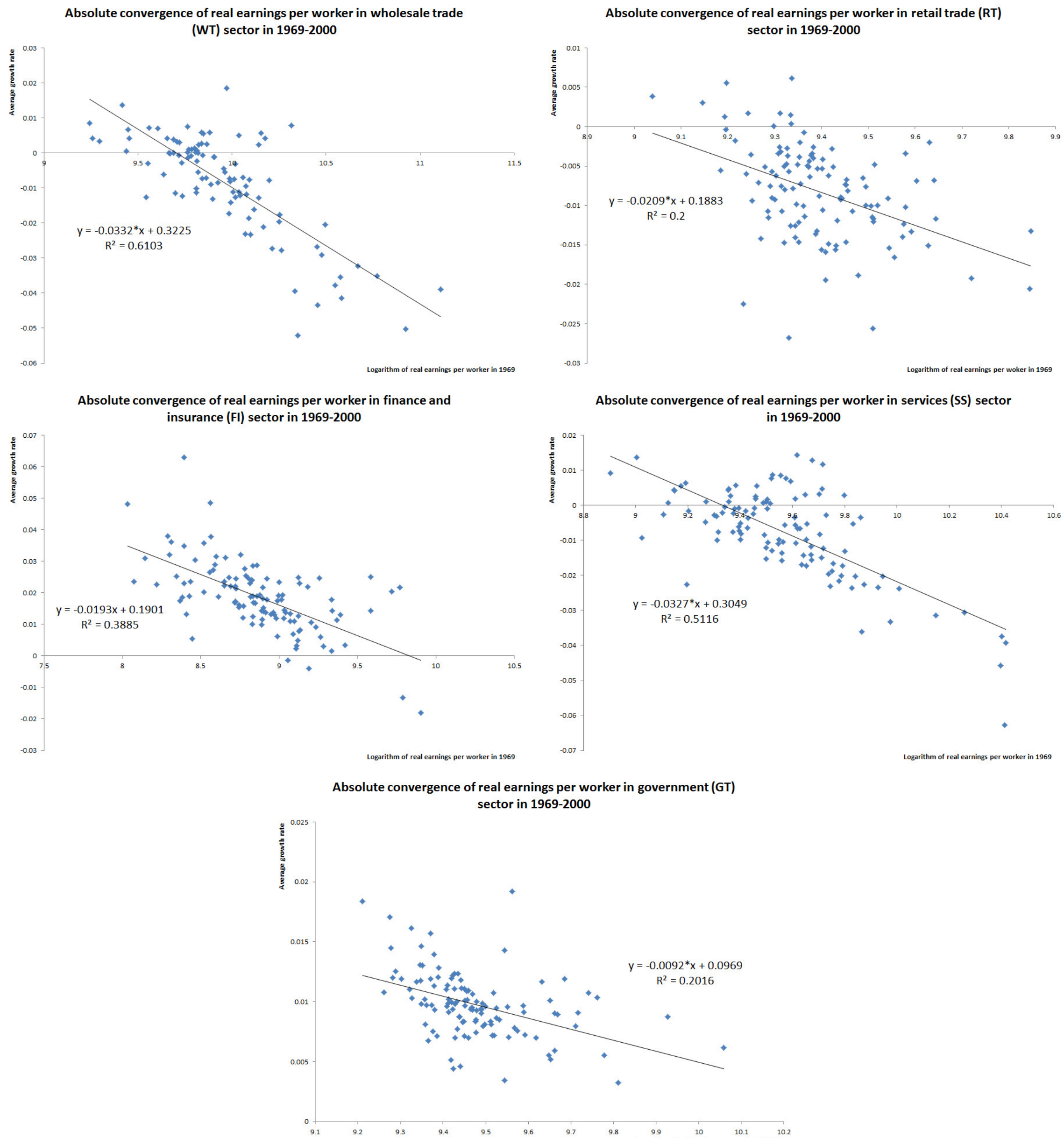

Figure 3.2: Convergence plots of earnings per worker in sectors of economy for Missouri counties in 1969-2000 (continued).

Table 3.1: Comparison of means and variances for original and complete datasets for 6 sectors after Amelia imputation.

Sector	Number of missing points	%% of missing points	Original data		Complete data	
			Mean	Variance	Mean	Variance
CO	74	2.01	16.4660	2.4182	16.4712	2.4068
MA	75	2.04	17.3779	3.1901	17.3795	3.1803
TU	36	0.01	16.6341	2.2358	16.6349	2.2276
WT	164	4.46	15.9402	2.9355	15.9460	2.9302
FI	19	0.01	15.6132	2.4753	15.6146	2.4727
SS	82	2.23	17.0462	2.4827	17.0461	2.4824

Table 3.2: Results of Moran's I bivariate test for global spatio-temporal randomness for sectoral portion of aggregate earnings per worker in the counties of the state of Missouri in 1969-2000.

Year for center	**Year for neighbors**	**Global Moran's I for sectors**							
		CO	**MA**	**TU**	**WT**	**RT**	**FI**	**SS**	**GT**
1970	1969	0.1210	(0.0325)	(0.0099)	(-0.0180)	(-0.0132)	0.0866	(0.0073)	0.1293
1971	1970	0.1195	(0.0461)	(-0.0128)	(-0.0081)	(0.0039)	(0.0621)	(0.0213)	0.1306
1972	1971	0.1481	0.2380	(0.0133)	(-0.0347)	(-0.0017)	0.0661	(-0.0022)	0.1328
1973	1972	0.2039	0.2781	(0.0078)	(-0.0514)	(-0.0156)	0.0757	(0.0516)	0.1379
1974	1973	0.2387	0.2519	(-0.0027)	(-0.0559)	(-0.0449)	0.0848	(0.0028)	0.1399
1975	1974	0.1931	0.1775	(0.0138)	(-0.0648)	(-0.0480)	0.0856	(0.0054)	0.1469
1976	1975	0.2123	0.1544	(0.0137)	(0.0108)	(-0.0330)	0.1157	(0.0038)	0.1496
1977	1976	0.2517	0.1881	(0.0412)	(0.0203)	(-0.0358)	0.1395	(-0.0132)	0.1472
1978	1977	0.2909	0.2338	(0.0297)	(0.0204)	(-0.0406)	0.1531	(-0.0139)	0.1360
1979	1978	0.3225	0.2417	(0.0286)	(0.0356)	(-0.0519)	0.1513	(-0.0031)	0.1130
1980	1979	0.2852	0.2334	0.0686	(0.0604)	(-0.0340)	0.1418	(0.0171)	0.1041
1981	1980	0.2445	0.1479	0.0975	0.1184	(-0.0143)	0.1585	(0.0147)	0.1130
1982	1981	0.2352	0.1372	0.1317	0.1083	(0.0006)	0.1552	(0.0236)	0.1237
1983	1982	0.2687	0.2407	0.1354	0.1206	(0.0307)	0.1600	(0.0429)	0.1173
1984	1983	0.3296	0.1800	0.1090	0.1647	(0.0519)	0.2098	(0.0613)	0.1122
1985	1984	0.3844	0.1992	0.0923	0.2367	0.0680	0.2311	(0.0486)	0.1212
1986	1985	0.4301	0.1944	0.0795	0.3125	0.1104	0.2217	0.0748	0.1332
1987	1986	0.4507	0.1614	0.0912	0.3019	0.1423	0.1757	0.0649	0.1409
1988	1987	0.4525	0.2369	0.1130	0.2666	0.1370	0.1817	(0.0644)	0.1427
1989	1988	0.4093	0.2586	0.1189	0.2607	0.1299	0.2008	0.0740	0.1334
1990	1989	0.3685	0.1824	0.1355	0.3178	0.1192	0.2302	0.0756	0.1238
1991	1990	0.2295	0.1558	0.1404	0.3388	0.1276	0.2331	0.1142	0.1167
1992	1991	0.1914	0.2285	0.1390	0.2902	0.1319	0.2403	0.1216	0.1233
1993	1992	0.2648	0.2573	0.1473	0.2235	0.1373	0.2371	0.1212	0.1303
1994	1993	0.2458	0.2497	0.1566	0.2177	0.1303	0.2248	0.1394	0.1286
1995	1994	0.2174	0.2408	0.1706	0.2079	0.1267	0.2486	0.1245	0.1196
1996	1995	0.2312	0.2404	0.1696	0.2318	0.1318	0.3252	0.1159	0.1168
1997	1996	0.2167	0.2525	0.1225	0.2620	0.1248	0.2370	0.1949	0.1220
1998	1997	0.1840	0.2205	0.1066	0.2200	0.0972	0.3393	0.1915	0.1259
1999	1998	(0.0626)	0.1580	(0.0195)	0.1379	0.0837	0.3364	0.1709	0.1229
2000	1999	(0.0349)	0.1019	(0.0187)	0.1469	0.1038	0.3012	0.1803	0.1244

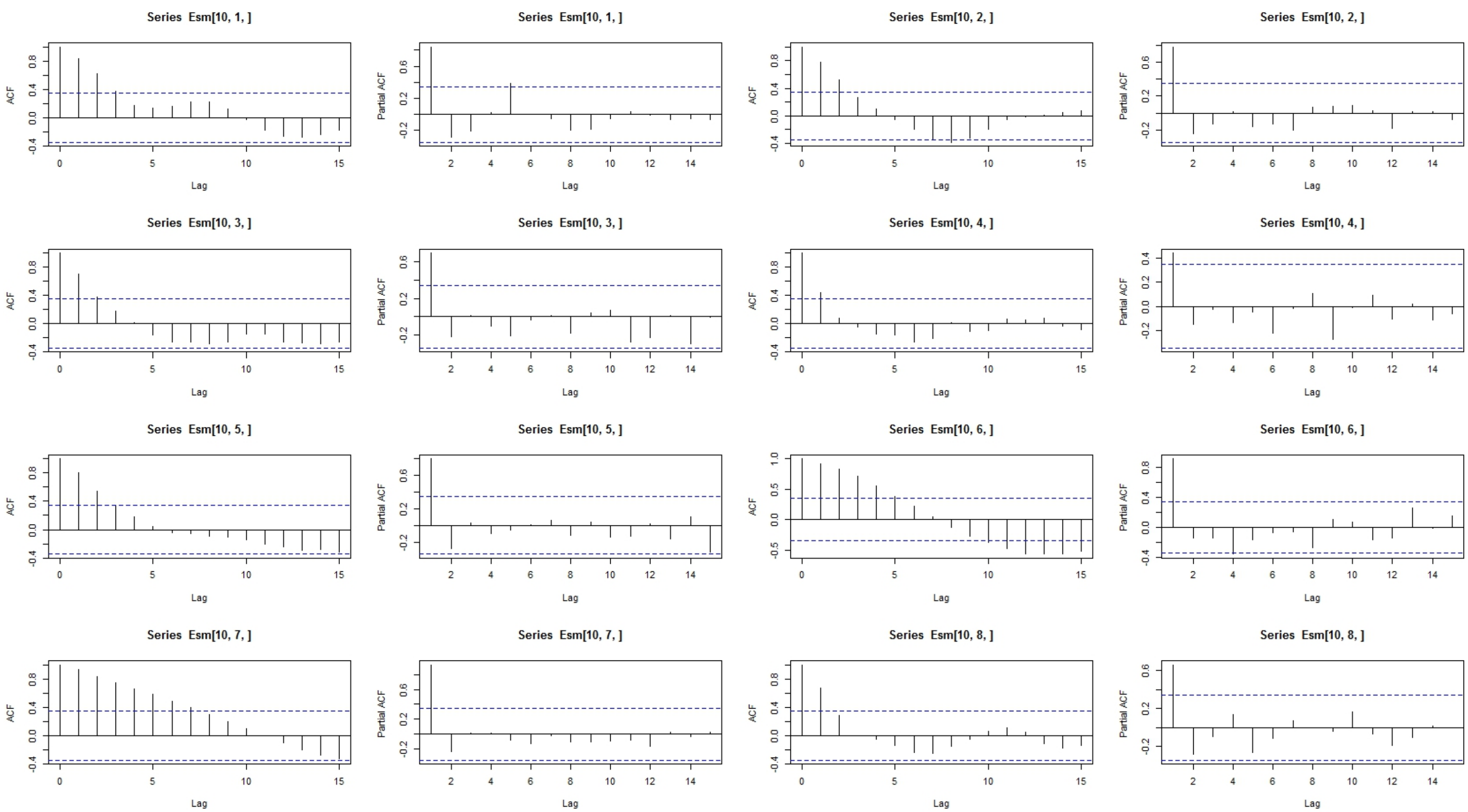

Figure 3.3: Plots of ACF and PACF for sectoral portion of aggregate earnings for CO, MA, TU, WT, RT, FI, SS, and GT sectors in Boone county in 1969-2000.

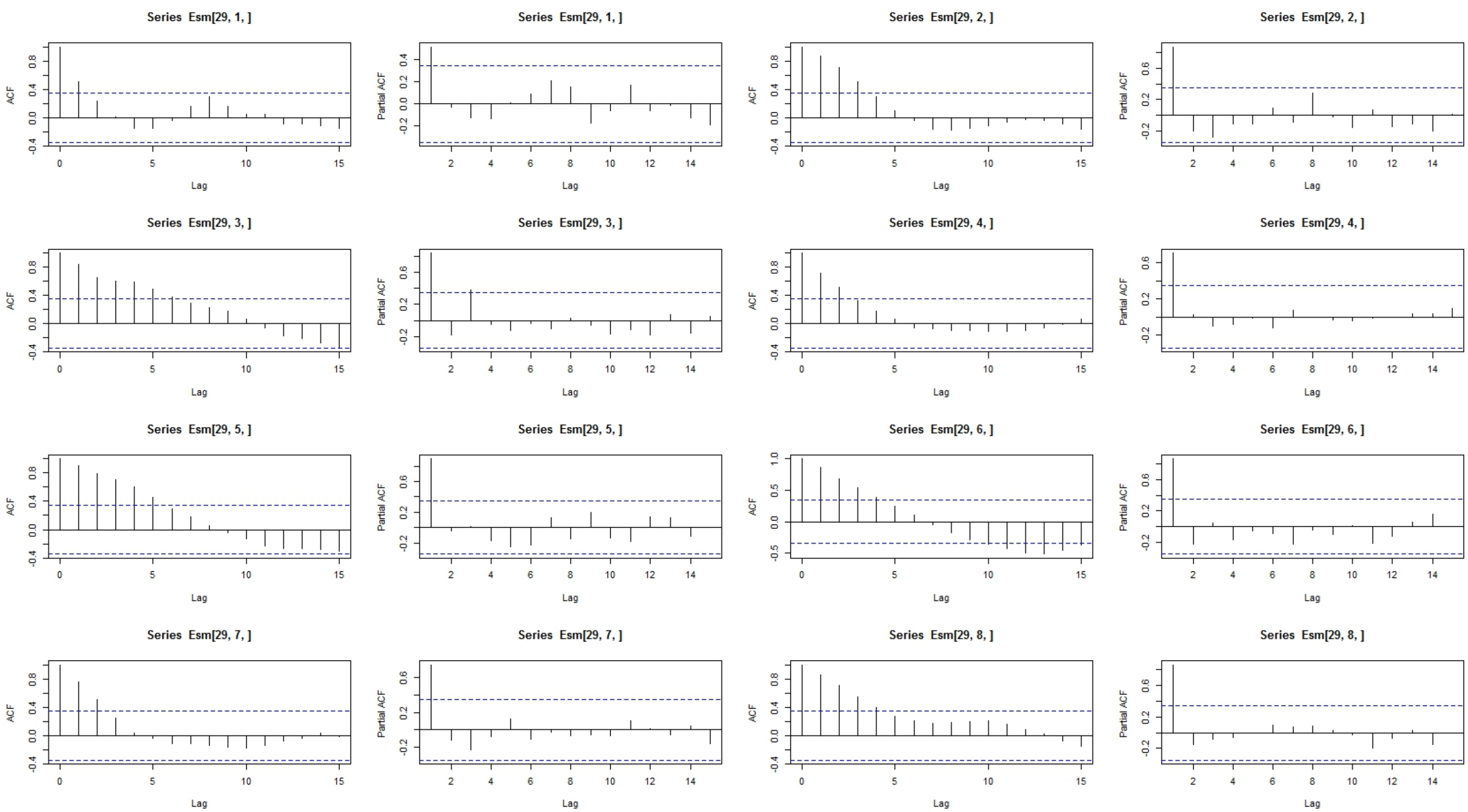

Figure 3.4: Plots of ACF and PACF for sectoral portion of aggregate earnings for CO, MA, TU, WT, RT, FI, SS, and GT sectors in Dade county in 1969-2000.

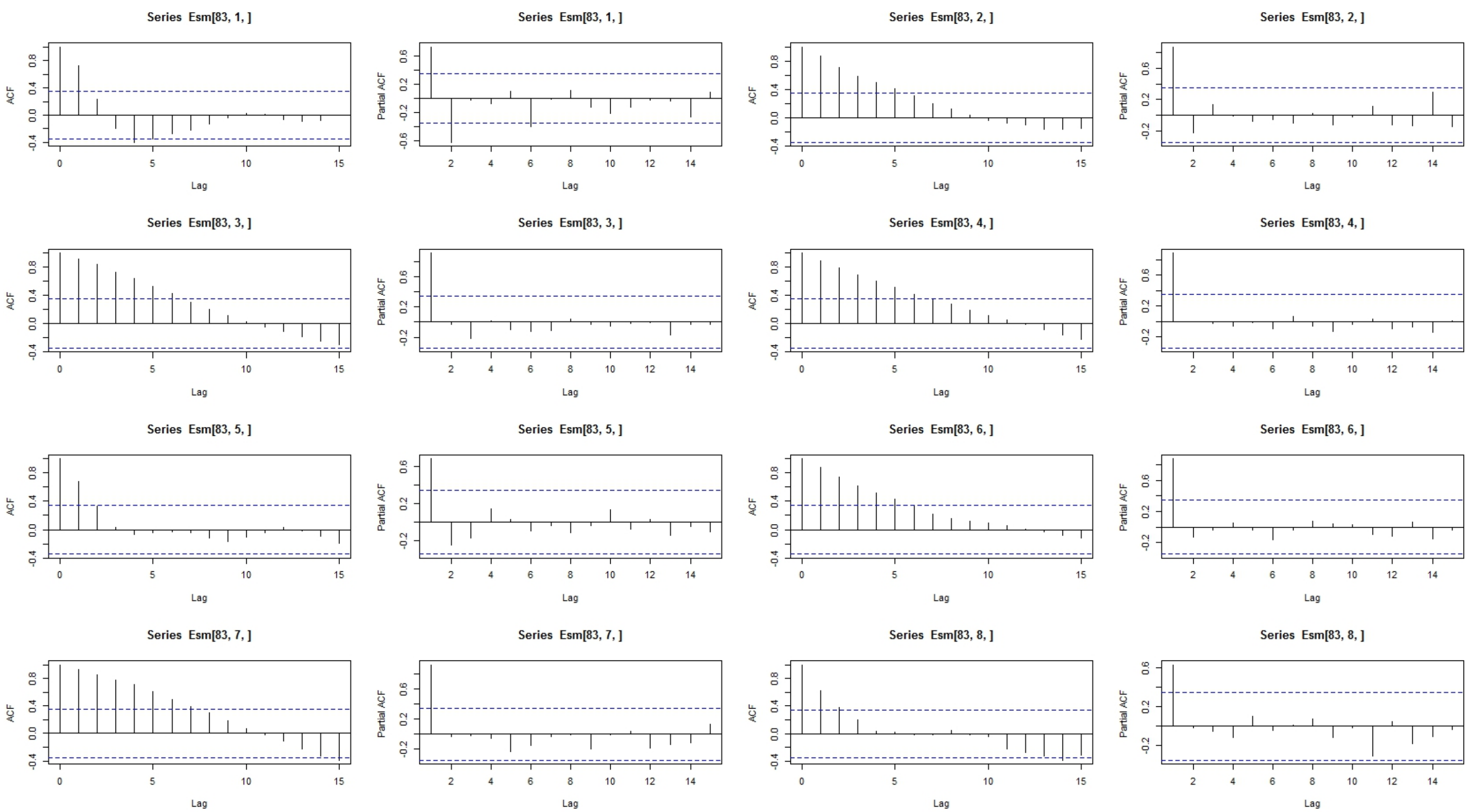

Figure 3.5: Plots of ACF and PACF for sectoral portion of aggregate earnings for CO, MA, TU, WT, RT, FI, SS, and GT sectors in Platte county in 1969-2000.

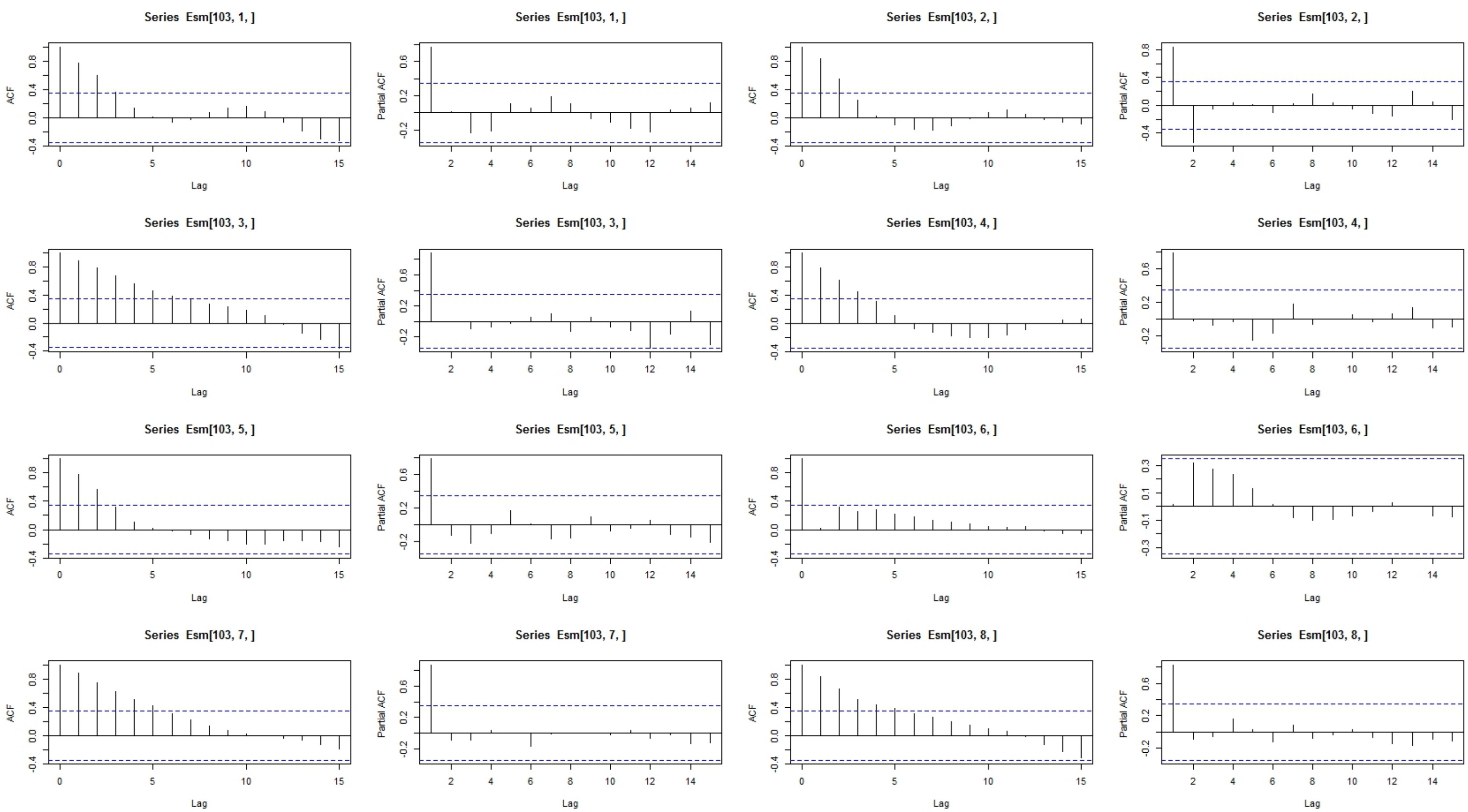

Figure 3.6: Plots of ACF and PACF for sectoral portion of aggregate earnings for CO, MA, TU, WT, RT, FI, SS, and GT sectors in Stoddard county in 1969-2000.

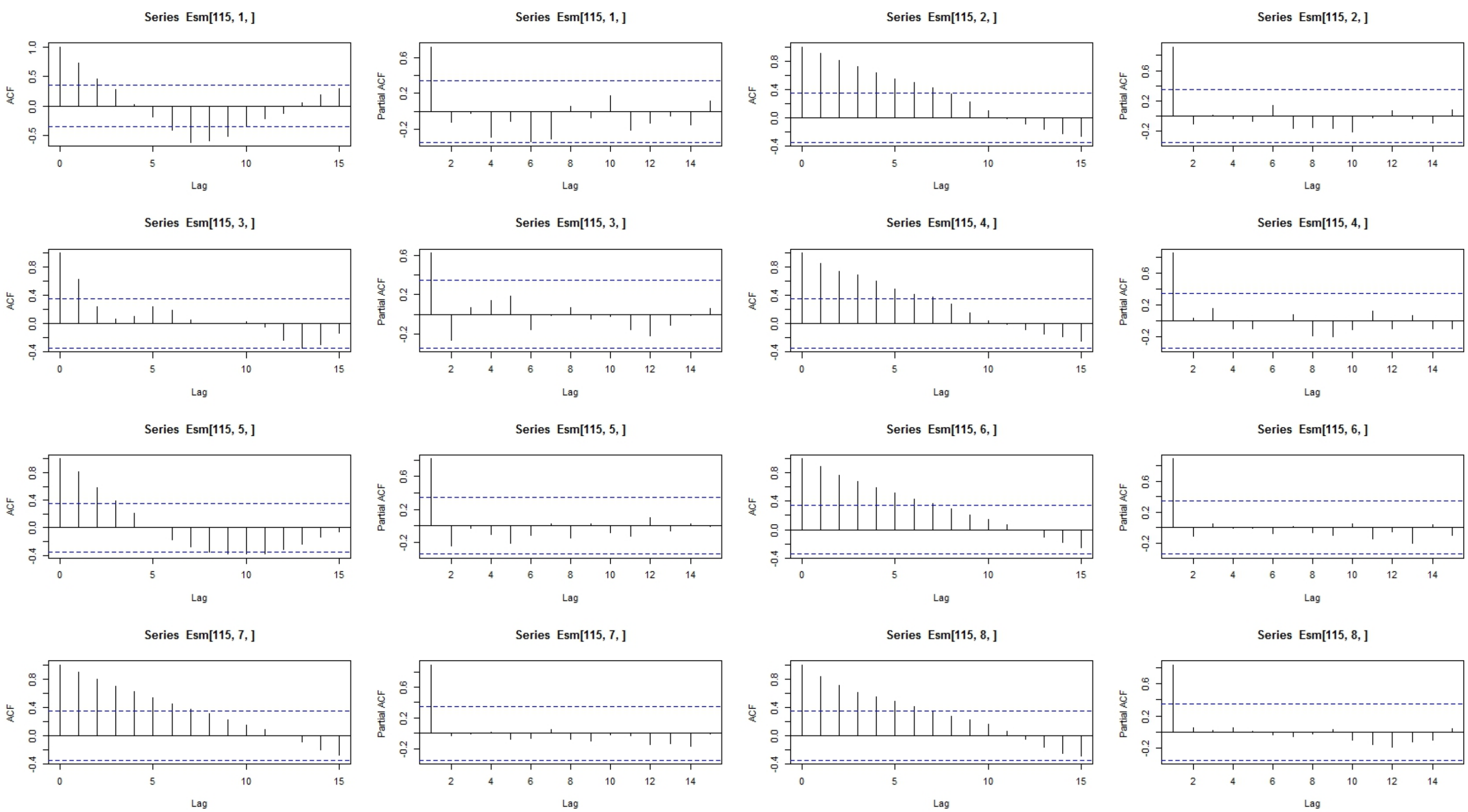

Figure 3.7: Plots of ACF and PACF for sectoral portion of aggregate earnings for CO, MA, TU, WT, RT, FI, SS, and GT sectors in St. Louis city in 1969-2000.

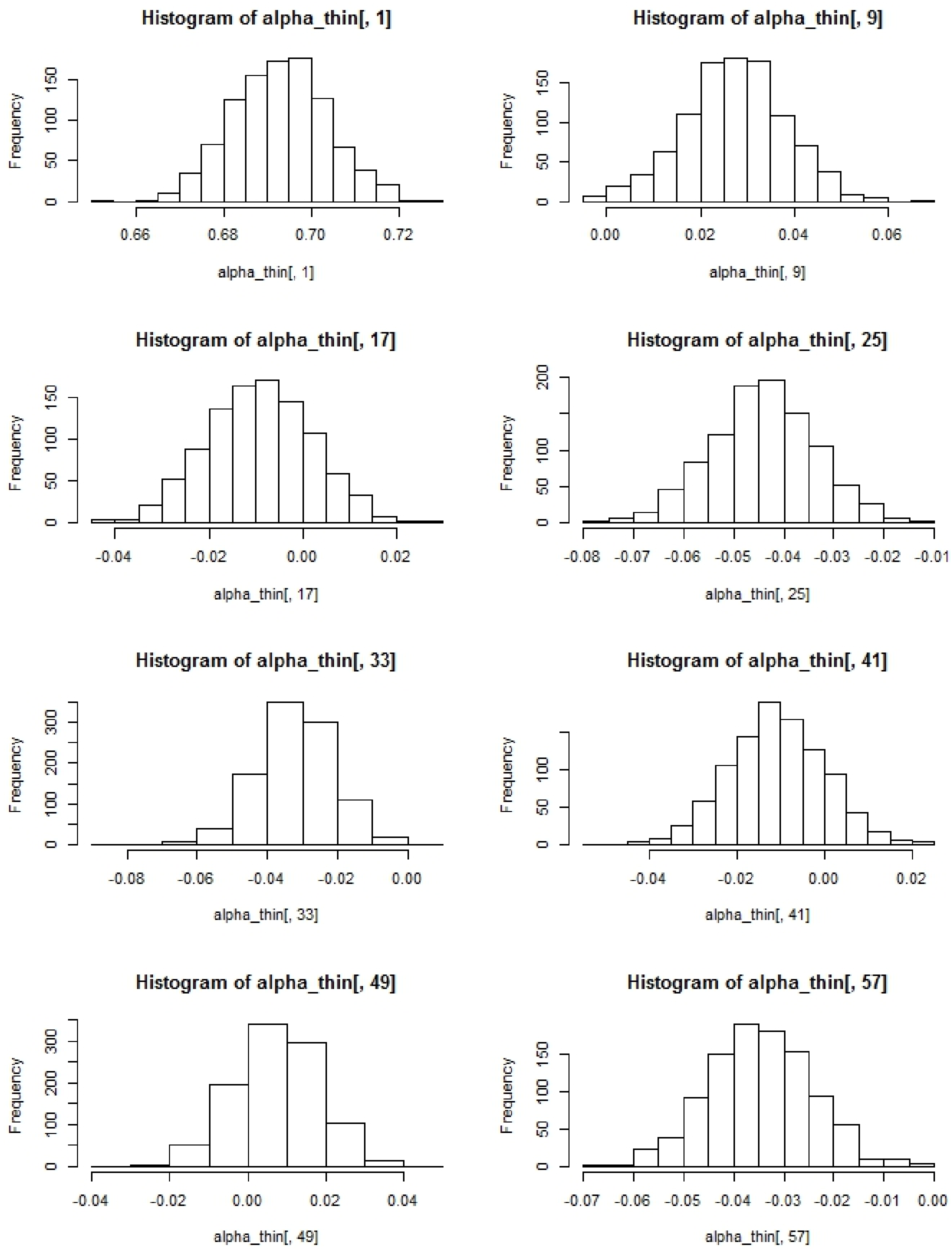

Figure 3.8: Histograms of thinned posterior distributions for some of the growth term coefficients.

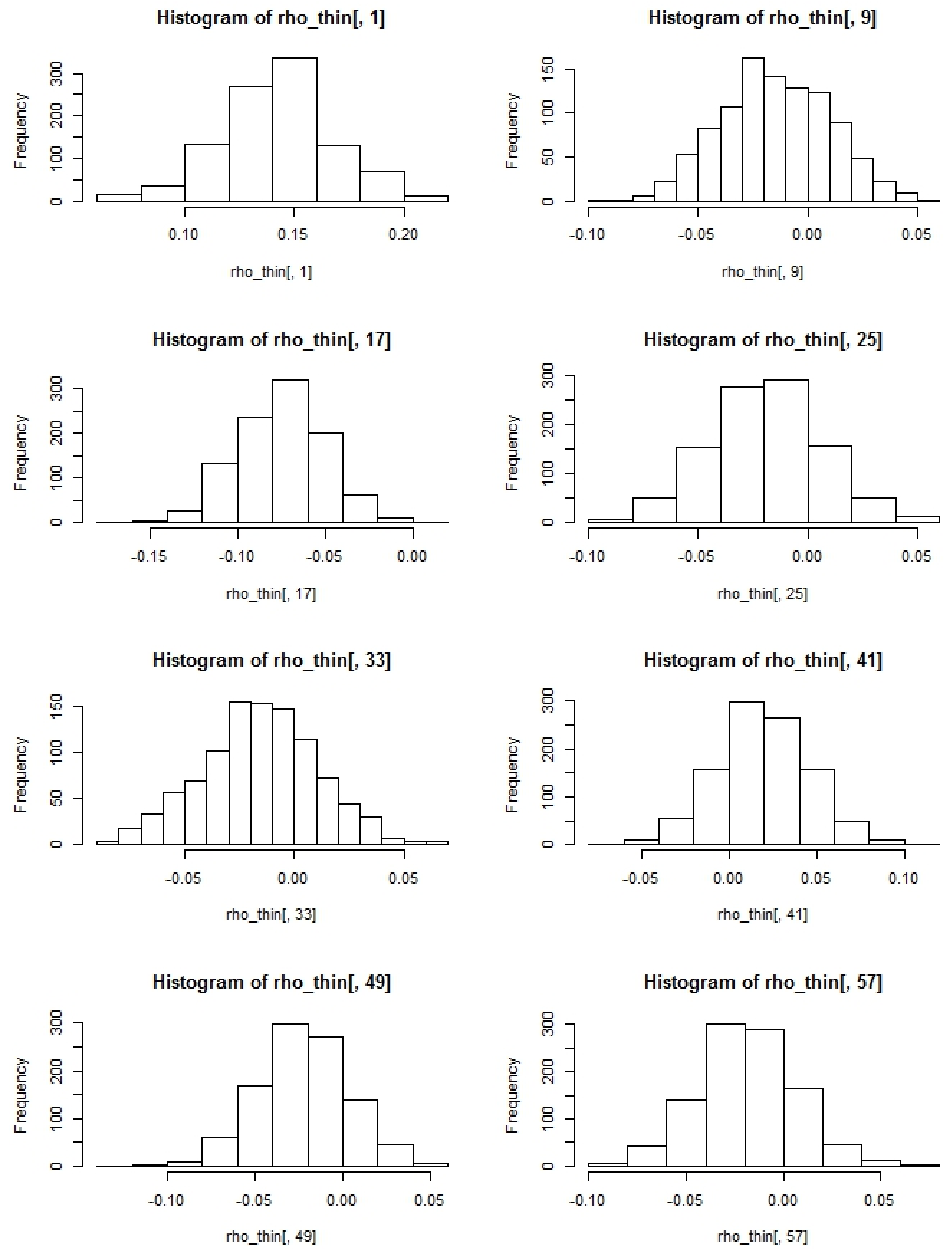

Figure 3.9: Histograms of thinned posterior distributions for some of the diffusion term coefficients.

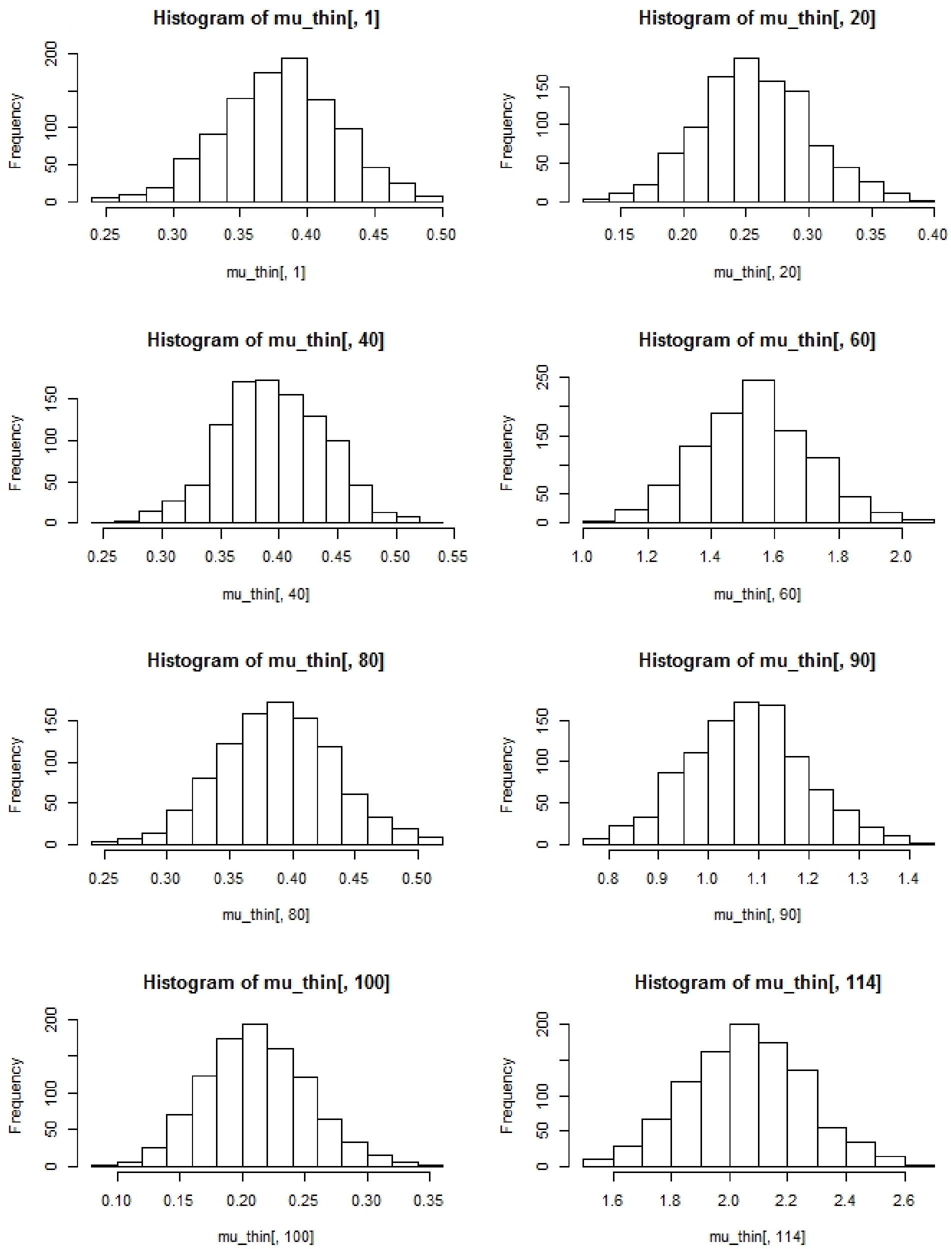

Figure 3.10: Histogram of thinned posterior distributions for some of the county fixed effects.

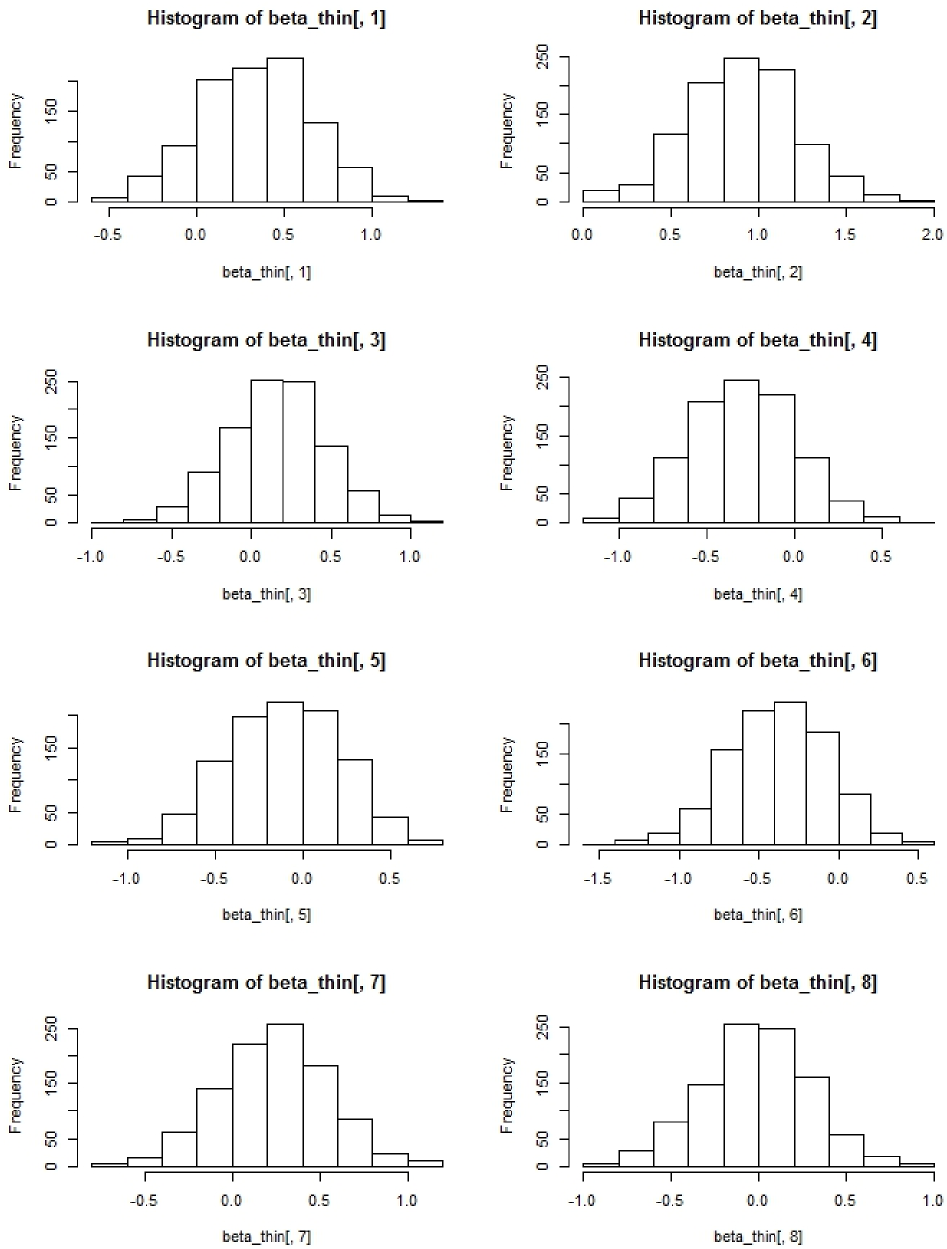

Figure 3.11: Histogram of thinned posterior distributions for the sector fixed effects.

Table 3.3: Temporal lag parameters estimation results.

Sector at year t	Sector at year $t-1$							
	CO	MA	TU	WT	RT	FI	SS	GT
CO	0.6930	-0.0391	-0.0434	-0.0207	0.0409	0.0065	-0.0187	-0.0394
	(0.0108)	(0.0064)	(0.0100)	(0.0077)	(0.0233)	(0.0147)	(0.0134)	(0.0191)
MA	0.0274	0.7971	-0.0297	0.0042	0.0816	-0.0290	-0.0654	-0.0688
	(0.0108)	(0.0065)	(0.0103)	(0.0076)	(0.0246)	(0.0153)	(0.0128)	(0.0194)
TU	-0.0092	-0.0410	0.8473	-0.0332	-0.0307	-0.0232	-0.0465	-0.0326
	(0.0112)	(0.0067)	(0.0101)	(0.0079)	(0.0240)	(0.0148)	(0.0134)	(0.0190)
WT	-0.0441	-0.0229	0.0141	0.06856	0.1072	0.0689	-0.0898	-0.0417
	(0.0104)	(0.0067)	(0.0102)	(0.0077)	(0.0242)	(0.0149)	(0.0135)	(0.0192)
RT	-0.0320	-0.0451	-0.0415	-0.0292	0.9127	-0.0313	-0.0471	-0.0243
	(0.0109)	(0.0066)	(0.0101)	(0.0078)	(0.0237)	(0.0148)	(0.0135)	(0.0197)
FI	-0.0110	-0.0467	-0.0377	-0.0111	-0.0111	0.8114	-0.0080	-0.0034
	(0.01110)	(0.0067)	(0.0103)	(0.0081)	(0.0246)	(0.0151)	(0.0129)	(0.0194)
SS	0.0073	-0.0387	-0.0176	-0.0201	0.1089	0.0812	0.5646	-0.0232
	(0.0107)	(0.0068)	(00.0097)	(0.0081)	(0.0237)	(0.0147)	(0.0138)	(0.0193)
GT	-0.0347	-0.0476	-0.0396	-0.0295	-0.0575	-0.0346	-0.0608	0.9476
	(0.0103)	(0.0066)	(0.0101)	(0.0076)	(0.0247)	(0.0147)	(0.0136)	(0.0189)

Table 3.4: Spatio-temporal lag parameters estimation results.

Sector in center	Sector in neighborhood							
	CO	MA	TU	WT	RT	FI	SS	GT
CO	0.1422	-0.0721	-0.0757	-0.0013	0.0604	0.0572	0.0939	0.1120
	(0.02260)	(0.0172)	(0.0263)	(0.0175)	(0.0385)	(0.0312)	(0.0329)	(0.0345)
MA	-0.0149	0.0578	0.1004	-0.0140	0.0209	0.0340	-0.1190	0.2309
	(0.0248)	(0.0173)	(0.0259)	(0.0177)	(0.0391)	(0.0312)	(0.0334)	(0.0341)
TU	-0.0749	-0.0227	-0.0149	0.0121	0.1331	0.1218	0.0206	0.1316
	(0.0245)	(0.0165)	(0.0264)	(0.0179)	(0.0407)	(0.0310)	(0.0345)	(0.0349)
WT	-0.0195	-0.0749	0.1285	0.1029	-0.0384	0.0817	-0.1069	0.2465
	(0.0255)	(0.0171)	(0.0264)	(0.0172)	(0.0400)	(0.0313)	(0.0355)	(0.0350)
RT	-0.0158	-0.0420	-0.0307	-0.0118	0.1127	0.0532	0.0670	0.1608
	(0.0260)	(0.0163)	(0.0264)	(0.0178)	(0.0382)	(0.0322)	(0.0344)	(0.0354)
FI	0.0192	-0.0382	-0.0761	0.0108	0.0623	0.1314	0.0750	0.1541
	(0.0261)	(0.0170)	(0.0268)	(0.0168)	(0.0396)	(0.0301)	(0.0347)	(0.0357)
SS	-0.0224	-0.0236	0.0272	-0.0110	-0.1134	0.0672	0.1310	0.2301
	(0.0258)	(0.0170)	(0.0264)	(0.0178)	(0.0398)	(0.0307)	(0.0337)	(0.0352)
GT	-0.0188	-0.0447	-0.0015	-0.0020	0.1133	0.0599	0.0412	0.1524
	(0.0248)	(0.0170)	(0.0272)	(0.0172)	(0.0390)	(0.0320)	(0.0335)	(0.0339)

Table 3.5: Estimation results for county fixed effects.

Parameter	**County**	**Posterior mean**	**Standard error**
μ_1	Adair	0.3795	(0.0432)
μ_2	Andrew	0.4553	(0.0632)
μ_3	Atchison	1.8281	(0.2126)
μ_4	Audrain	0.3782	(0.0455)
μ_5	Barry	1.0811	(0.1054)
μ_6	Barton	0.7370	(0.0683)
μ_7	Bates	0.9089	(0.1023)
μ_8	Benton	0.2247	(0.0416)
μ_9	Bollinger	0.2752	(0.0423)
μ_{10}	Boone	0.3652	(0.0386)
μ_{11}	Buchanan	1.1858	(0.1107)
μ_{12}	Butler	0.7770	(0.0605)
μ_{13}	Caldwell	0.1149	(0.0437)
μ_{14}	Callaway	0.2937	(0.0410)
μ_{15}	Camden	0.3298	(0.0513)
μ_{16}	Cape Girardeau	1.2531	(0.1072)
μ_{17}	Carroll	0.2463	(0.0445)
μ_{18}	Carter	0.3031	(0.0400)
μ_{19}	Cass	0.9649	(0.1015)
μ_{20}	Cedar	0.2568	(0.0442)
μ_{21}	Chariton	0.2778	(0.0456)
μ_{22}	Christian	0.3341	(0.0442)
μ_{23}	Clark	1.2125	(0.1535)
μ_{24}	Clay	0.9205	(0.0707)
μ_{25}	Clinton	0.1889	(0.0453)
μ_{26}	Cole	0.4044	(0.0365)
μ_{27}	Cooper	0.2880	(0.0436)
μ_{28}	Crawford	0.2912	(0.0471)
μ_{29}	Dade	0.1708	(0.0411)
μ_{30}	Dallas	0.1988	(0.0433)
μ_{31}	Daviess	0.0844	(0.0422)
μ_{32}	DeKalb	0.1354	(0.0404)
μ_{33}	Dent	0.3060	(0.0452)
μ_{34}	Douglas	0.2035	(0.0417)
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Parameter	**County**	**Posterior mean**	**Standard error**
μ_{35}	Dunklin	1.4236	(0.1498)
μ_{36}	Franklin	0.4223	(0.0473)
μ_{37}	Gasconade	0.3366	(0.0431)
μ_{38}	Gentry	0.2094	(0.0450)
μ_{39}	Greene	0.5719	(0.0462)
μ_{40}	Grundy	0.3951	(0.0436)
μ_{41}	Harrison	0.7899	(0.0962)
μ_{42}	Henry	0.2515	(0.0480)
μ_{43}	Hickory	0.1387	(0.0383)
μ_{44}	Holt	1.3408	(0.1521)
μ_{45}	Howard	0.2197	(0.0463)
μ_{46}	Howell	0.6648	(0.0594)
μ_{47}	Iron	0.2395	(0.0458)
μ_{48}	Jackson	1.1673	(0.0928)
μ_{49}	Jasper	1.2248	(0.1062)
μ_{50}	Jefferson	0.7961	(0.0592)
μ_{51}	Johnson	0.1383	(0.0302)
μ_{52}	Knox	0.1362	(0.0430)
μ_{53}	Laclede	0.3380	(0.0503)
μ_{54}	Lafayette	0.2265	(0.0457)
μ_{55}	Lawrence	0.3502	(0.0387)
μ_{56}	Lewis	1.0258	(0.1061)
μ_{57}	Lincoln	0.7857	(0.0684)
μ_{58}	Linn	0.3101	(0.0455)
μ_{59}	Livingston	0.4581	(0.0453)
μ_{60}	McDonald	1.5345	(0.1771)
μ_{61}	Macon	0.2894	(0.0407)
μ_{62}	Madison	0.3176	(0.0413)
μ_{63}	Maries	0.1751	(0.0497)
μ_{64}	Marion	0.1842	(0.1099)
μ_{65}	Mercer	0.9058	(0.1014)
μ_{66}	Miller	0.3060	(0.0501)
μ_{67}	Mississippi	1.8305	(0.2117)
μ_{68}	Moniteau	0.1978	(0.0484)
μ_{69}	Monroe	0.2834	(0.0429)
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Parameter	County	Posterior mean	Standard error
μ_{70}	Montgomery	0.3299	(0.0462)
μ_{71}	Morgan	0.2469	(0.0447)
μ_{72}	New Madrid	0.9269	(0.0874)
μ_{73}	Newton	1.1240	(0.1052)
μ_{74}	Nodaway	0.9151	(0.0954)
μ_{75}	Oregon	1.1367	(0.1281)
μ_{76}	Osage	0.2706	(0.0481)
μ_{77}	Ozark	1.2268	(0.1498)
μ_{78}	Pemiscot	1.6267	(0.1790)
μ_{79}	Perry	1.1740	(0.1132)
μ_{80}	Pettis	0.3883	(0.0460)
μ_{81}	Phelps	0.3258	(0.0384)
μ_{82}	Pike	1.0966	(0.1042)
μ_{83}	Platte	1.4914	(0.1464)
μ_{84}	Polk	0.2959	(0.0448)
μ_{85}	Pulaski	-	-
μ_{86}	Putnam	1.0512	(0.1068)
μ_{87}	Ralls	0.7782	(0.0650)
μ_{88}	Randolph	0.4083	(0.0477)
μ_{89}	Ray	0.1893	(0.0414)
μ_{90}	Reynolds	0.1777	(0.0403)
μ_{91}	Ripley	1.0755	(0.1179)
μ_{92}	St. Charles	1.4261	(0.1328)
μ_{93}	St. Clair	0.1436	(0.0420)
μ_{94}	Ste. Genevieve	1.2154	(0.1182)
μ_{95}	St. Francois	0.4270	(0.0415)
μ_{96}	St. Louis	1.5035	(0.1291)
μ_{97}	Saline	0.3634	(0.0397)
μ_{98}	Schuyler	0.9651	(0.1181)
μ_{99}	Scotland	0.8604	(0.1066)
μ_{100}	Scott	0.9266	(0.0699)
μ_{101}	Shannon	0.2116	(0.0417)
μ_{102}	Shelby	0.2657	(0.0433)
μ_{103}	Stoddard	0.3224	(0.0463)
μ_{104}	Stone	0.7225	(0.0711)

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Parameter	**County**	**Posterior mean**	**Standard error**
μ_{105}	Sullivan	0.1952	(0.0454)
μ_{106}	Taney	1.2739	(0.1350)
μ_{107}	Texas	0.2505	(0.0464)
μ_{108}	Vernon	1.2433	(0.1335)
μ_{109}	Warren	0.3736	(0.0467)
μ_{110}	Washington	0.2422	(0.0385)
μ_{111}	Wayne	0.2651	(0.0419)
μ_{112}	Webster	0.3393	(0.0405)
μ_{113}	Worth	1.0635	(0.1212)
μ_{114}	Wright	0.3298	(0.0431)
μ_{115}	St. Louis (City)	2.0563	(0.2012)

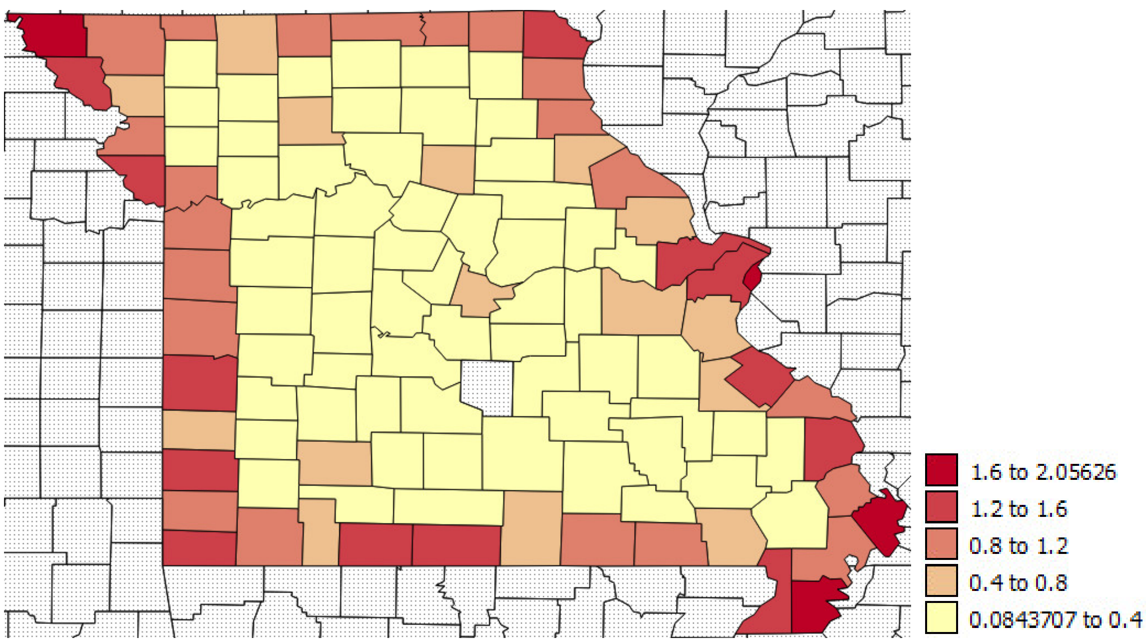


Figure 3.12: Map of posterior means of county fixed effect coefficients.

Table 3.6: Estimation results for sector fixed effects.

Sector	Posterior mean	Standard error
CO	0.3370	(0.3074)
MA	0.9001*	(0.3092)
TU	0.1588	(0.3087)
WT	-0.2994	(0.3045)
RT	-0.1067	(0.3234)
FI	-0.3819	(0.3141)
SS	0.2381	(0.3105)
GT	-0.0188	(0.3058)

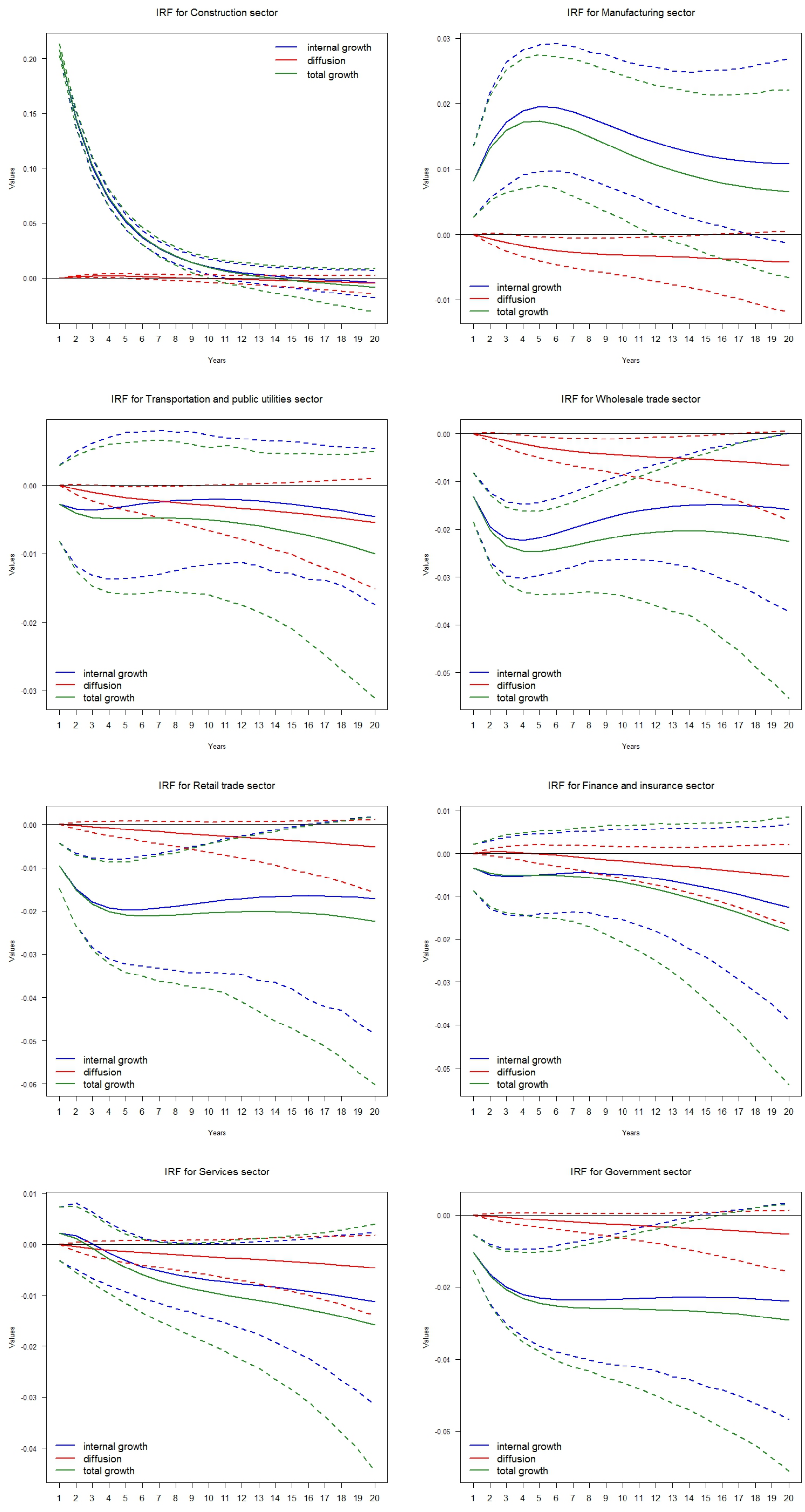


Figure 3.13: Impulse response functions in different sectors to a shock in construction sector in Boone county.

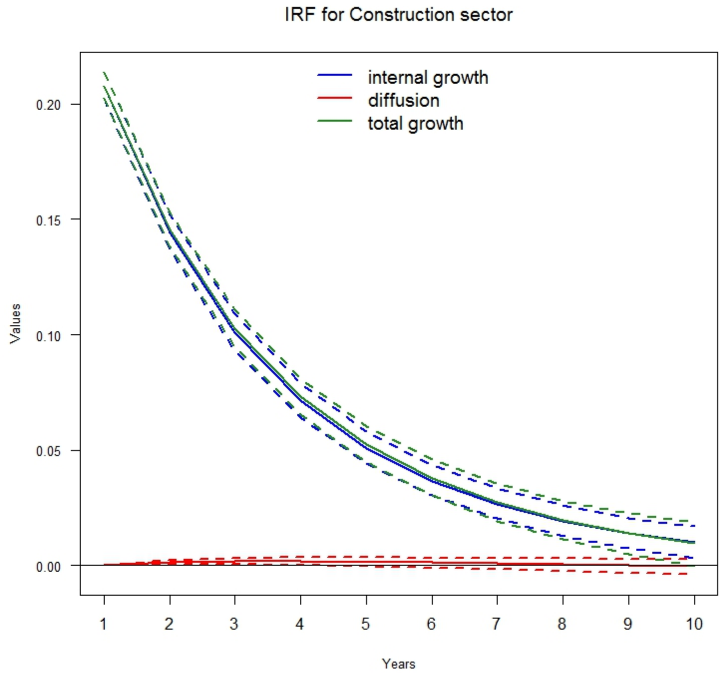


Figure 3.14: Impulse response function of construction sector to a shock in construction sector in Boone county.

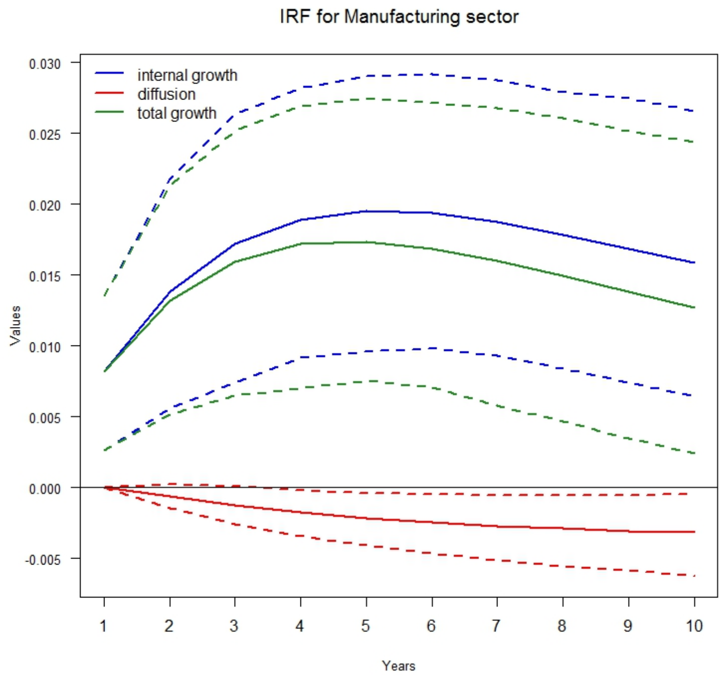


Figure 3.15: Impulse response function of manufacturing sector to a shock in construction sector in Boone county.

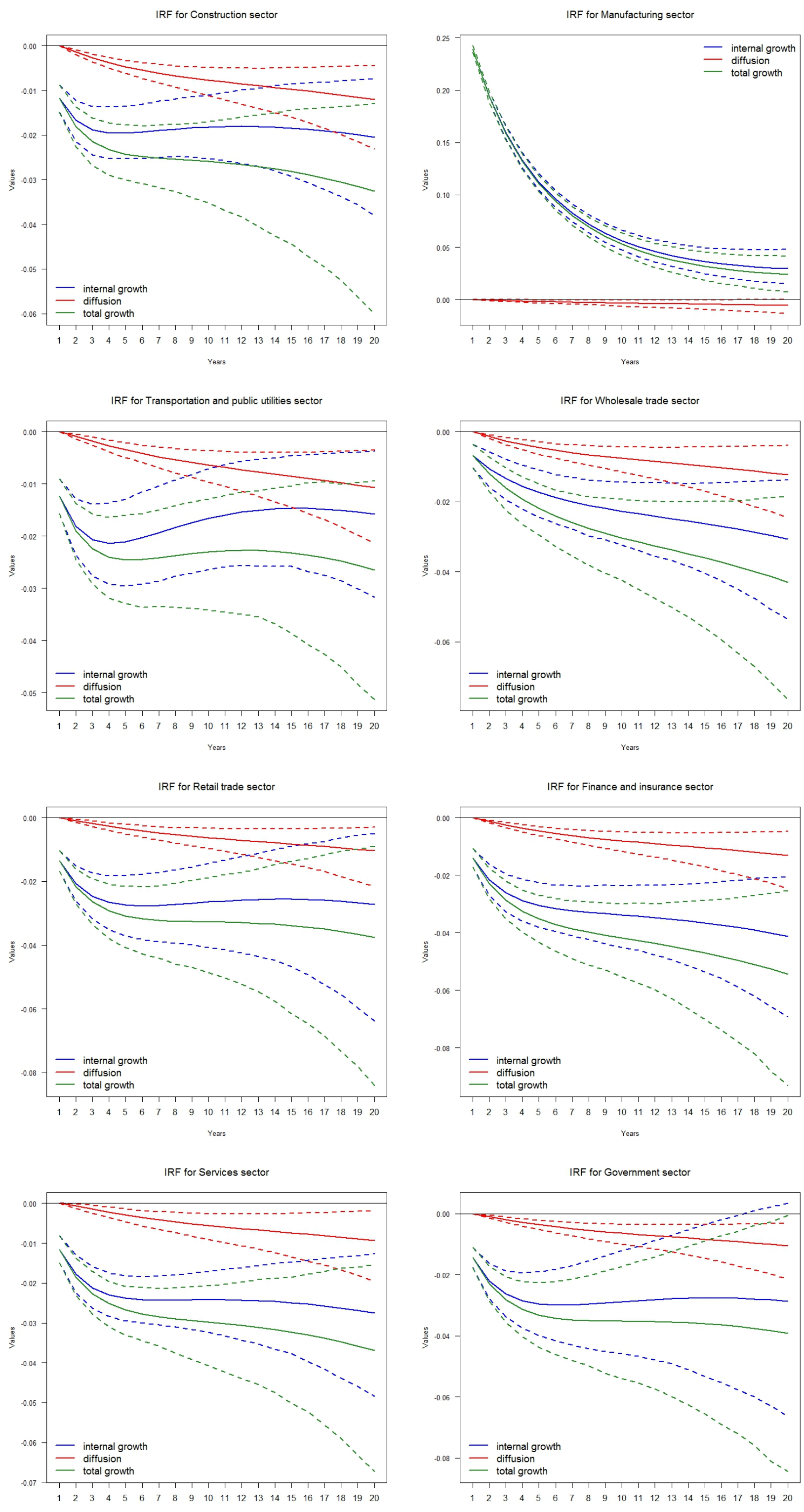


Figure 3.16: Impulse response functions in different sectors to a shock in manufacturing sector in Boone county.

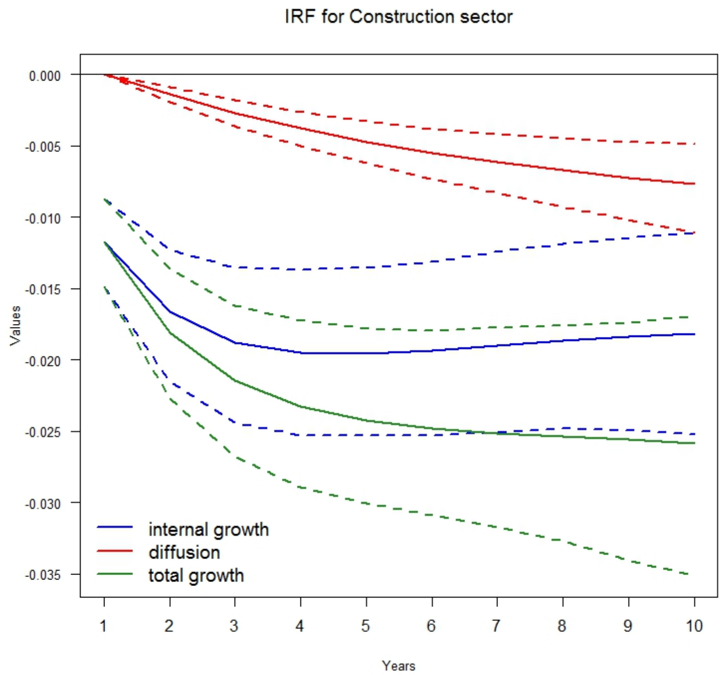


Figure 3.17: Impulse response function of construction sector to a shock in manufacturing sector in Boone county.

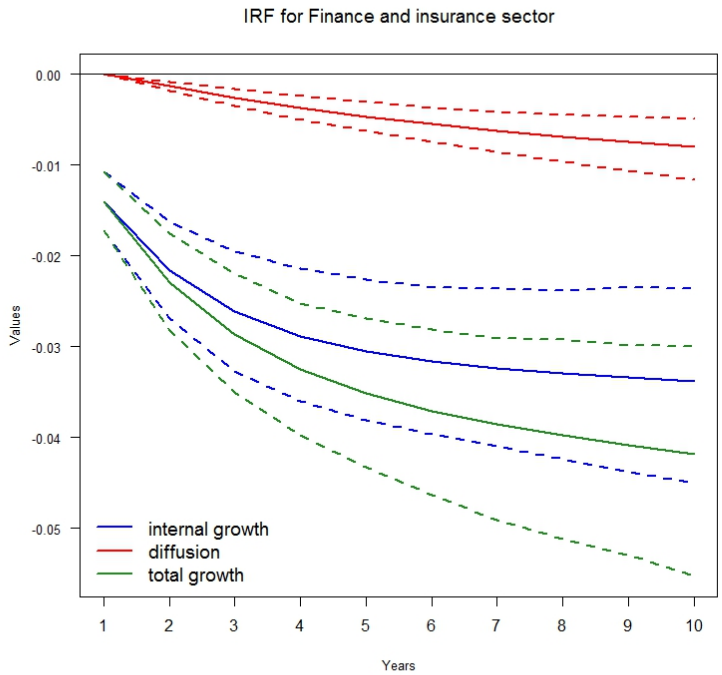


Figure 3.18: Impulse response function of finance and insurance sector to a shock in manufacturing sector in Boone county.

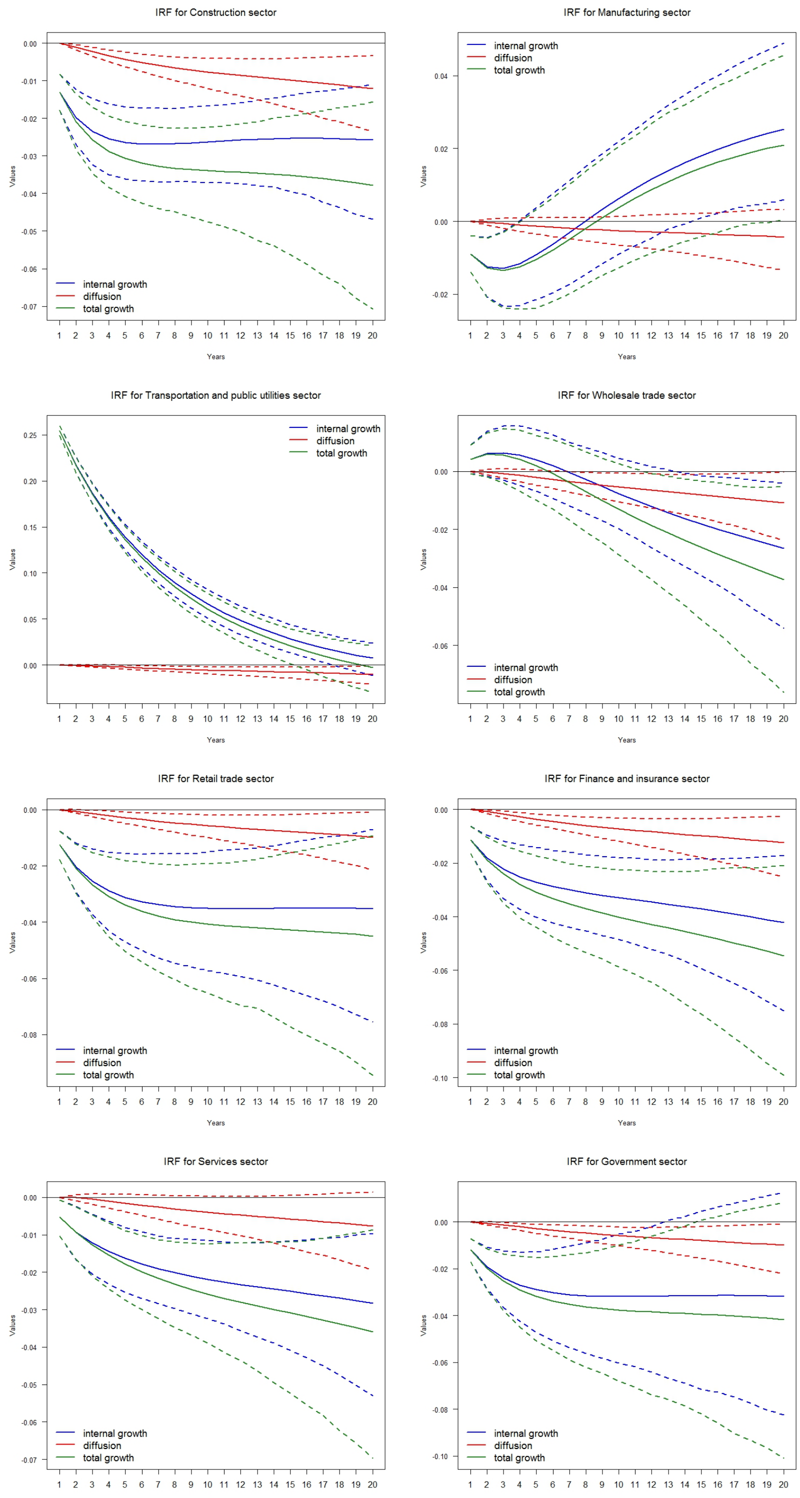


Figure 3.19: Impulse response functions in different sectors to a shock in transportation and public utilities sector in Boone county.

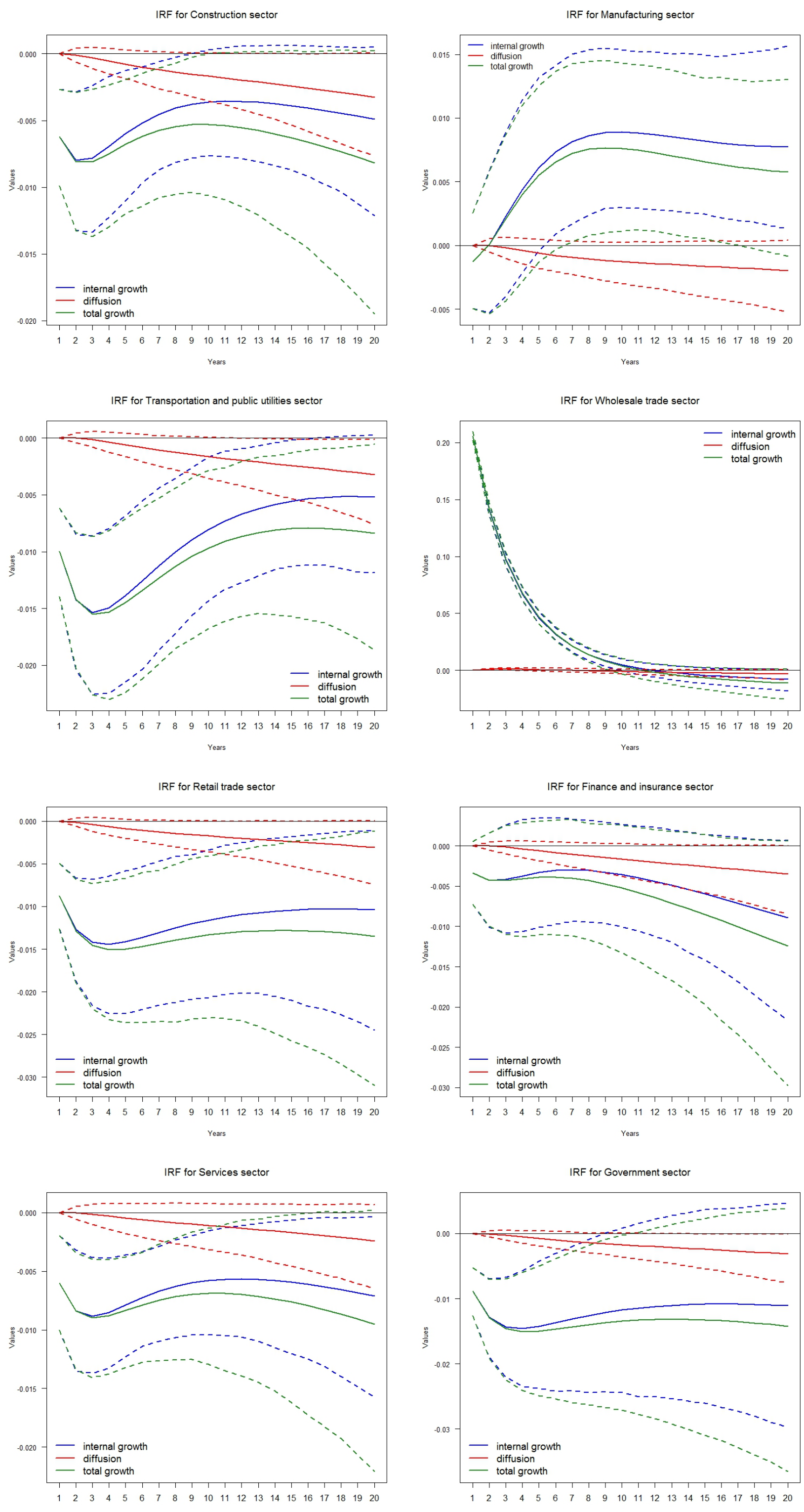


Figure 3.20: Impulse response functions in different sectors to a shock in wholesale trade sector in Boone county.

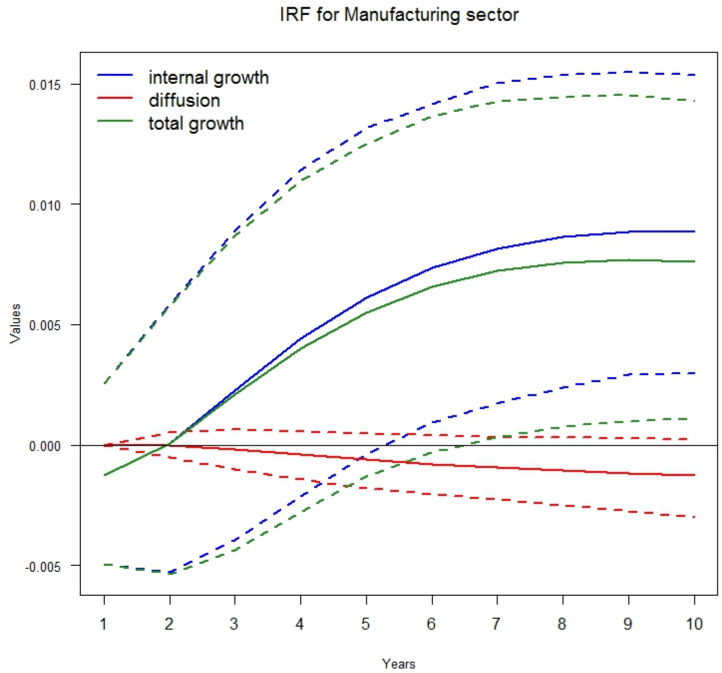


Figure 3.21: Impulse response function of manufacturing sector to a shock in wholesale trade sector in Boone county.

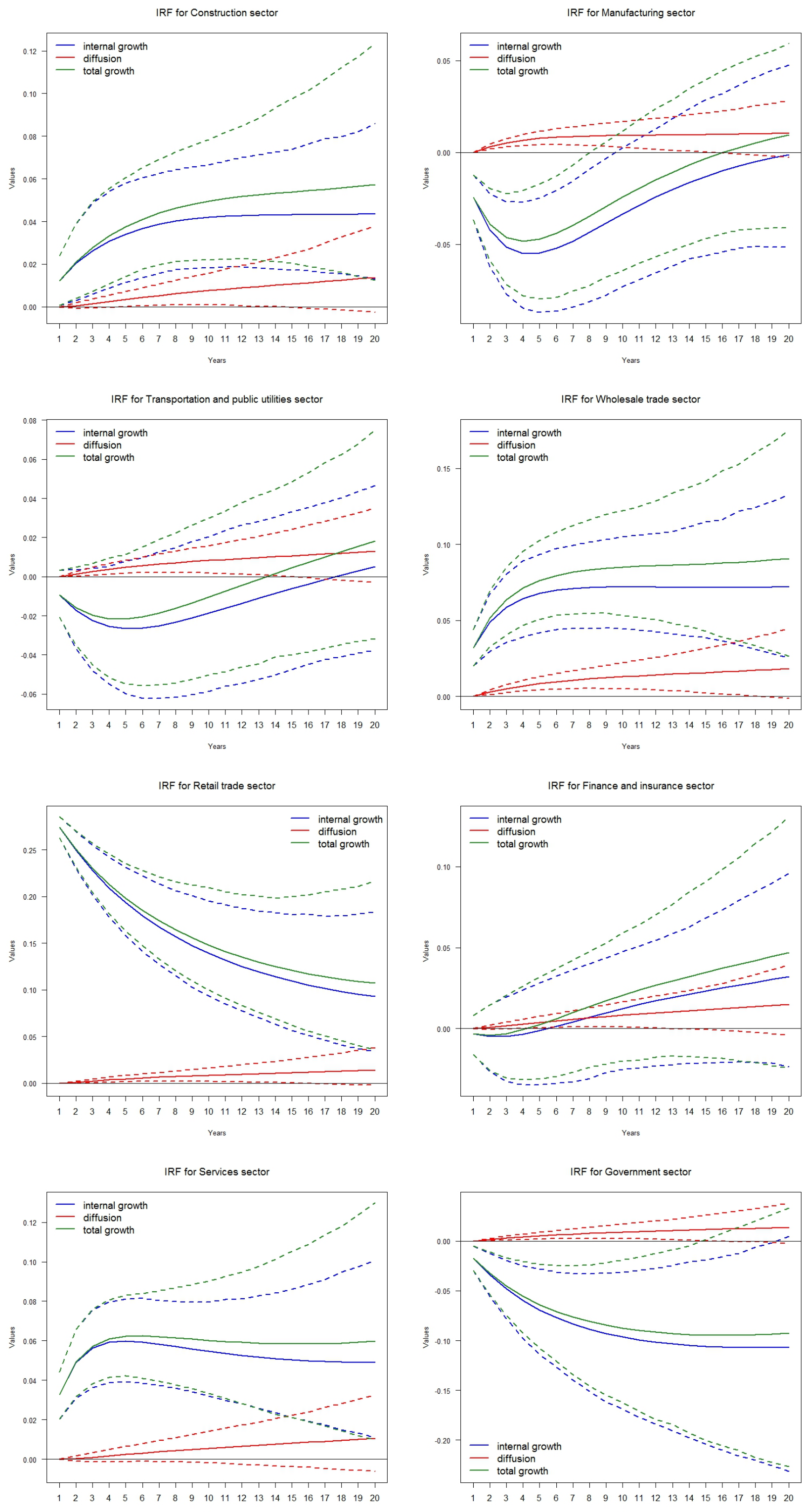


Figure 3.22: Impulse response functions in different sectors to a shock in retail trade sector in Boone county.

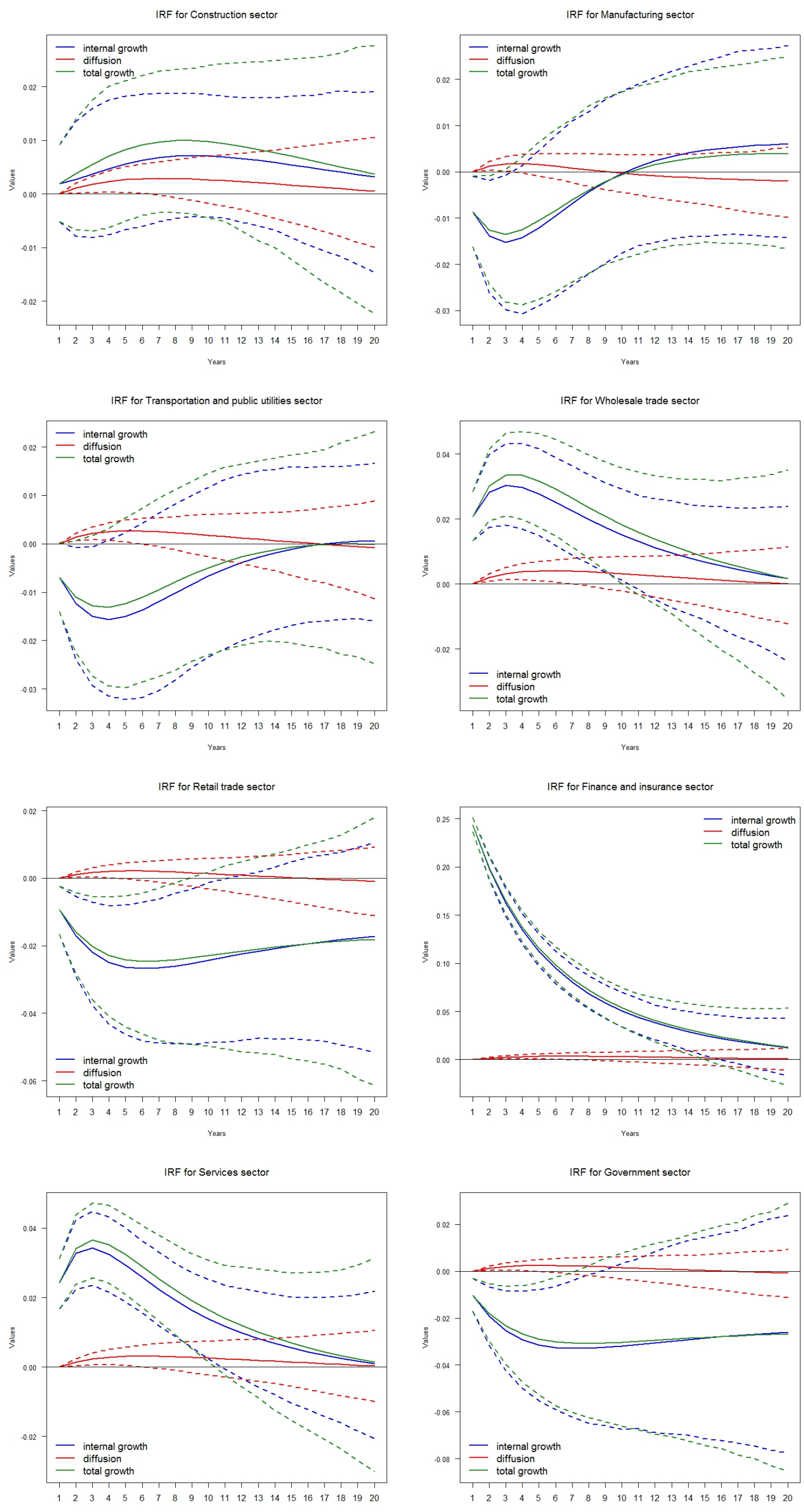


Figure 3.23: Impulse response functions in different sectors to a shock in finance and insurance sector in Boone county.

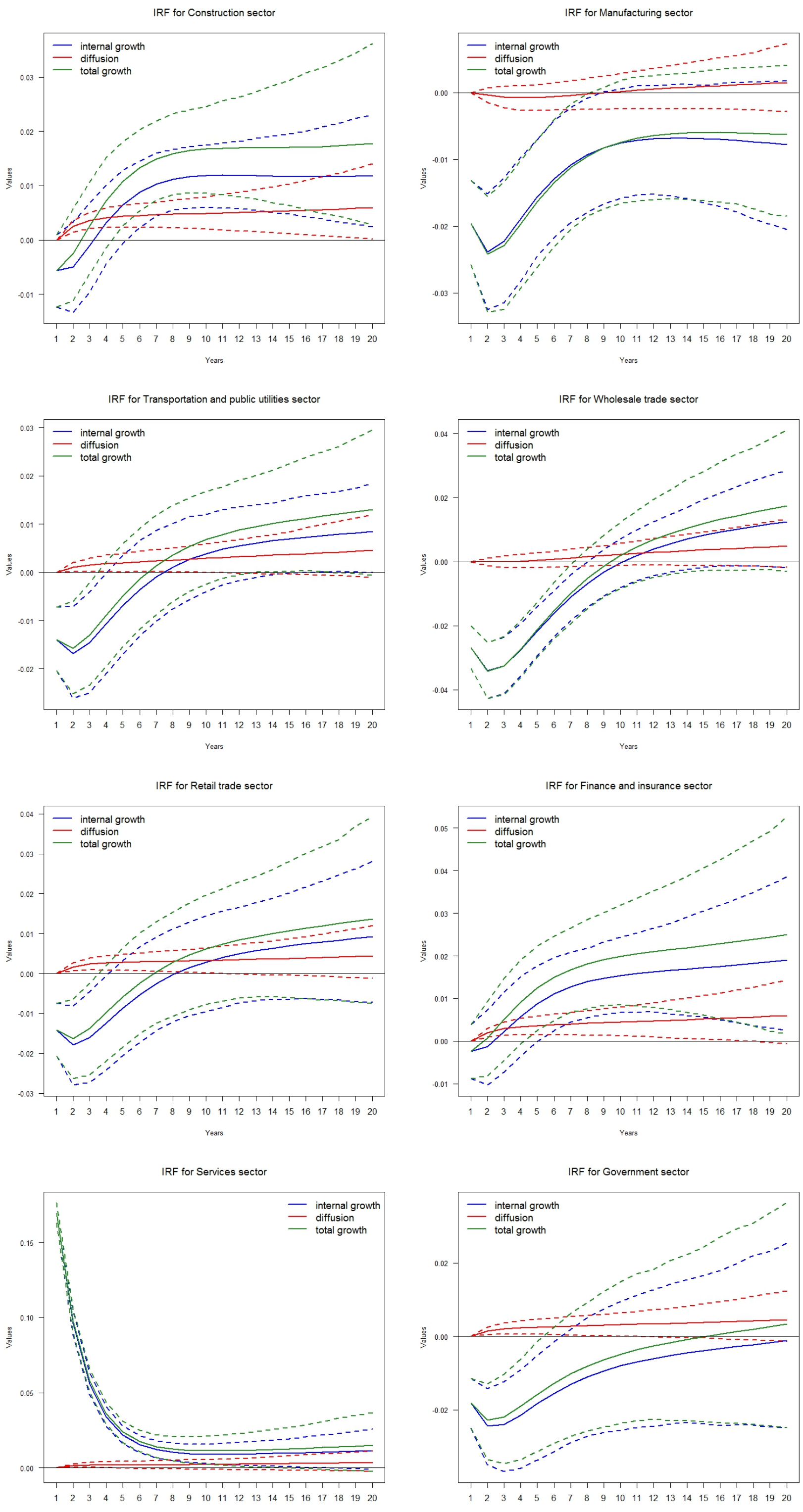


Figure 3.24: Impulse response functions in different sectors to a shock in services sector in Boone county.

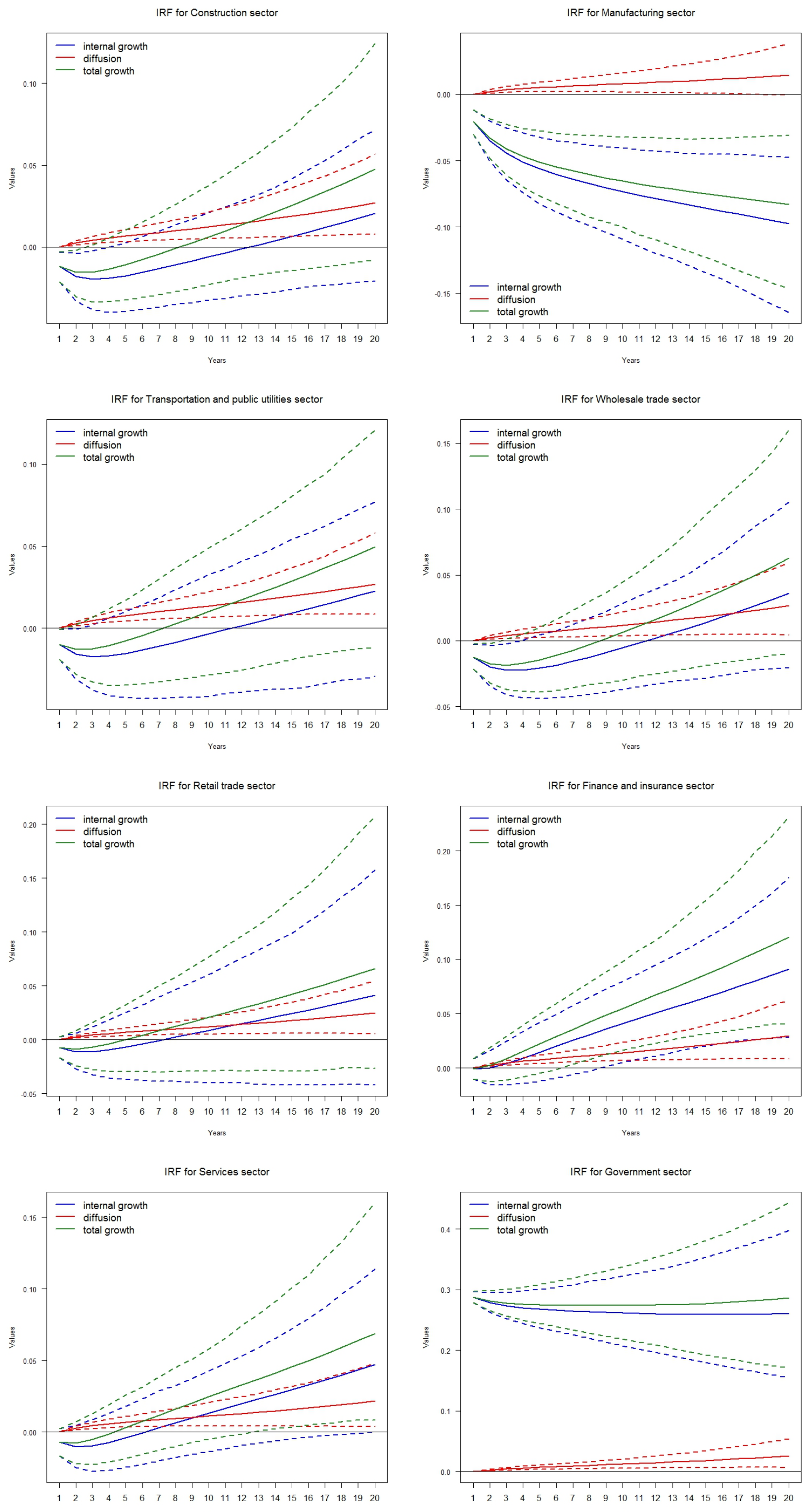


Figure 3.33: Impulse response functions in different sectors to a shock in government sector in Boone county.

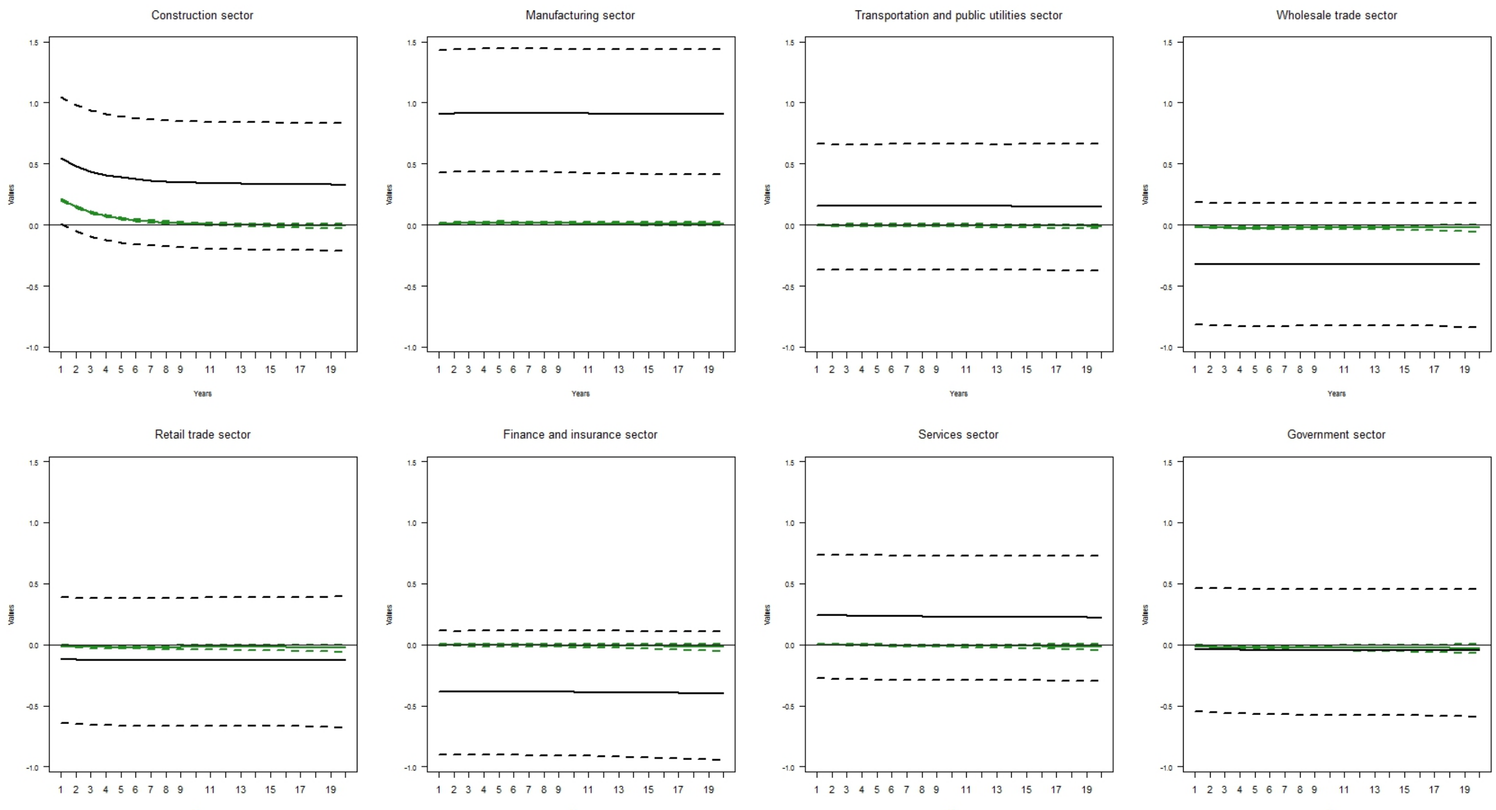


Figure 3.25: Impulse response functions with sector fixed effects in different sectors to a shock in construction sector in Boone county.

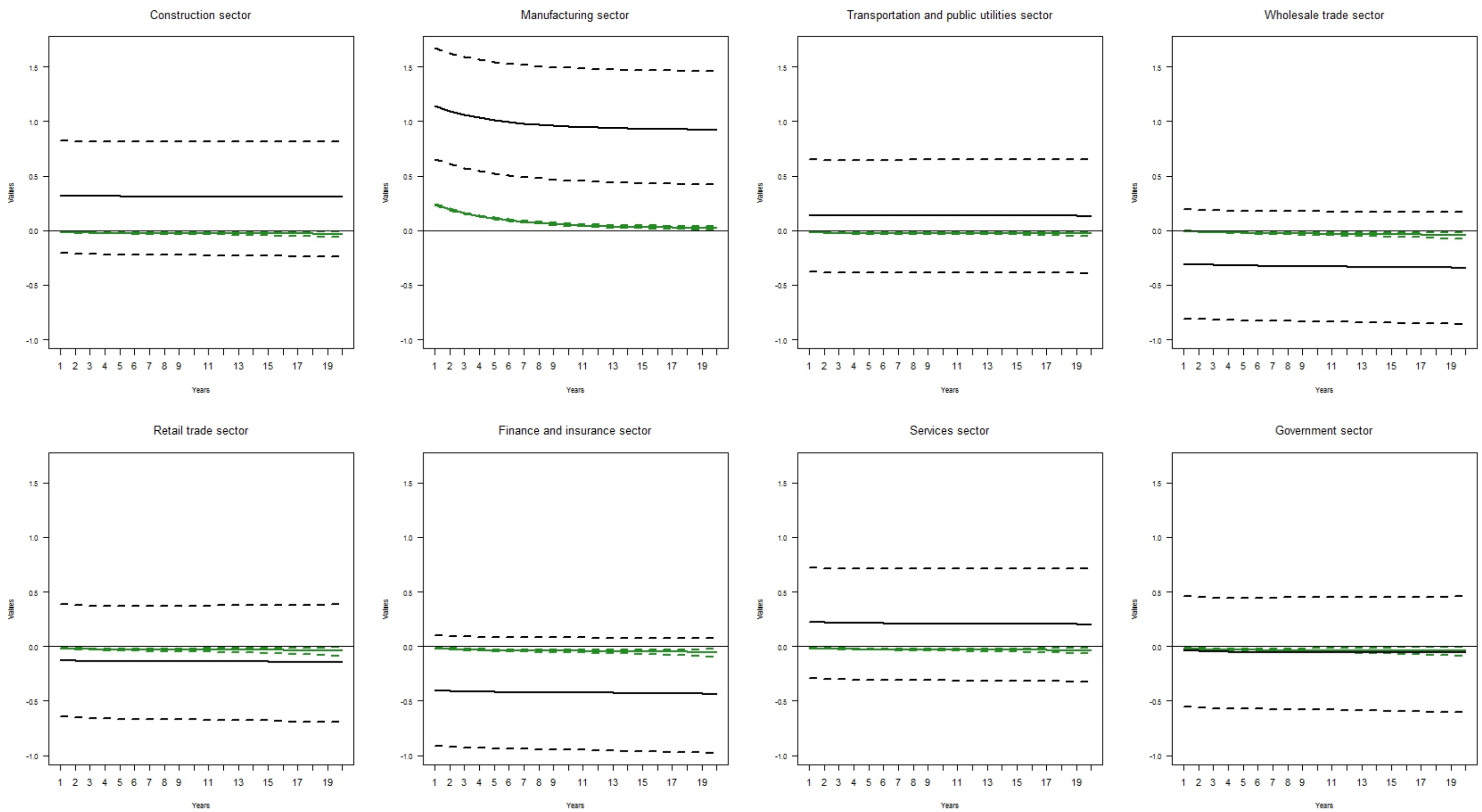


Figure 3.26: Impulse response functions with sector fixed effects in different sectors to a shock in manufacturing sector in Boone county.

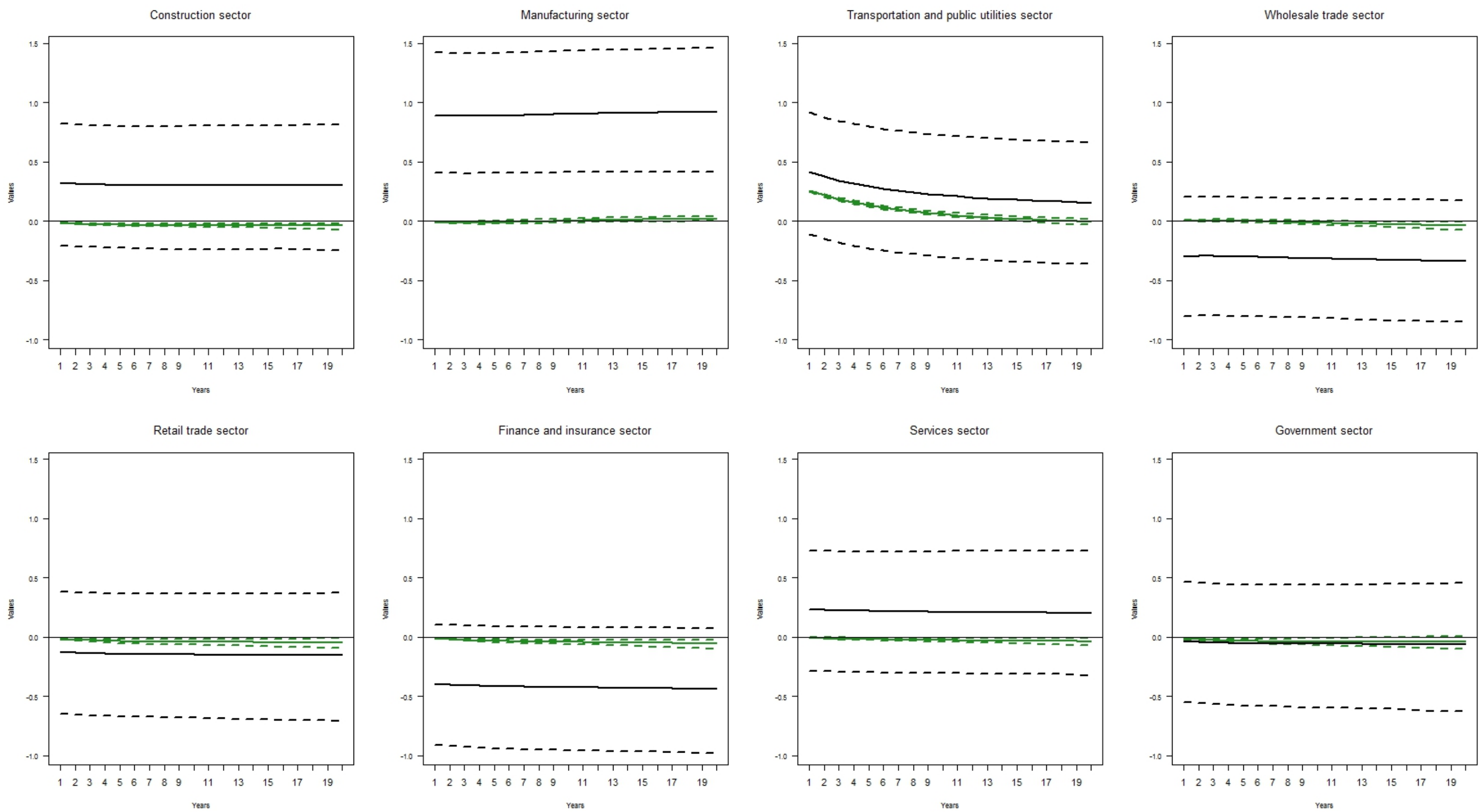


Figure 3.27: Impulse response functions with sector fixed effects in different sectors to a shock in transportation and public utilities sector in Boone county.

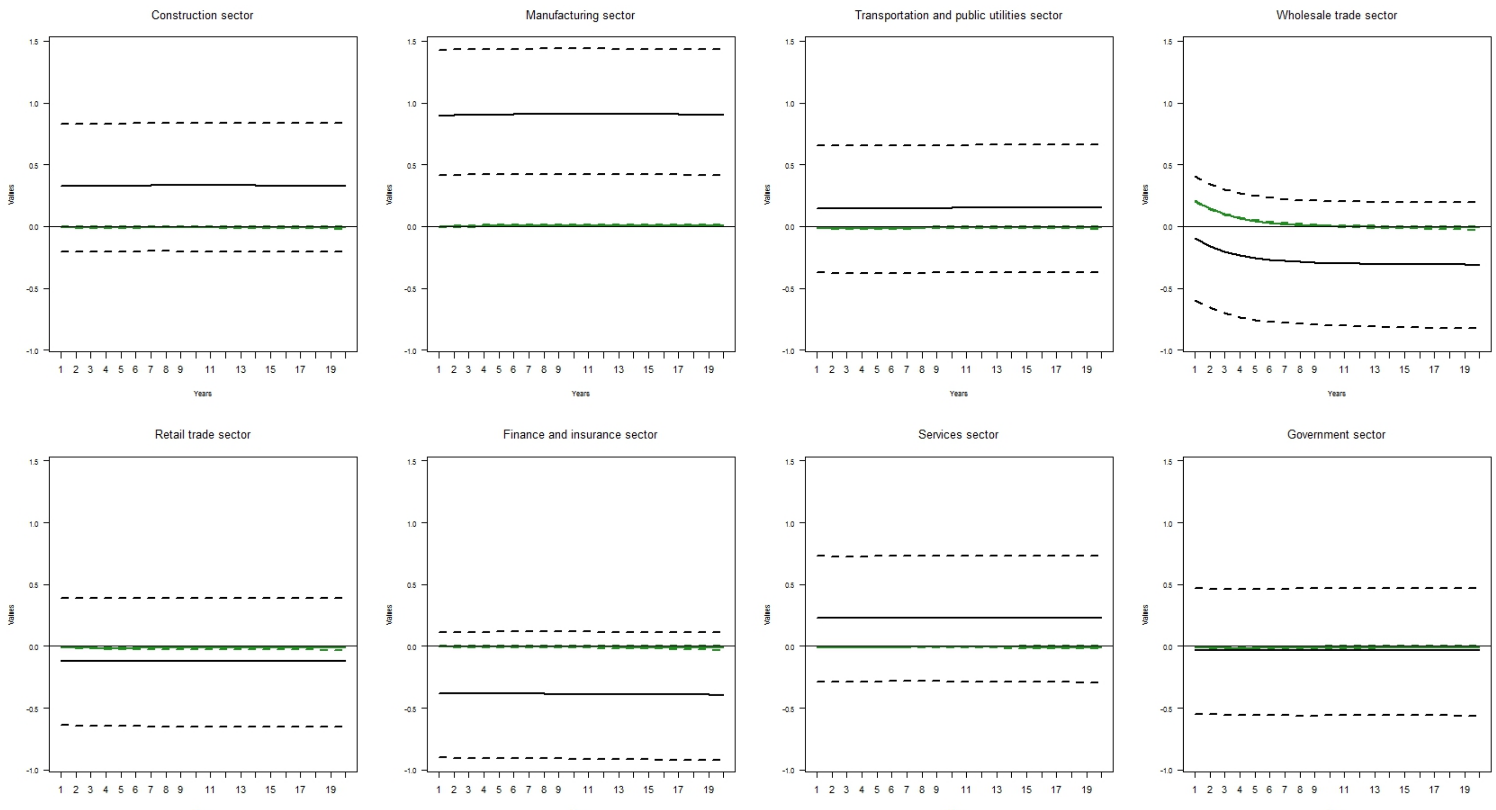


Figure 3.28: Impulse response functions with sector fixed effects in different sectors to a shock in wholesale trade sector in Boone county.

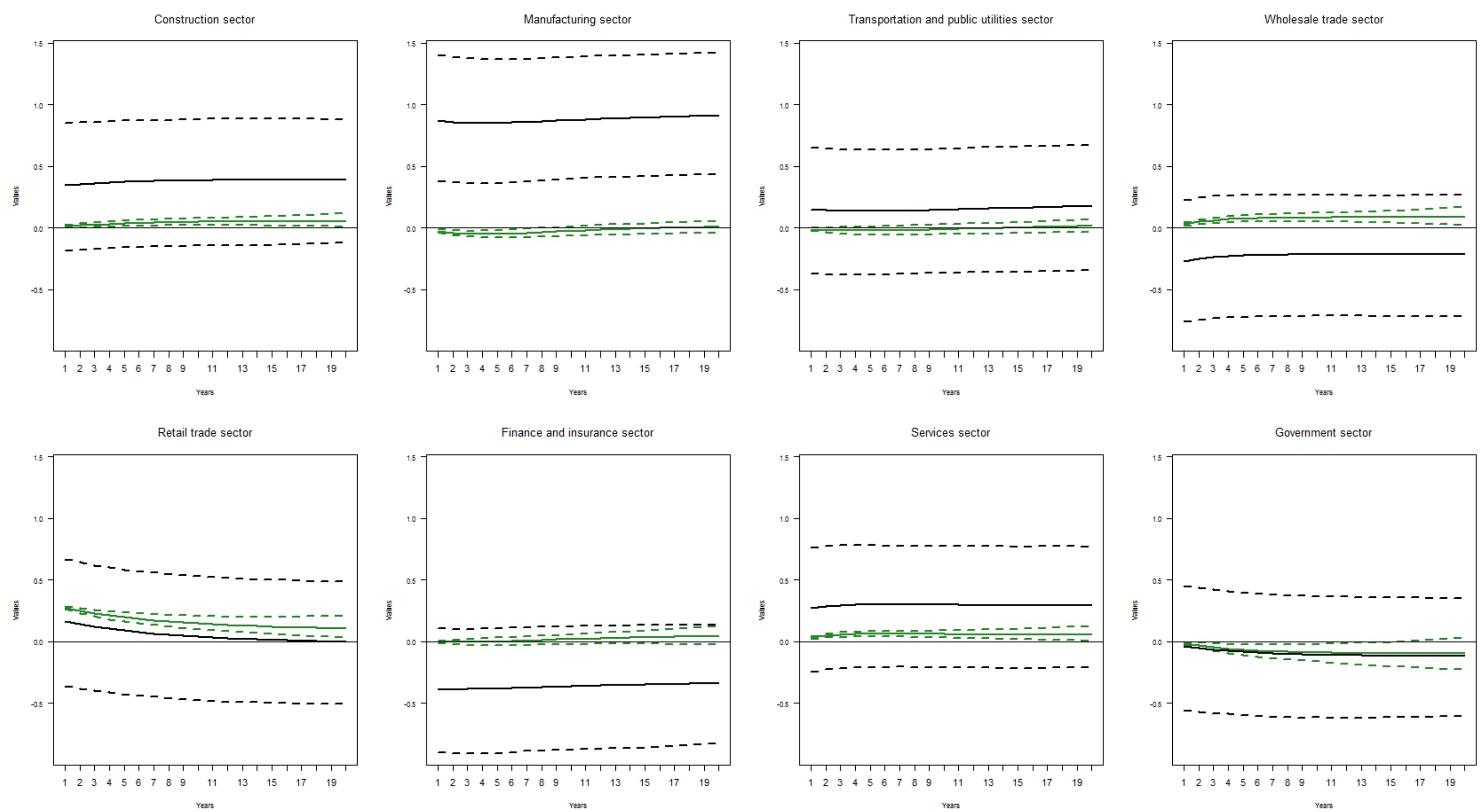


Figure 3.29: Impulse response functions with sector fixed effects in different sectors to a shock in retail trade sector in Boone county.

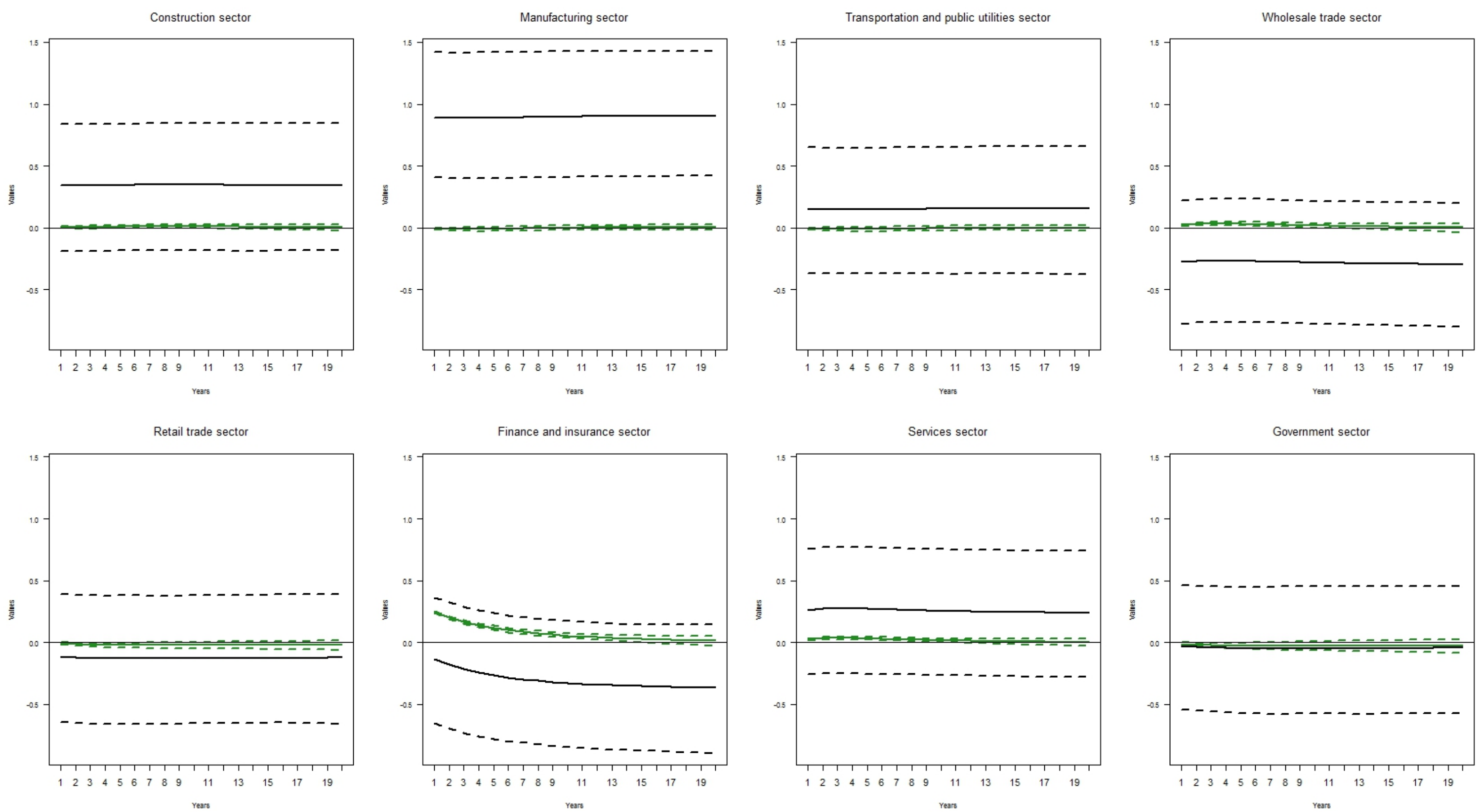


Figure 3.30: Impulse response functions with sector fixed effects in different sectors to a shock in finance and insurance sector in Boone county.

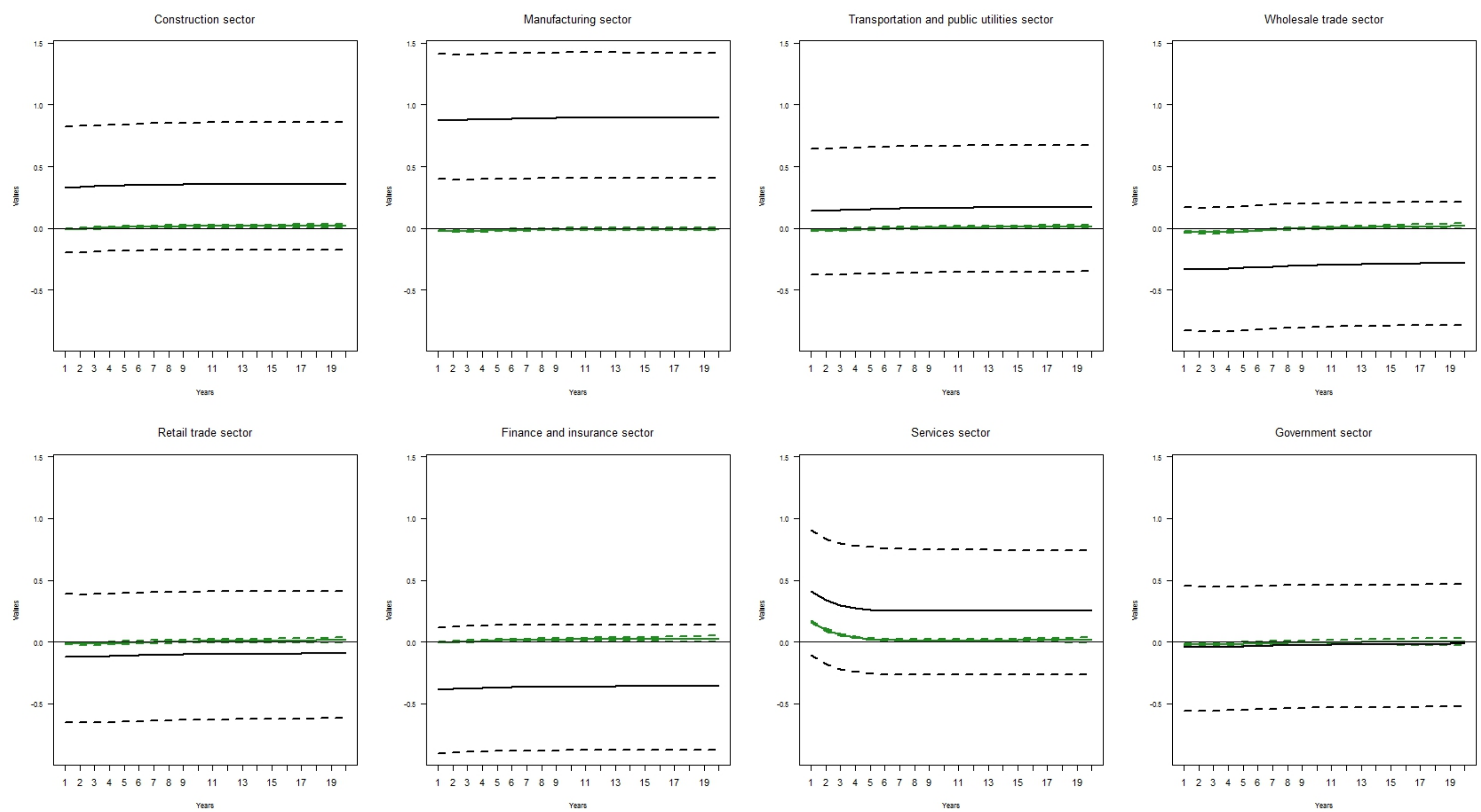


Figure 3.31: Impulse response functions with sector fixed effects in different sectors to a shock in services sector in Boone county.

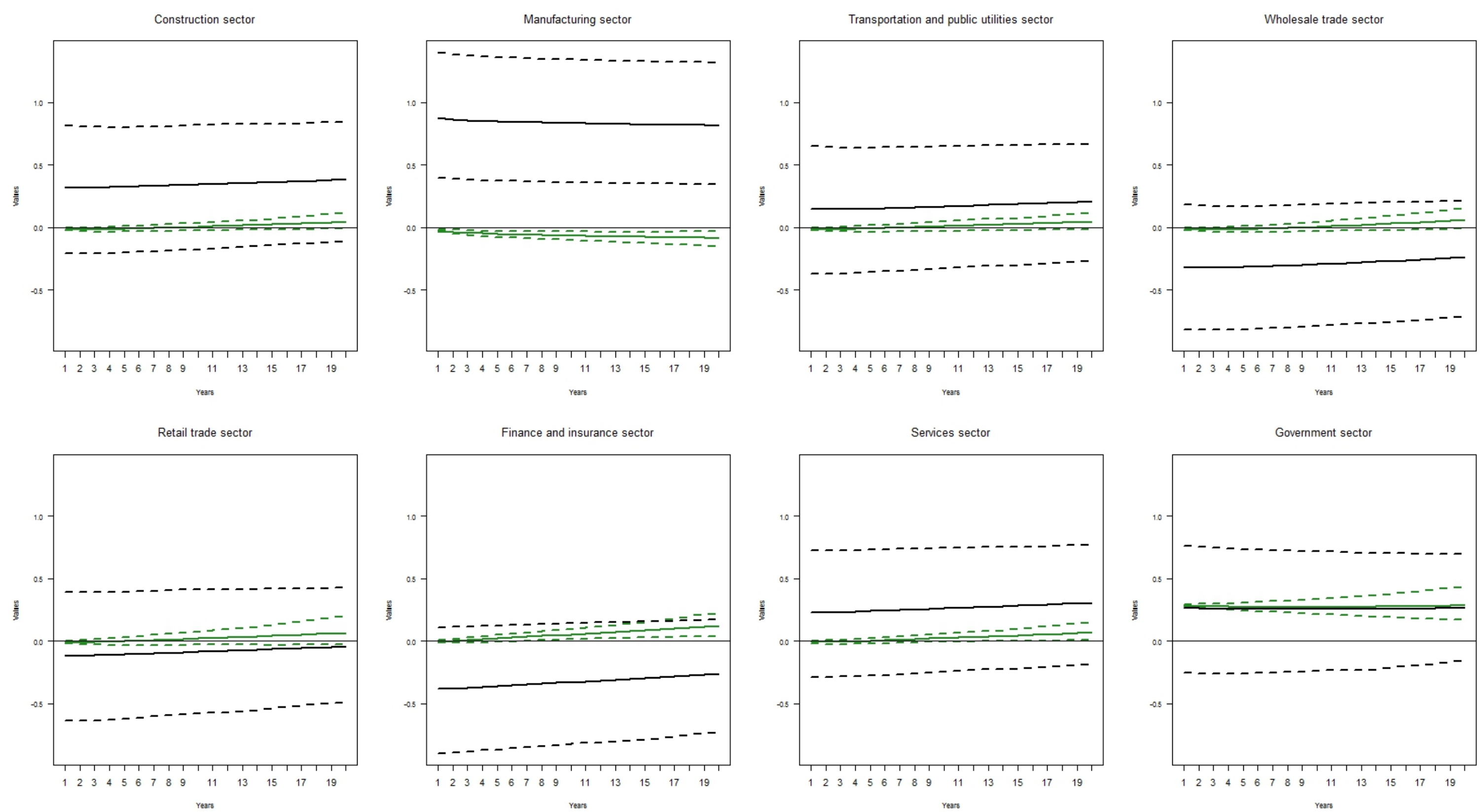


Figure 3.32: Impulse response functions with sector fixed effects in different sectors to a shock in government sector in Boone county.

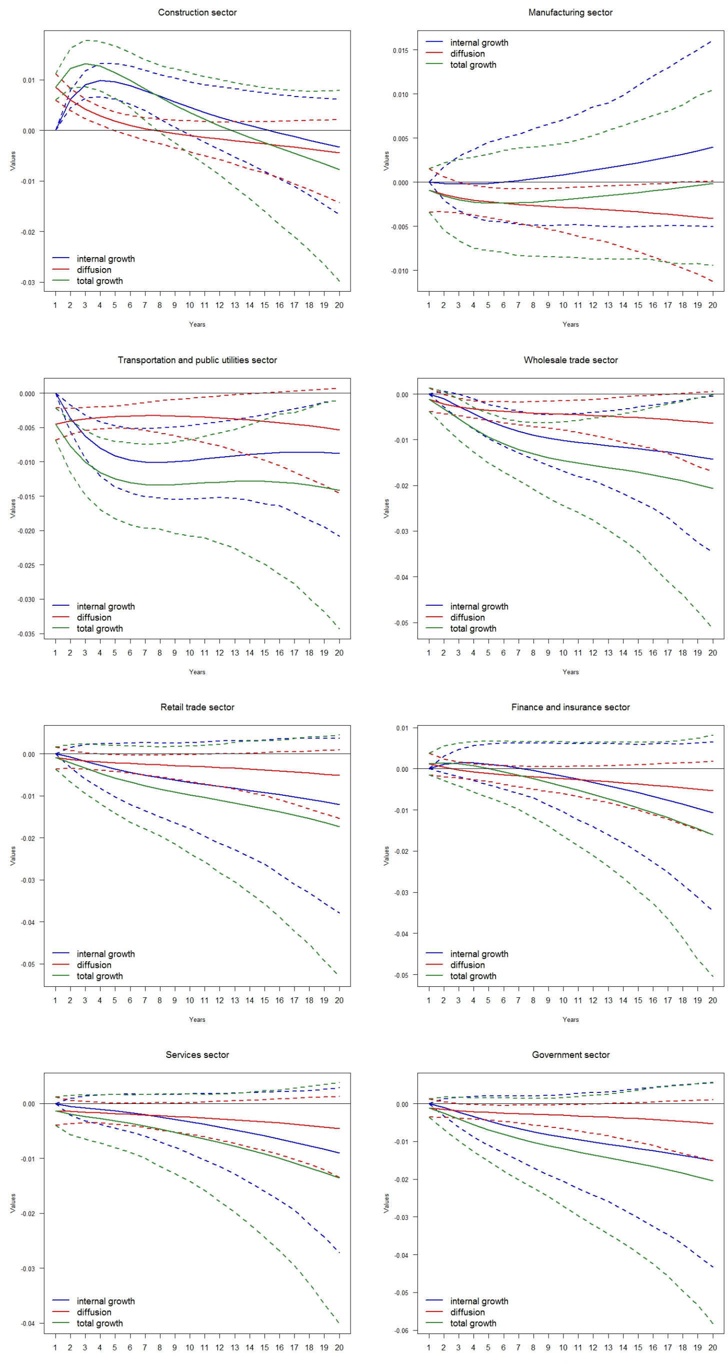


Figure 3.34: Impulse response functions in different sectors in Cole county to a shock in construction sector in Boone county.

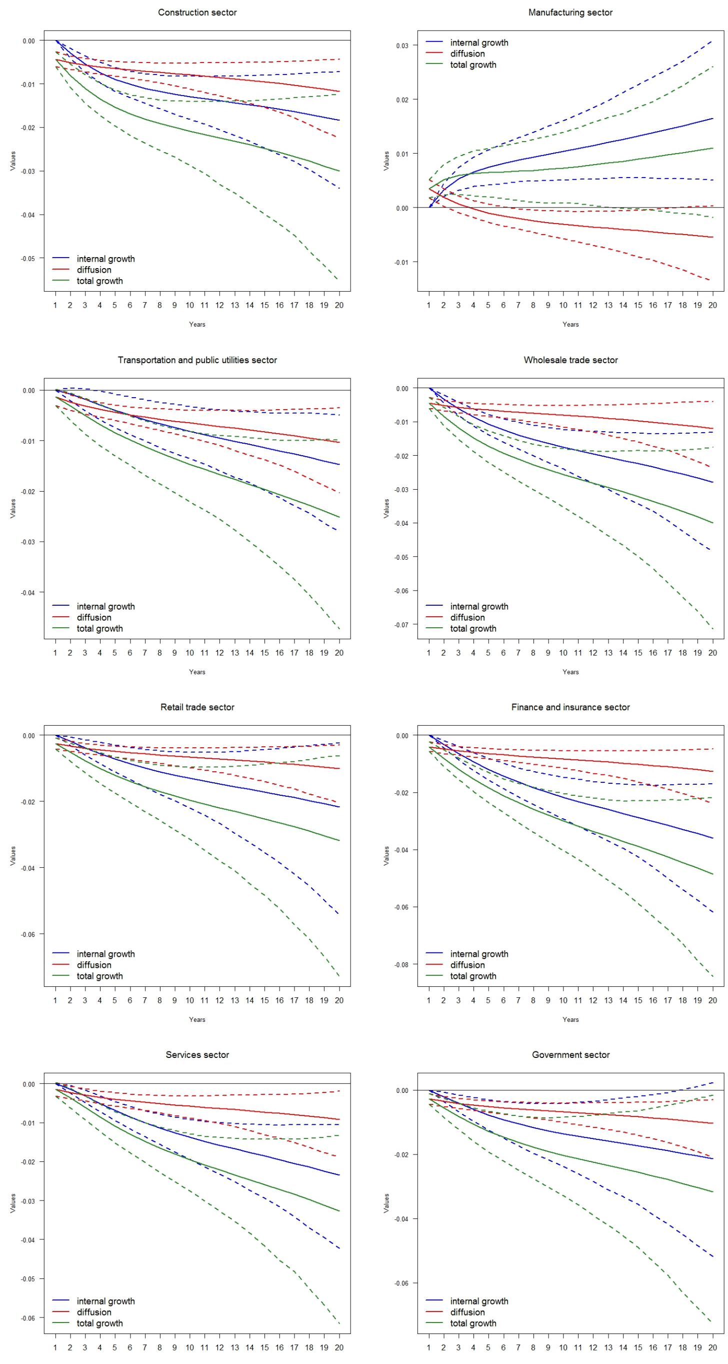


Figure 3.35: Impulse response functions in different sectors in Cole county to a shock in manufacturing sector in Boone county.

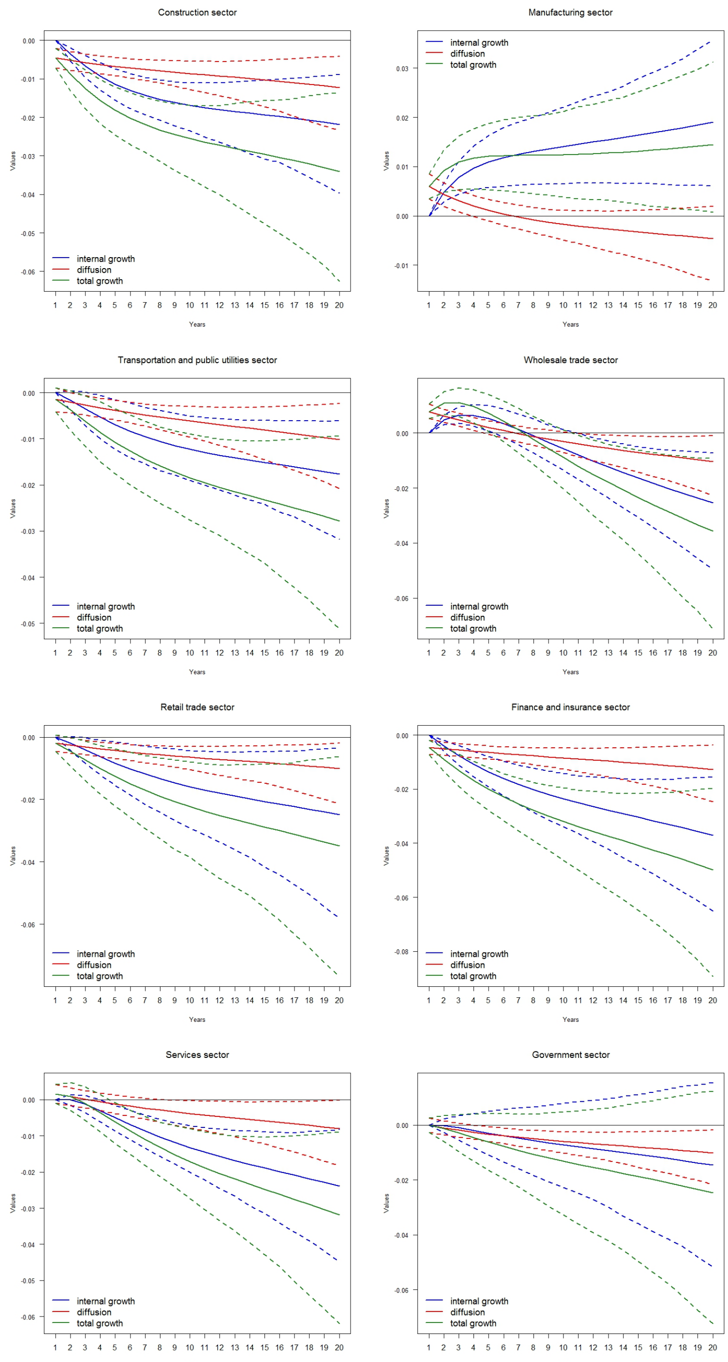


Figure 3.36: Impulse response functions in different sectors in Cole county to a shock in transportation and public utilities sector in Boone county.

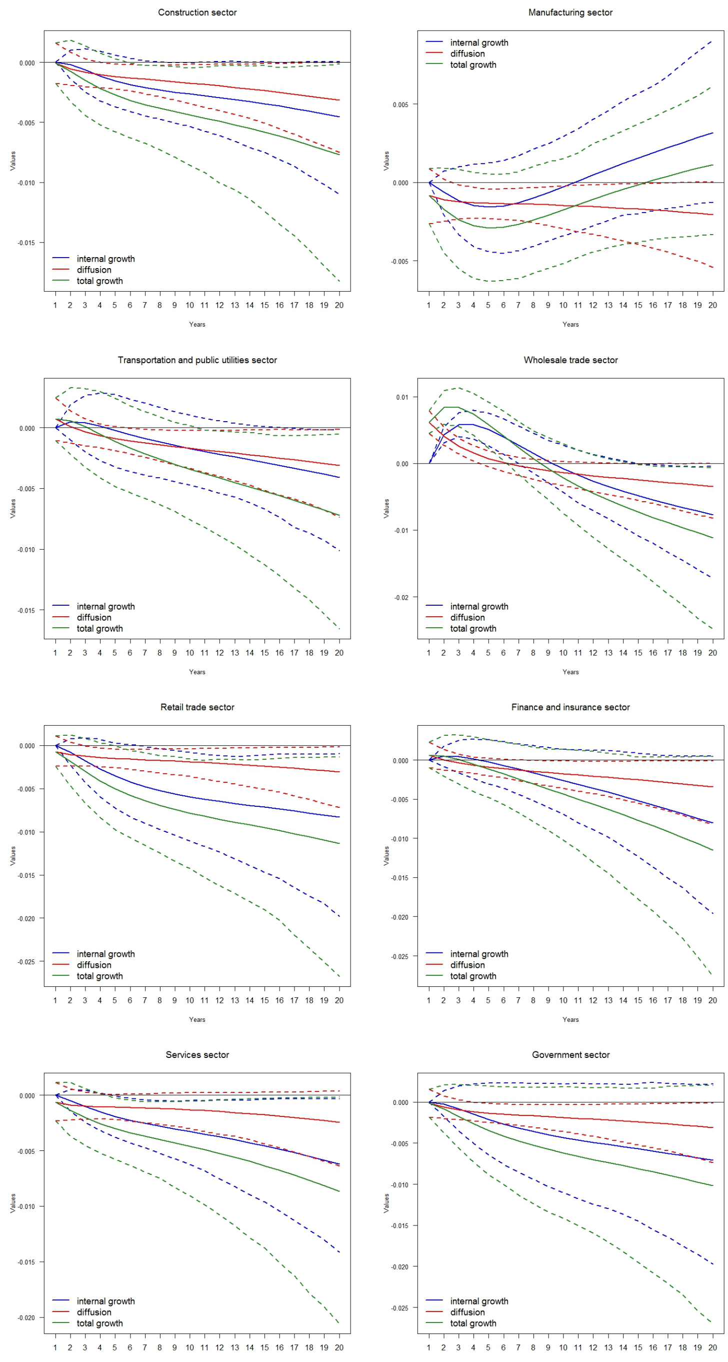


Figure 3.37: Impulse response functions in different sectors in Cole county to a shock in wholesale trade sector in Boone county.

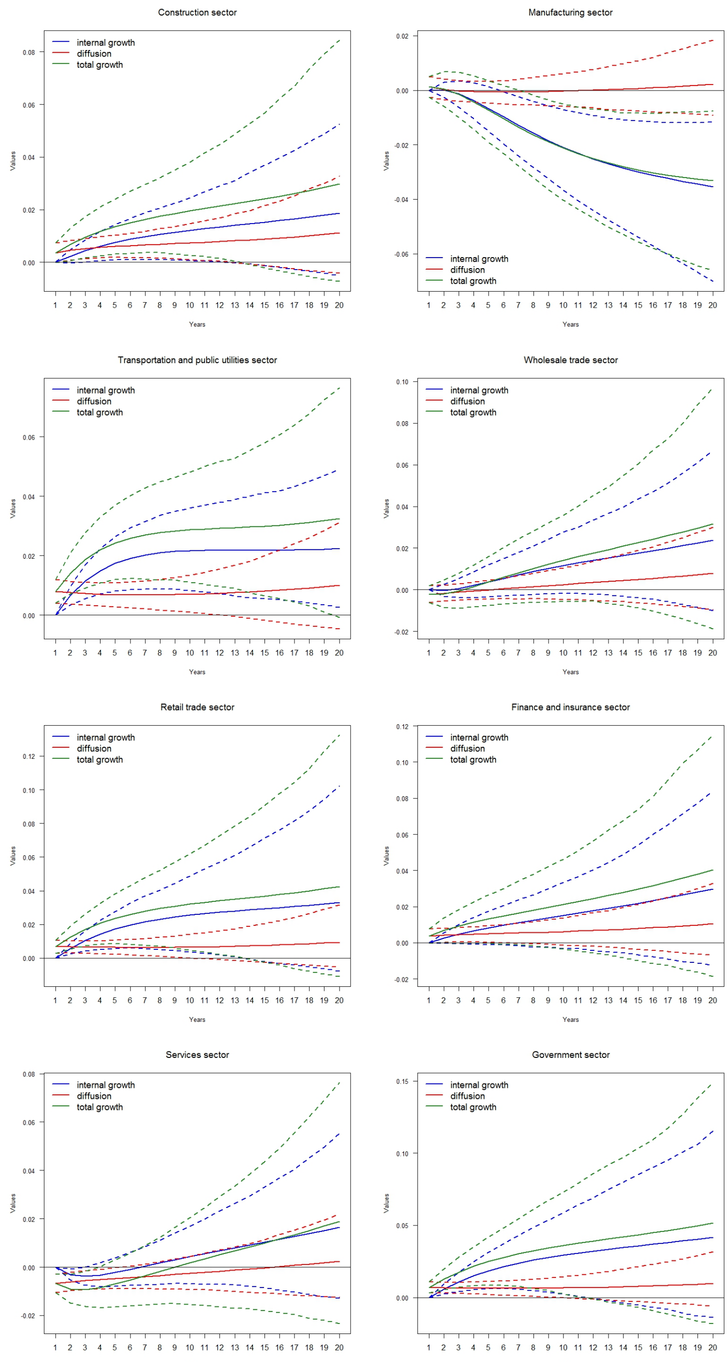


Figure 3.38: Impulse response functions in different sectors in Cole county to a shock in retail trade sector in Boone county.

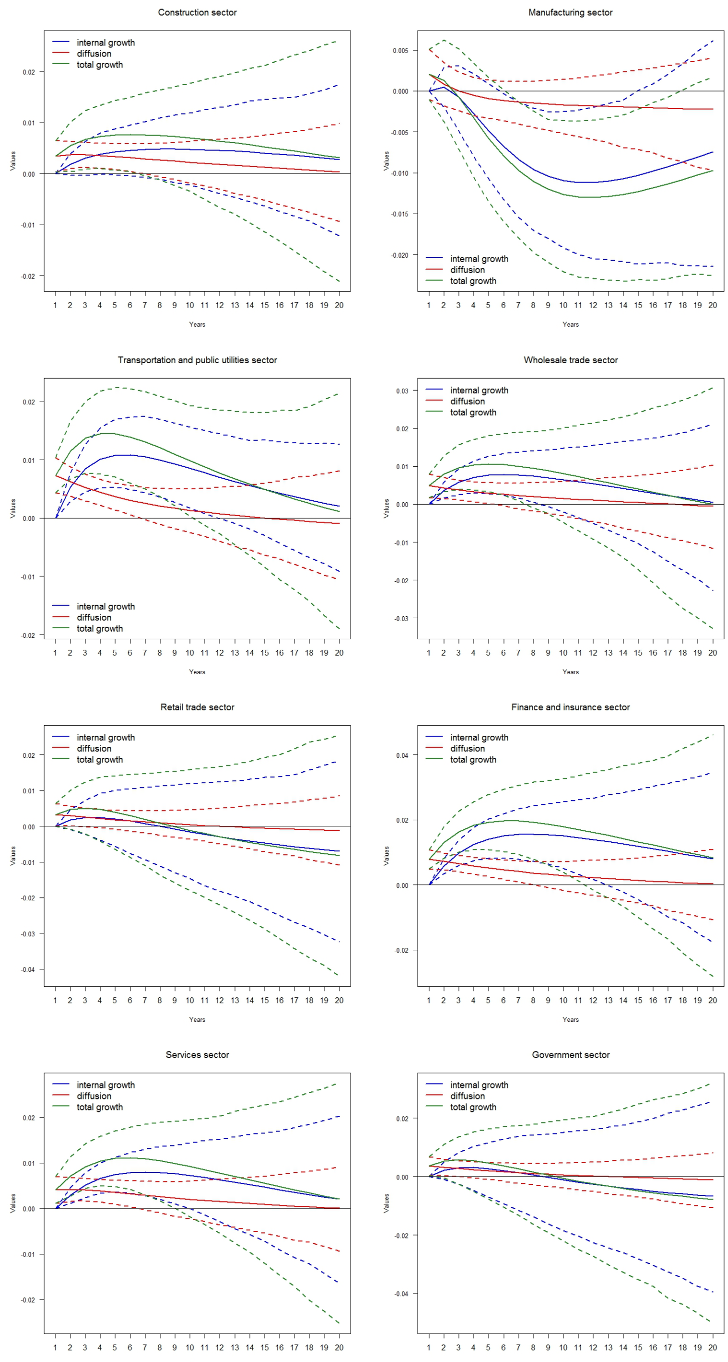


Figure 3.39: Impulse response functions in different sectors in Cole county to a shock in finance and insurance sector in Boone county.

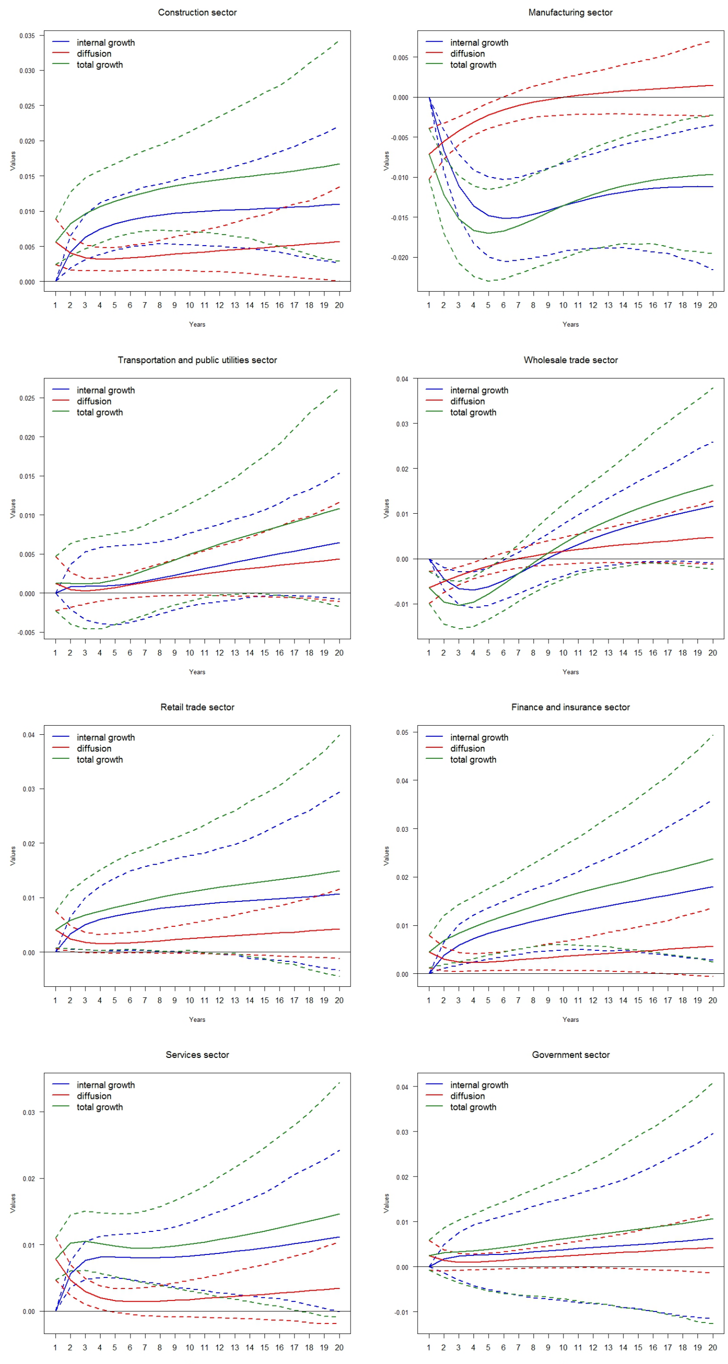


Figure 3.40: Impulse response functions in different sectors in Cole county to a shock in services sector in Boone county.

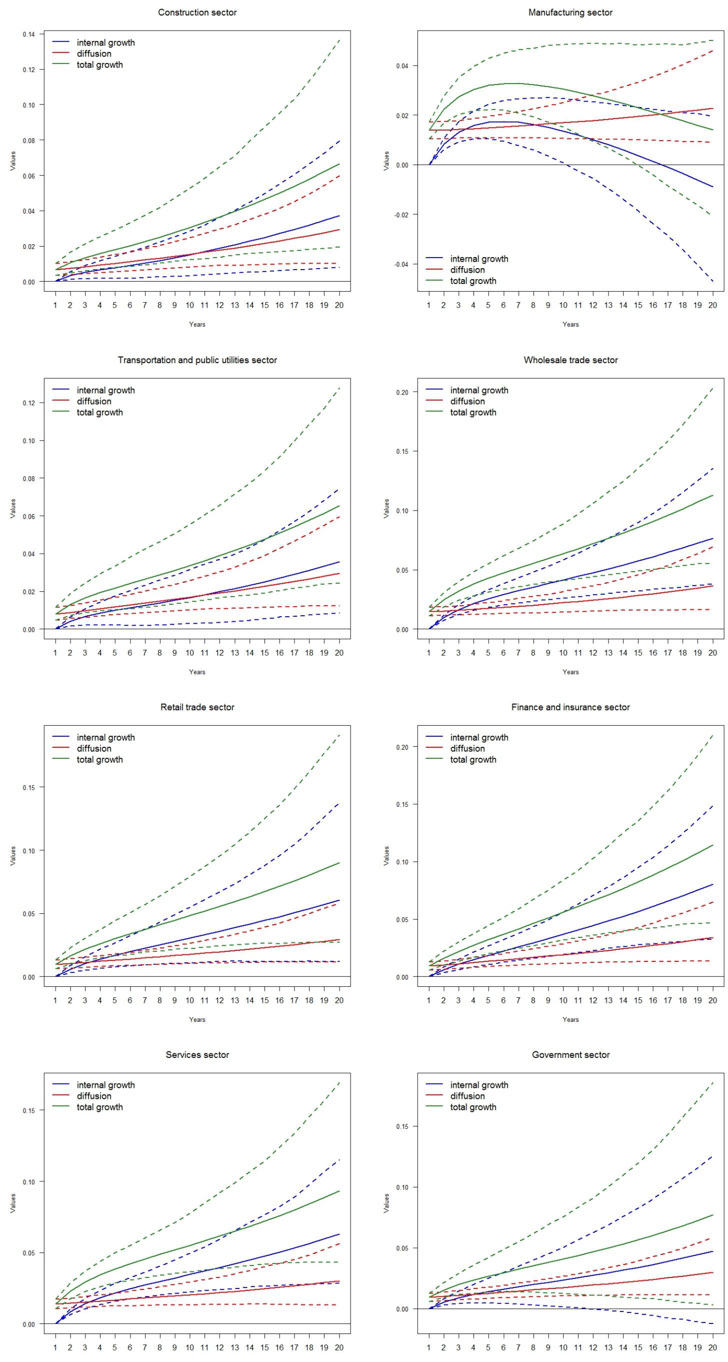


Figure 3.49: Impulse response functions in different sectors in Cole county to a shock in government sector in Boone county.

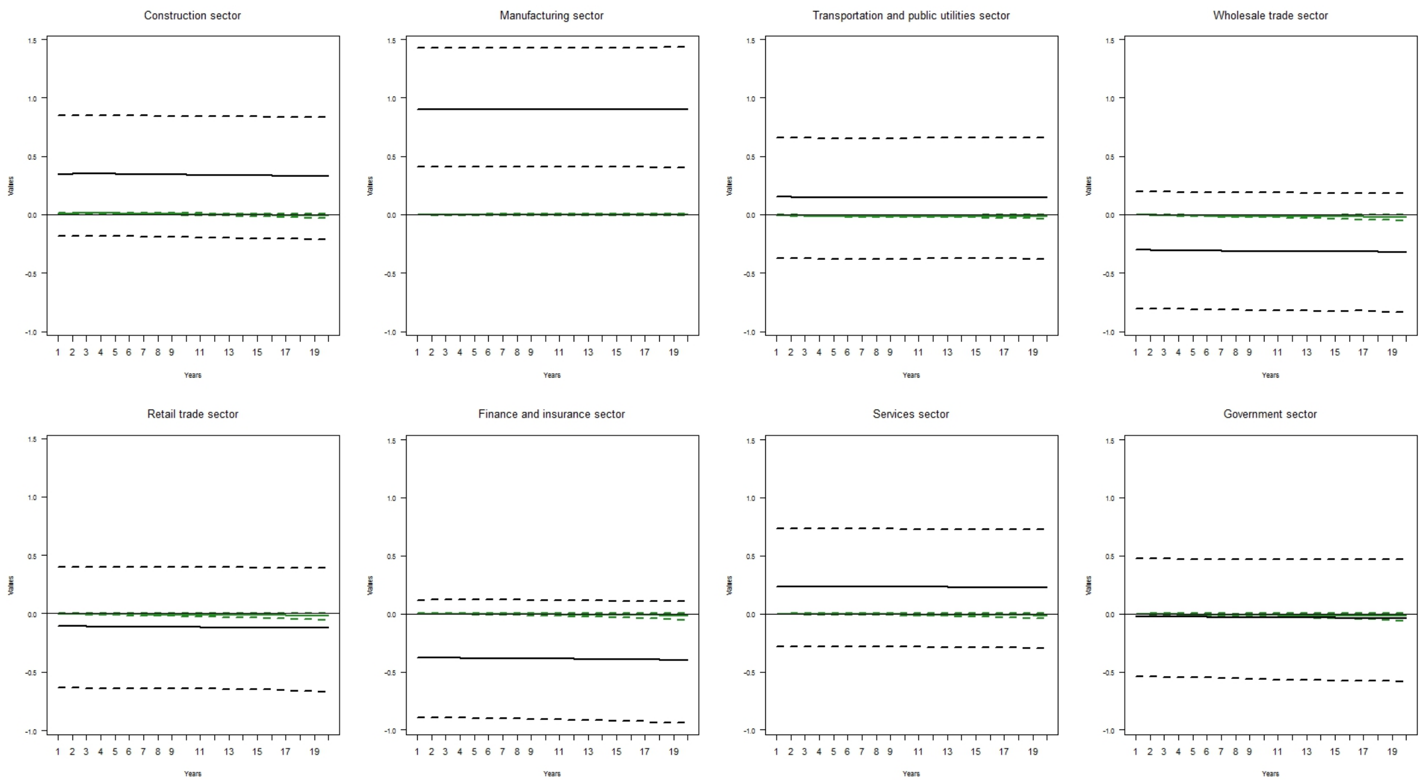


Figure 3.41: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in construction sector in Boone county.

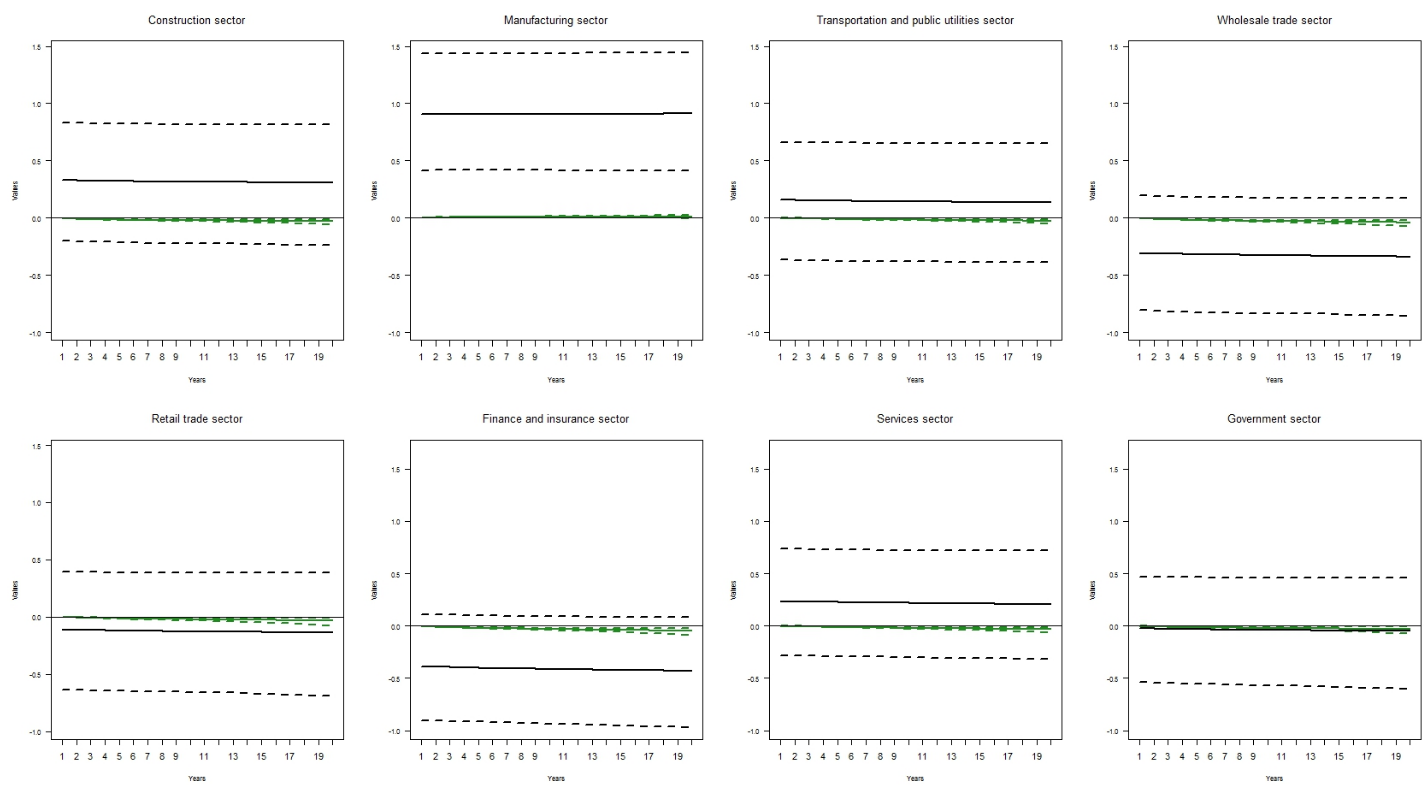


Figure 3.42: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in manufacturing sector in Boone county.

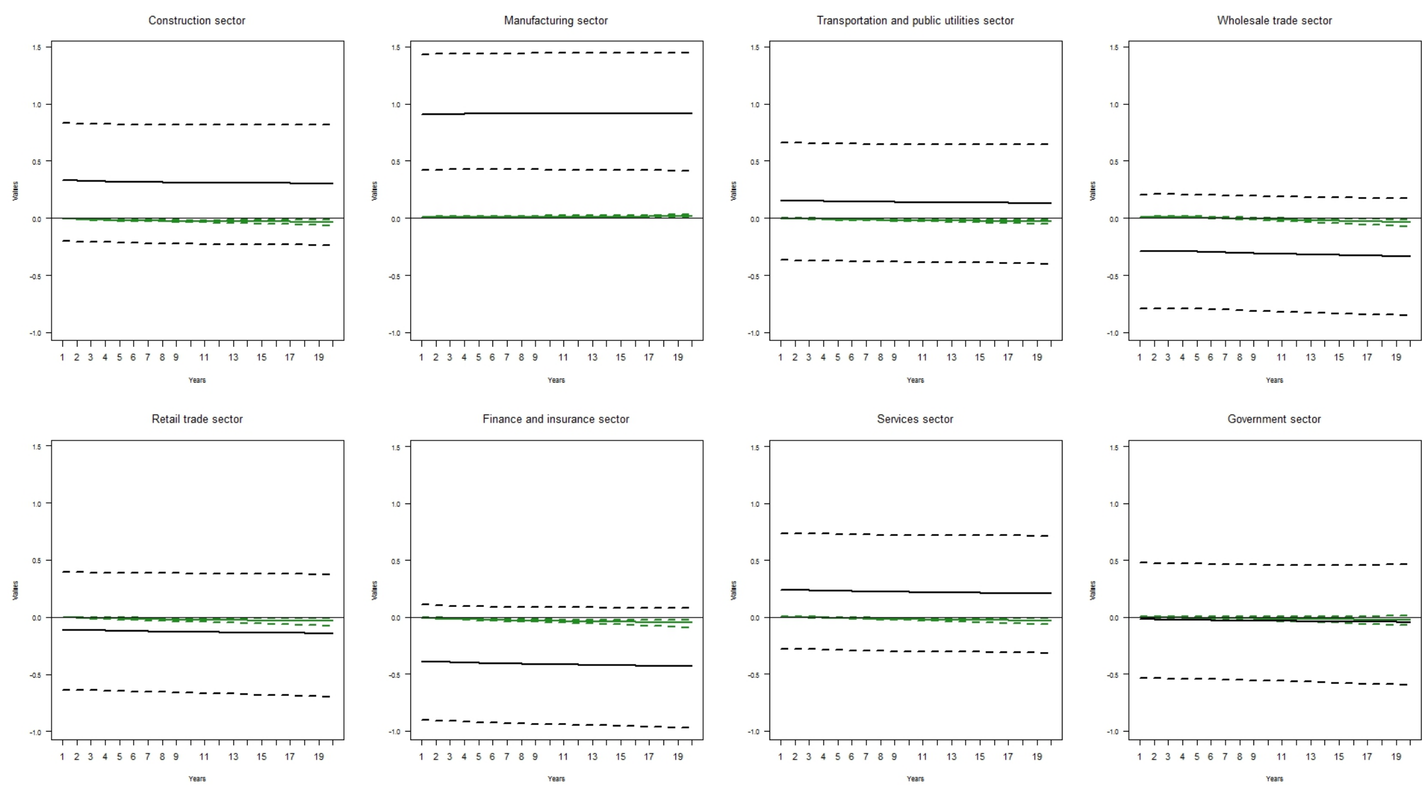


Figure 3.43: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in transportation and public utilities sector in Boone county.

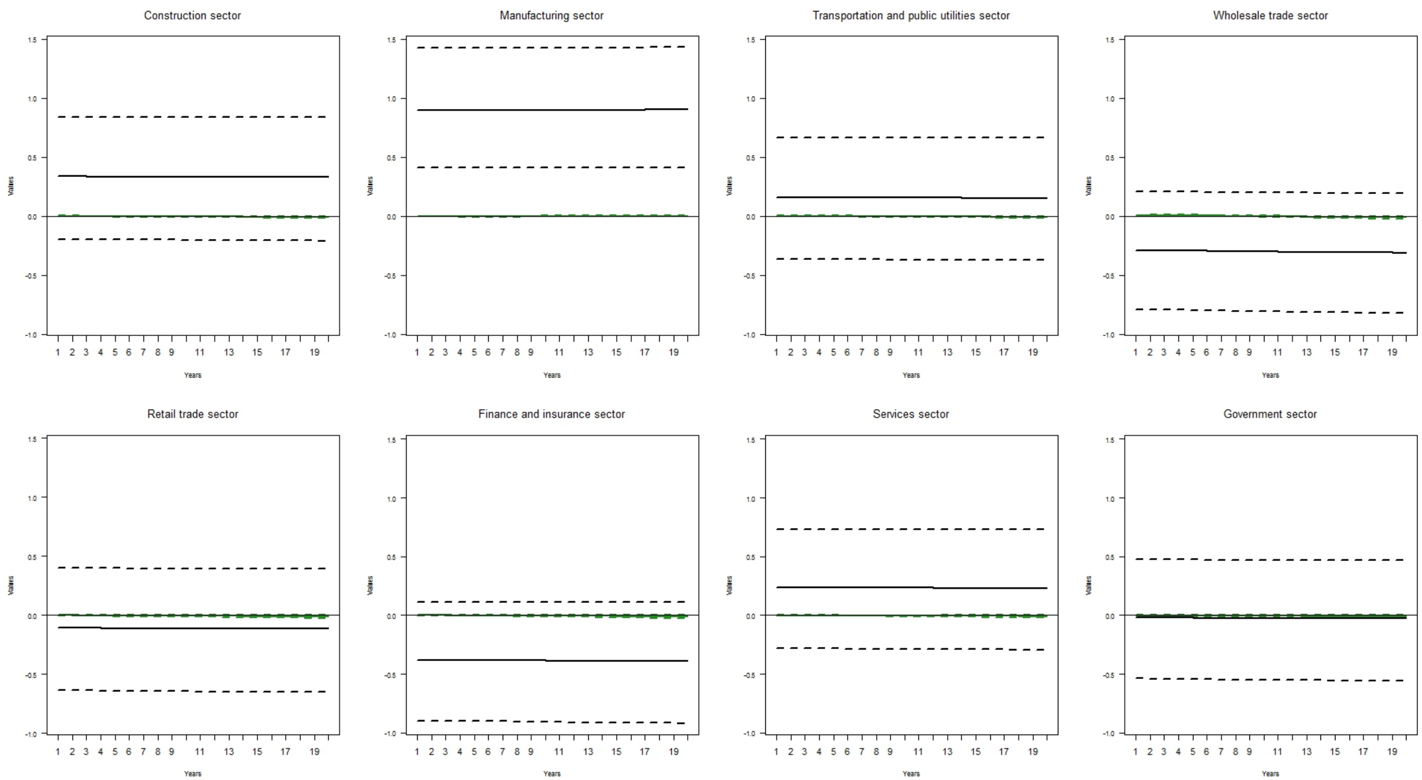


Figure 3.44: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in wholesale trade sector in Boone county.

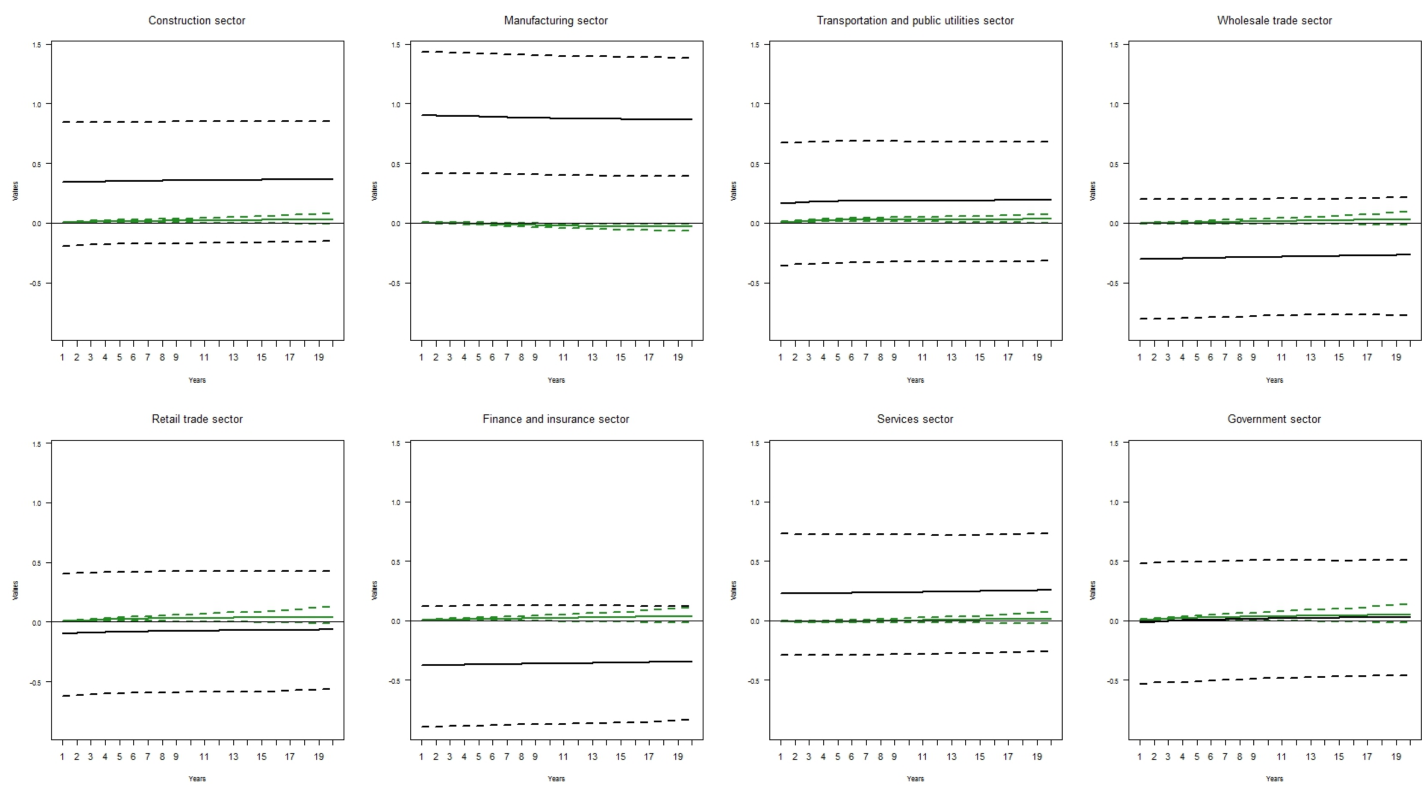


Figure 3.45: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in retail trade sector in Boone county.

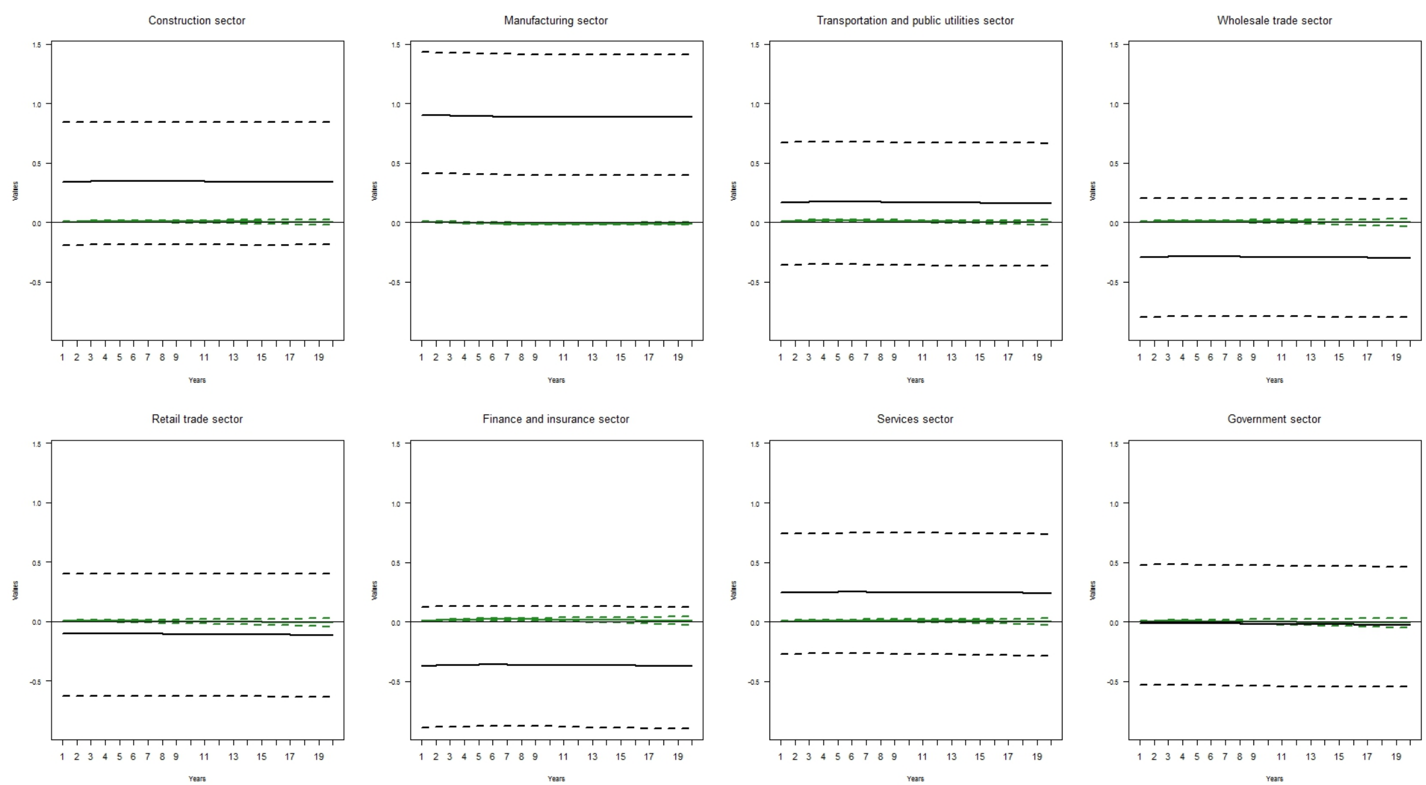


Figure 3.46: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in finance and insurance sector in Boone county.

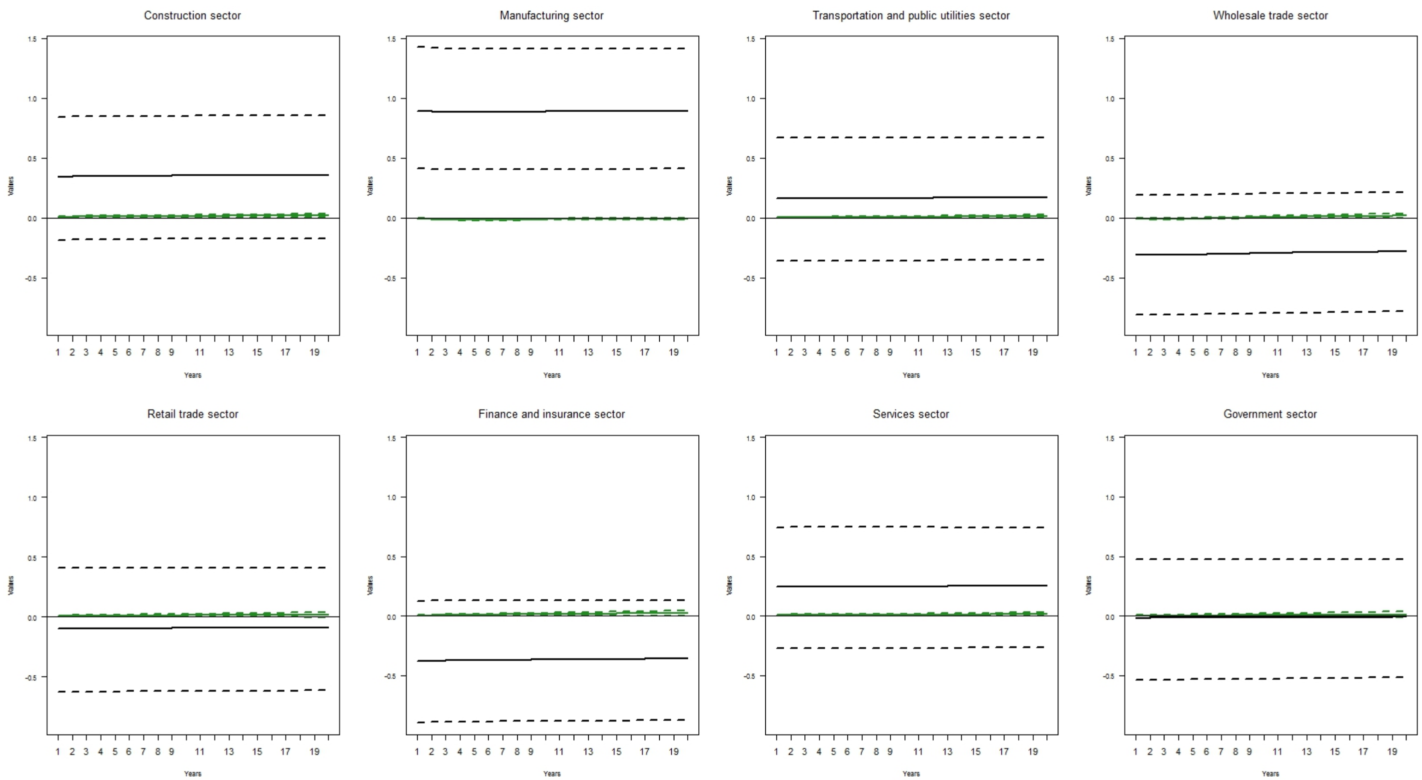


Figure 3.47: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in services sector in Boone county.

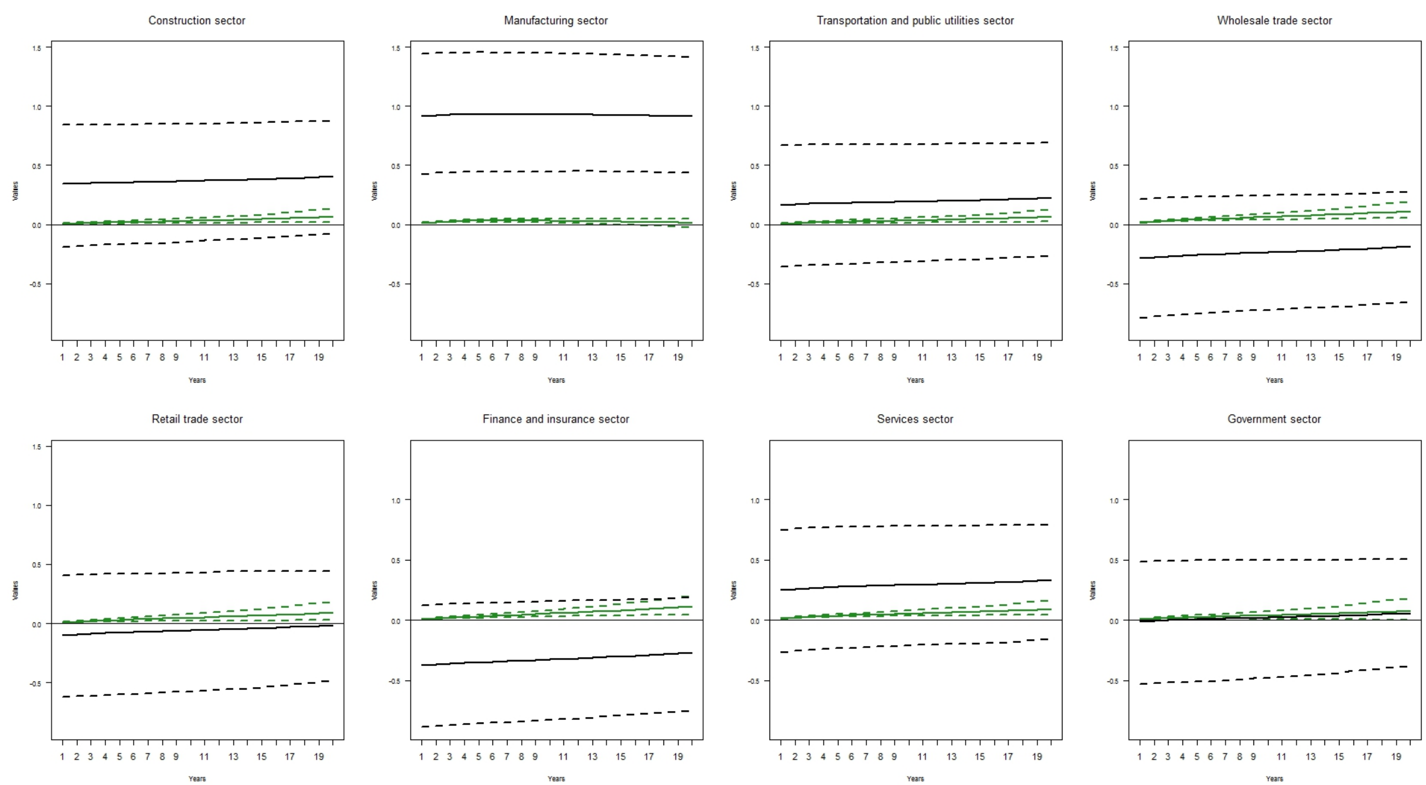


Figure 3.48: Impulse response functions with sector fixed effects in different sectors in Cole county to a shock in government sector in Boone county.

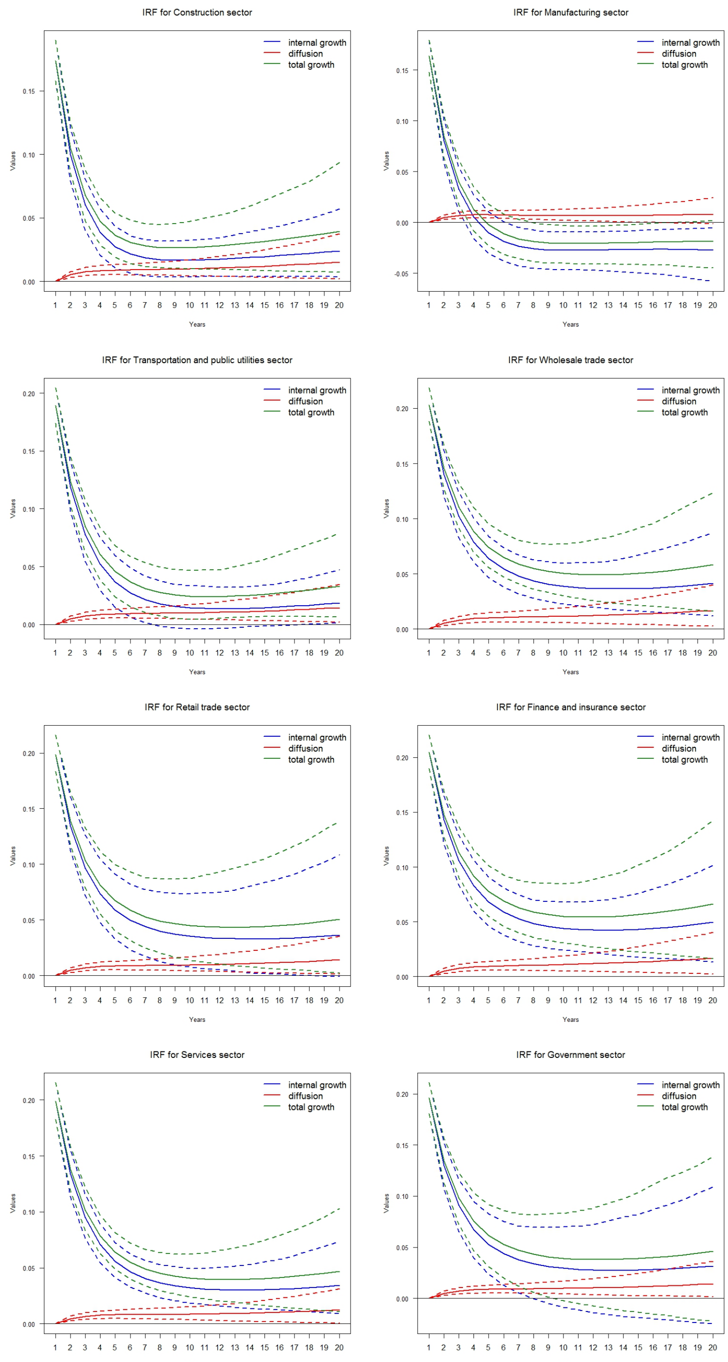


Figure 3.50: Impulse response functions for a county shock in Boone county.

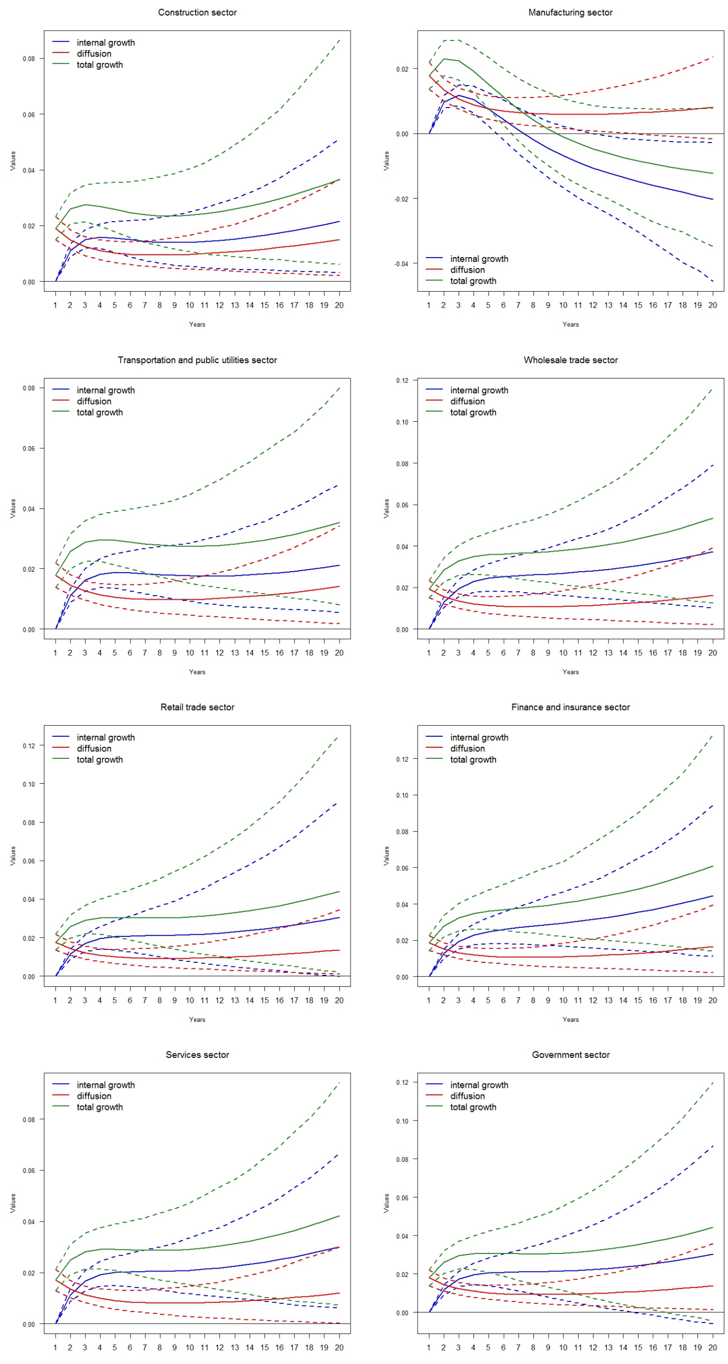


Figure 3.51: Impulse response functions in a neighboring (Cole) county for a shock in a core (Boone) county.

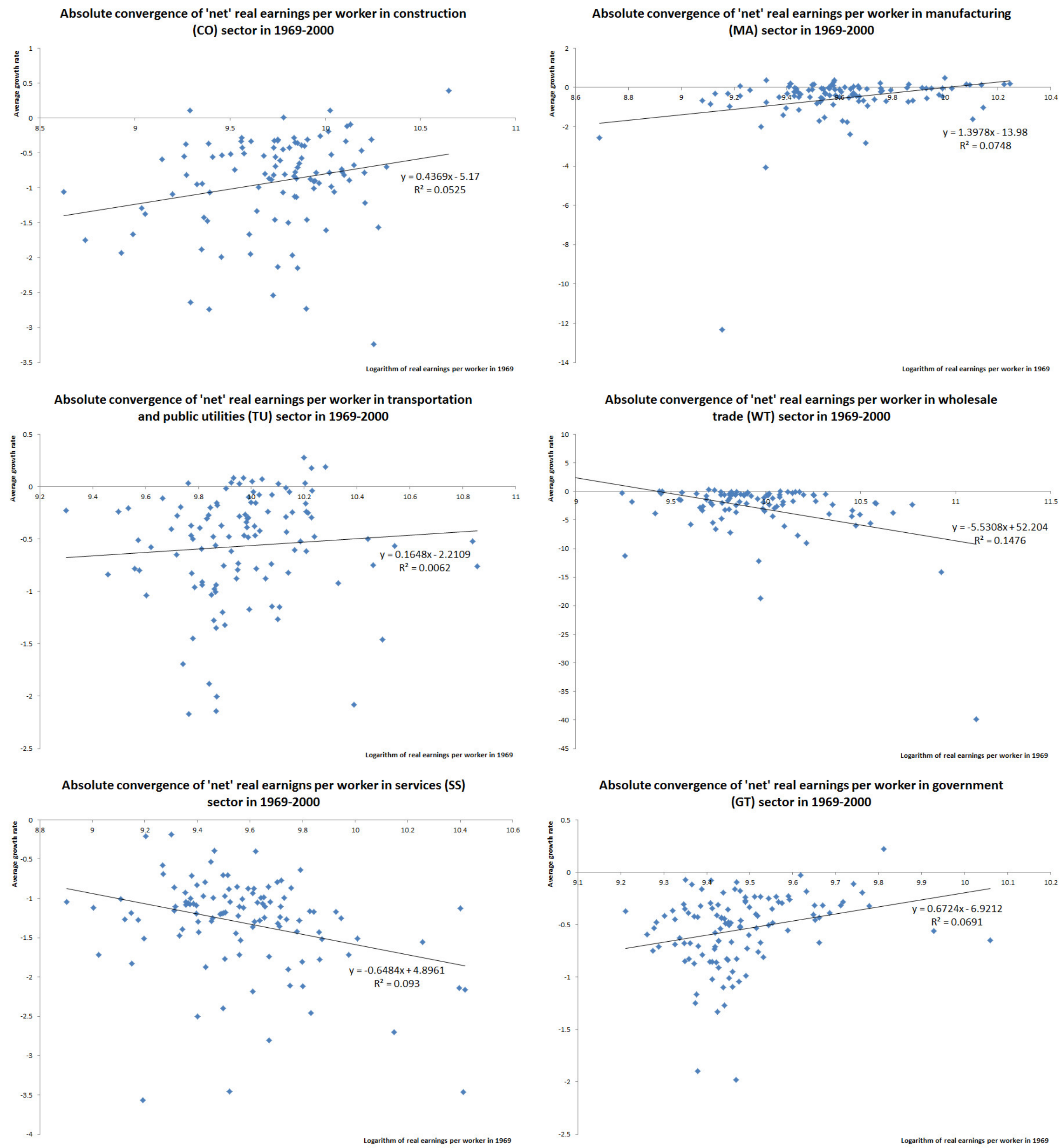
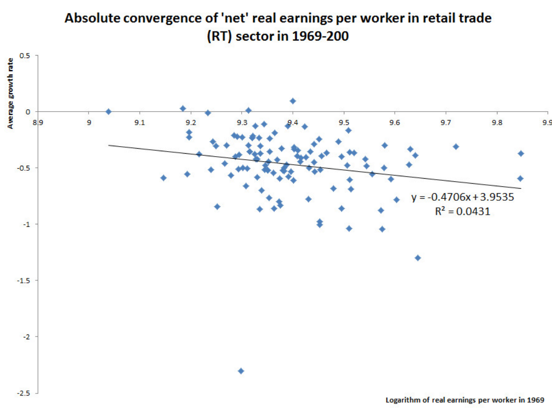


Figure 3.52: Absolute convergence plots of 'net' sectoral earnings per worker for Missouri counties in 1969-2000.



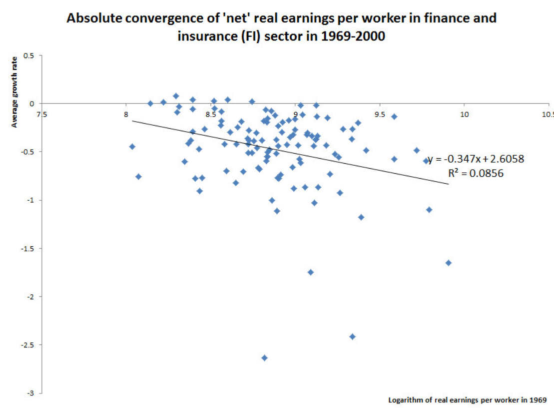


Figure 3.53: Absolute convergence plots of 'net' sectoral earnings per worker for Missouri counties in 1969-2000 (continued.)

Chapter 4

Conclusions

Based on the aforementioned results of study of aggregate earnings per worker and earnings per worker in sectors we answer the questions from section 1.1.

1. Estimates of the model with county-specific growth parameters and a vector of spatio-temporal coefficients show that if we want to model spatial externalities for county-level earnings per worker we should not rely upon spatio-temporal term with a scalar coefficient because of its inability to produce good fit for the data and to allow different spillover effects between counties and, thus, different dynamics of aggregate earnings per worker for counties with different industrial change. This can be achieved by replacing scalar coefficient with a vector of coefficients each of which shows interaction of counties that belong to different groups or clusters.

2. Growth accounting exercise shows that for all counties in the state of Missouri services sector has the largest positive sectoral effect among all sectors combined

with a large positive earnings growth effect while farming has the largest sectoral and earnings growth effects. Manufacturing sector is the only sector for which a positive earnings growth effect is combined with a negative sectoral effect. We may conclude that for the state of Missouri overall growth of aggregate earnings per worker growth of earnings per worker in the sectors of the economy is more important than the change in the industrial structure, and earnings per worker in manufacturing, services, and government sectors show faster growth in comparison to the rest of the sectors. The overall total effect is positive, i.e., we observe increase in real aggregate earnings per worker.

A separation of counties into clusters based on industrial change allows us to track the combination of earnings growth effect and sectoral effect when the latter has different from the state's pattern. Thus, when the growth accounting exercise is performed for the clusters of counties based on industrial change, it shows that in some counties aggregate earnings per worker have increased in 1969-2000 while in others they have decreased or stayed the same. We also see that there is no clear pattern of changes in either industrial structure or sectoral earnings per worker for these different dynamics of aggregate earnings except for the fact that the dynamics of the prevailing sector by employment share in some cases has an effect on aggregate earnings.

3. Impulse response functions used to assess dynamics of real aggregate earnings per worker after an exogenous shock to a county show that in main interaction happens between counties that belong to clusters with growing aggregate earnings per worker in 1969-2000. These clusters are the ones with highest employment share of government sector (cluster 1), growing employment share of

manufacturing sector (cluster 4), growing employment share of services sector and declining employment share of manufacturing sector (cluster 6), and growing employment shares of services and government sectors (cluster 5). Even counties in cluster 7 in which aggregate earnings per worker stayed almost the same in 1969-2000 and movement of workers mostly happened from manufacturing and government sectors into services and construction sectors affect counties in aforementioned counties. At the same time, rise in the aggregate earnings per worker in counties in cluster 1 seem to be attributed to the positive influence of neighboring counties rather their own internal forces while for the counties in the rest of the clusters with rising aggregate earnings per worker this growth seem to be due to the internal forces accompanied with a positive spillover effects that aggregate earnings per worker in these counties have on their neighbors.

Counties in clusters with decreasing aggregate earnings per worker (clusters 2 and 3) do not share similarity in terms of their industrial change – in the county in cluster 2 employment share of transportation and public utilities sector fell more than twice within 32 years while services sector's employment share more than tripled and in the counties in cluster 3 farming sector's employment share shrank in size to less than a half while government sector's employment share more than doubled – but both are more economically isolated from the rest of the counties, i.e., the spillover effects between counties in these clusters and the rest of the clusters are smaller and do not show in the impulse response functions.

4. Convergence plot and absolute convergence equation estimates for 'net' growth

rates of aggregate earnings per worker obtained from the temporal term coefficients in the spatial VAR model show that in the absence of spillover effects aggregate earnings per worker across Missouri counties do not converge even weakly. To the contrary, they diverge, thus, demonstrating features of agglomeration economy with spillover effects mitigating this process.

5. We propose to use a new measure of earnings per worker – sectoral portion of aggregate earning per worker – for study of spillover effects across sectors and counties because existing measures such as sectoral earnings per worker or earnings share of a sector do not account for two compounding factors at work in this case, e.g., sectoral earnings per worker and number of workers in a sector.

6. Analysis of sectoral portion of aggregate earnings shows that exogenous shocks to sectoral portions of aggregate earnings produce long-lasting increase in government, manufacturing, and retail trade sectors' portions of aggregate earnings which means that in these sectors exist strong internal forces capable to sustain this increase. In other sectors' portions of aggregate earnings the same kind of shocks produce temporary increase indicating absence of strong internal forces and, possibly, reliance on external forces, e.g., spillover effects, to sustain growth in the long-run. As for the spillover effects on other sectors' portions of aggregate earnings in the same county, government sector's portion of aggregate earnings has the smallest effect on the other sectors' portions. Transportation and public utilities and manufacturing sectors' portions of aggregate earnings have mostly negative effect on other sectors' portions while retail trade, services, and finance and insurance sectors' portion have mostly positive effect. In terms of the effects that the sectors' portions of aggregate earnings experience

after the shocks transportation and public utilities' portion is the least affected by other sectors while government and retail trade sectors' portions are mostly affected negatively, i.e., their portions fall after shocks. For the rest of the sectors' portions of aggregate earnings the shocks' effects are a mix of rises, falls, and no changes.

The effects that sectoral portions of aggregate earnings in neighboring counties experience after the exogenous shocks to a sector in a core county are the following. A shock to government sector in a core county positively affects all sectors in a neighboring county which is similar to the effect of this shock to sectors in the core county. A shock to manufacturing sector in the core county affects negatively all sectors in the neighboring county except manufacturing itself for which the effect is negligible. These effects also resemble the effect of a shock to manufacturing sector onto the sectors in the core county. A shock to retail trade sector in the core county raises sectoral portions of aggregate earnings in all sectors except manufacturing in the neighboring county while a shock to transportation and public utilities sector decreases sectoral portions of aggregate earnings in all sectors in the neighboring county except manufacturing.

7. A simultaneous exogenous shock to all sectors' portions of aggregate earnings in the core county increases sectoral portions of aggregate earnings in all sectors except manufacturing by 3-7 percent. As for the neighboring county, its sectors respond to the shock to the core county in a similar way – with a growth of 3 to 6 percent while the temporary rise in growth of manufacturing's portion of aggregate earnings disappears in about 7 years.

8. Convergence plots for the 'net', i.e., obtained after removing spillover effects, sectoral earnings (not the sectoral portions of aggregate earnings) per worker show convergence of these earnings in wholesale trade, retail trade, finance and insurance, and services sectors, and divergence in all other sectors – construction, manufacturing, transportation and public utilities, and government. These findings show that if inter-sectoral spillover effects are accounted for then in economic sectors that produce goods rather than services (except for government sector) workers' productivity does not converge, i.e., in counties with lower initial workers' productivity it does not grow faster than in counties with higher initial workers' productivity.

We have to keep in mind that the shown above results for the sectoral earnings are obtained with a model that includes a scalar temporal and spatio-temporal parameter. A possible improvement in reliability of the results may be obtained with modification of the model through either replacement of the scalar coefficients with vectors of coefficients or usage of complete data for the earnings per worker in all sectors included into our study or all sectors of the economy.

There is also a room for improvement of the models used for study of dynamics of aggregate earnings per worker, for example, with a choice of different set of clustering variables or different approach to existing spatial heterogeneity of the counties in the neighborhood from point of view of either behavior of their aggregate earnings per worker or their industrial structure. Another way to look at this dynamics is to include the measures of industrial structure – employment shares – directly into models.

Appendix A

Technical note

This technical note describes construction of the spatio-temporal (diffusion) term $\boldsymbol{Z^W}_{t-1}\boldsymbol{\rho}$ in spatial VAR model.

This term is constructed as a combination of $m^2 \times 1$ vector of spatio-temporal coefficients $\boldsymbol{\rho}$ (where m is the number of the clusters), $n \times m$ incidence matrix $\boldsymbol{H}$ (where n is the number of locations under study), $n \times n$ spatial weights matrix $\boldsymbol{W}$, and $n \times 1$ vector $\boldsymbol{Z}_{t-1}$.

Since instead of a scalar spatio-temporal parameter ρ we use a vector-parameter $\boldsymbol{\rho}$, we would like to describe proper construction of this parameter using an example with a small number of locations and clusters.

Suppose we have only 5 locations ($n = 5$) that belong to 3 clusters ($m = 3$). The row-stochastic weights matrix for the locations is $\boldsymbol{W} = \begin{pmatrix} 0 & w_{12} & 0 & w_{14} & w_{15} \\ w_{21} & 0 & w_{23} & w_{24} & 0 \\ 0 & w_{32} & 0 & w_{34} & w_{35} \\ w_{41} & w_{42} & w_{43} & 0 & w_{45} \\ w_{51} & 0 & w_{53} & w_{54} & 0 \end{pmatrix}$ and the incidence matrix is $\boldsymbol{H} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix}$.

This term can be arranged differently depending on the purpose – estimation or inference. Let consider first the case when we assume that vector $\boldsymbol{Z}_{t-1}$ is known along with matrices $\boldsymbol{W}$ and $\boldsymbol{H}$. Then in order to estimate vector $\boldsymbol{\rho}$ the whole term can be represented as a product of the matrices: ${\boldsymbol{Z}^{\boldsymbol{W}}}_{t-1}=$

$$\begin{pmatrix} 0 & w_{14}Z_{4,t-1}+w_{15}Z_{5,t-1} & w_{12}Z_{2,t-1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{21}Z_{1,t-1}+w_{23}Z_{3,t-1} & w_{24}Z_{4,t-1} & 0 \\ 0 & w_{34}Z_{4,t-1}+w_{35}Z_{5,t-1} & w_{32}Z_{2,t-1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{41}Z_{1,t-1}+w_{43}Z_{3,t-1} & w_{45}Z_{5,t-1} & w_{42}Z_{2,t-1} & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{51}Z_{1,t-1}+w_{53}Z_{3,t-1} & w_{54}Z_{4,t-1} & 0 & 0 & 0 & 0 \end{pmatrix}$$

and $\boldsymbol{\rho}^T = \begin{pmatrix} \rho_{11}\rho_{12}\rho_{13}\rho_{21}\rho_{22}\rho_{23}\rho_{31}\rho_{32}\rho_{33} \end{pmatrix}$.

The former matrix consists of three 5×3 submatrices each representing the connections of the counties that belong to the respective clusters with their neighbors. For example, the first submatrix

$$\begin{pmatrix} 0 & w_{14}Z_{4,t-1}+w_{15}Z_{5,t-1} & w_{12}Z_{2,t-1} \\ 0 & 0 & 0 \\ 0 & w_{34}Z_{4,t-1}+w_{35}Z_{5,t-1} & w_{32}Z_{2,t-1} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

shows that locations 1 and 3 belong to the first cluster and their connections with the neighbors' values Z_2, Z_4, and Z_5 are weighted appropriately. The same applies to the second and the third submatrices.

Construction of this 9×9 matrix can be done in the following way.

1. 3-dimensional $5 \times 5 \times 3$ matrix $\boldsymbol{B_1}$ is a product of 5×1 vector of 1's and each column of the transpose of incidence matrix $\boldsymbol{H}$. These three 5×5 slices of matrix $\boldsymbol{B_1}$ are $\begin{pmatrix} 1&0&1&0&0 \\ 1&0&1&0&0 \\ 1&0&1&0&0 \\ 1&0&1&0&0 \\ 1&0&1&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&1&1 \\ 0&0&0&1&1 \\ 0&0&0&1&1 \\ 0&0&0&1&1 \\ 0&0&0&1&1 \end{pmatrix}$, and $\begin{pmatrix} 0&1&0&0&0 \\ 0&1&0&0&0 \\ 0&1&0&0&0 \\ 0&1&0&0&0 \\ 0&1&0&0&0 \end{pmatrix}$.

2. 3-dimensional $5 \times 5 \times 3$ matrix $\boldsymbol{B_2}$ is a Hadamard product of each of slices of matrix $\boldsymbol{B_1}$ and weights matrix $\boldsymbol{W}$. These three 5×5 slices of matrix $\boldsymbol{B_2}$ are $\begin{pmatrix} 0&0&0&0&0 \\ w_{21}&0&w_{23}&0&0 \\ 0&0&0&0&0 \\ w_{41}&0&w_{43}&0&0 \\ w_{51}&0&w_{53}&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&w_{14}&w_{15} \\ 0&0&0&w_{24}&0 \\ 0&0&0&w_{34}&w_{35} \\ 0&0&0&0&w_{45} \\ 0&0&0&w_{54}&0 \end{pmatrix}$, and $\begin{pmatrix} 0&w_{12}&0&0&0 \\ 0&0&0&0&0 \\ 0&w_{32}&0&0&0 \\ 0&w_{42}&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$.

3. 3-dimensional $5\times5\times1$ matrix $\boldsymbol{B_3}$ is a product of each slice of matrix $\boldsymbol{B_2}$ and vector $\boldsymbol{Z}_{t-1}$. These three 5×5 slices are $\begin{pmatrix} 0 \\ w_{21}Z_{1,t-1}+w_{23}Z_{3,t-1} \\ 0 \\ w_{41}Z_{1,t-1}+w_{43}Z_{3,t-1} \\ w_{51}Z_{1,t-1}+w_{53}Z_{3,t-1} \end{pmatrix}$, $\begin{pmatrix} w_{14}Z_{4,t-1}+w_{15}Z_{5,t-1} \\ w_{24}Z_{4,t-1} \\ w_{34}Z_{4,t-1}+w_{35}Z_{5,t-1} \\ w_{45}Z_{5,t-1} \\ w_{54}Z_{4,t-1} \end{pmatrix}$,

and $\begin{pmatrix} w_{12}Z_{2,t-1} \\ 0 \\ w_{32}Z_{2,t-1} \\ w_{42}Z_{2,t-1} \\ 0 \end{pmatrix}$.

4. 2-dimensional 5×3 matrix $\boldsymbol{B_4}$= $\begin{pmatrix} 0 & w_{14}Z_{4,t-1}+w_{15}Z_{5,t-1} & w_{12}Z_{2,t-1} \\ w_{21}Z_{1,t-1}+w_{23}Z_{3,t-1} & w_{24}Z_{4,t-1} & 0 \\ 0 & w_{34}Z_{4,t-1}+w_{35}Z_{5,t-1} & w_{32}Z_{2,t-1} \\ w_{41}Z_{1,t-1}+w_{43}Z_{3,t-1} & w_{45}Z_{5,t-1} & w_{42}Z_{2,t-1} \\ w_{51}Z_{1,t-1}+w_{53}Z_{3,t-1} & w_{54}Z_{4,t-1} & 0 \end{pmatrix}$ is rearranged 3-dimensional matrix $\boldsymbol{B_3}$.

5. 3-dimensional $3 \times 5 \times 3$ matrix $\boldsymbol{B_5}$ is a product of 3×1 vector of 1's and each column of the transpose of incidence matrix $\boldsymbol{H}$. These three 3×5 slices are $\begin{pmatrix} 1&0&1&0&0 \\ 1&0&1&0&0 \\ 1&0&1&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&1&1 \\ 0&0&0&1&1 \\ 0&0&0&1&1 \end{pmatrix}$, and $\begin{pmatrix} 0&1&0&0&0 \\ 0&1&0&0&0 \\ 0&1&0&0&0 \end{pmatrix}$.

6. 3-dimensional $5 \times 3 \times 3$ matrix $\boldsymbol{B_6}$ is a transpose of the matrix $\boldsymbol{B_5}$. (Each slice of the matrix $\boldsymbol{B_6}$ is a transpose of the same slice of the matrix $\boldsymbol{B_5}$.) These three slices of the matrix $\boldsymbol{B_6}$ are $\begin{pmatrix} 1&1&1 \\ 0&0&0 \\ 1&1&1 \\ 0&0&0 \\ 0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 1&1&1 \\ 1&1&1 \end{pmatrix}$, and $\begin{pmatrix} 0&0&0 \\ 1&1&1 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \end{pmatrix}$.

7. 3-dimensional $5 \times 3 \times 3$ matrix $\boldsymbol{B_7}$ is a Hadamard product of each slice of 3-dimensional matrix $\boldsymbol{B_6}$ and 2-dimensional matrix $\boldsymbol{B_4}$. These three slices are $\begin{pmatrix} 0 & w_{14}Z_{4,t-1}+w_{15}Z_{5,t-1} & w_{12}Z_{2,t-1} \\ 0 & 0 & 0 \\ 0 & w_{34}Z_{4,t-1}+w_{35}Z_{5,t-1} & w_{32}Z_{2,t-1} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$,

$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ w_{41}Z_{1,t-1}+w_{43}Z_{3,t-1} & w_{43}Z_{5,t-1} & w_{42}Z_{2,t-1} \\ w_{51}Z_{1,t-1}+w_{53}Z_{3,t-1} & w_{54}Z_{4,t-1} & 0 \end{pmatrix}$, and $\begin{pmatrix} 0 & 0 & 0 \\ w_{21}Z_{1,t-1}+w_{23}Z_{3,t-1} & w_{24}Z_{4,t-1} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$.

8. 2-dimensional 5×9 matrix $\boldsymbol{Z^W}_{t-1} =$

$$\begin{pmatrix} 0 & w_{14}Z_{4,t-1}+w_{15}Z_{5,t-1} & w_{12}Z_{2,t-1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{21}Z_{1,t-1}+w_{23}Z_{3,t-1} & w_{24}Z_{4,t-1} & 0 \\ 0 & w_{34}Z_{4,t-1}+w_{35}Z_{5,t-1} & w_{32}Z_{2,t-1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{41}Z_{1,t-1}+w_{43}Z_{3,t-1} & w_{45}Z_{5,t-1} & w_{42}Z_{2,t-1} & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{51}Z_{1,t-1}+w_{53}Z_{3,t-1} & w_{54}Z_{4,t-1} & 0 & 0 & 0 & 0 \end{pmatrix}$$

is a rearranged 3-dimensional matrix $\boldsymbol{B_7}$ which will be used for estimation of the 9×1 vector $\boldsymbol{\rho}$.

Now suppose that vector $\boldsymbol{\rho}$ is known along with matrices $\boldsymbol{W}$ and $\boldsymbol{H}$. Then in order to estimate the 5×1 vectors $\boldsymbol{Z}_t$ and $\boldsymbol{Z}_{t-1}$ the whole term can be represented as a product of the vector $\boldsymbol{Z}_{t-1}$ and 5×5 matrix $\boldsymbol{W_H^\rho} = \begin{pmatrix} 0 & w_{12}\rho_{13} & 0 & w_{14}\rho_{12} & w_{15}\rho_{12} \\ w_{21}\rho_{31} & 0 & w_{23}\rho_{31} & w_{24}\rho_{32} & 0 \\ 0 & w_{32}\rho_{13} & 0 & w_{34}\rho_{12} & w_{35}\rho_{12} \\ w_{41}\rho_{21} & w_{42}\rho_{23} & w_{43}\rho_{21} & 0 & w_{45}\rho_{22} \\ w_{51}\rho_{21} & 0 & w_{53}\rho_{21} & w_{54}\rho_{22} & 0 \end{pmatrix}$. This matrix can be constructed in the following way.

1. 3-dimensional $5 \times 5 \times 3$ matrix $\boldsymbol{B_8}$ consists of transposed slices of 3-dimensional $5 \times 5 \times 3$ matrix $\boldsymbol{B1}$. These three slices are $\begin{pmatrix} 1\,1\,1\,1\,1 \\ 0\,0\,0\,0\,0 \\ 1\,1\,1\,1\,1 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \end{pmatrix}$, $\begin{pmatrix} 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 1\,1\,1\,1\,1 \\ 1\,1\,1\,1\,1 \end{pmatrix}$, and $\begin{pmatrix} 0\,0\,0\,0\,0 \\ 1\,1\,1\,1\,1 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \end{pmatrix}$.

2. 3-dimensional $5 \times 5 \times 9$ matrix $\boldsymbol{B_9}$ is a Hadamard product of each slice of the matrix $\boldsymbol{B_8}$ and each slice of the matrix $\boldsymbol{B_2}$. These nine slices are $\begin{pmatrix} 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&w_{14}&w_{15} \\ 0&0&0&0&0 \\ 0&0&0&w_{34}&w_{35} \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&w_{12}&0&0&0 \\ 0&0&0&0&0 \\ 0&w_{32}&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ w_{41}&0&w_{43}&0&0 \\ w_{51}&0&w_{53}&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&w_{45} \\ 0&0&0&w_{54}&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&w_{42}&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ w_{21}&0&w_{23}&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&w_{24}&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, and $\begin{pmatrix} 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \end{pmatrix}$.

3. 3-dimensional matrix $5 \times 5 \times 9$ matrix $\boldsymbol{B_{10}}$ is a Kronecker product of vector $\boldsymbol{\rho}$ and 5×5 matrix of 1's.

4. 3-dimensional matrix $5 \times 5 \times 9$ matrix $\boldsymbol{B_{11}}$ is a Hadamard product of matrices $\boldsymbol{B_9}$ and $\boldsymbol{B_{10}}$. These nine slices are $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&w_{14}\rho_{12}&w_{15}\rho_{12} \\ 0&0&0&0&0 \\ 0&0&0&w_{34}\rho_{12}&w_{35}\rho_{12} \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$,

$\begin{pmatrix} 0&w_{12}\rho_{13}&0&0&0 \\ 0&0&0&0&0 \\ 0&w_{32}\rho_{13}&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ w_{41}\rho_{21}&0&w_{43}\rho_{21}&0&0 \\ w_{51}\rho_{21}&0&w_{53}\rho_{21}&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&w_{45}\rho_{22} \\ 0&0&0&w_{54}\rho_{22}&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&w_{42}\rho_{23}&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$,

$\begin{pmatrix} 0&0&0&0&0 \\ w_{21}\rho_{31}&0&w_{23}\rho_{31}&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&w_{24}\rho_{32}&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$, and $\begin{pmatrix} 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \\ 0&0&0&0&0 \end{pmatrix}$.

5. All slices of matrix $\boldsymbol{B_{11}}$ are added together creating 2-dimensional 5×5 matrix

$$\boldsymbol{W_H^\rho} = \begin{pmatrix} 0 & w_{12}\rho_{13} & 0 & w_{14}\rho_{12} & w_{15}\rho_{12} \\ w_{21}\rho_{31} & 0 & w_{23}\rho_{31} & w_{24}\rho_{32} & 0 \\ 0 & w_{32}\rho_{13} & 0 & w_{34}\rho_{12} & w_{35}\rho_{12} \\ w_{41}\rho_{21} & w_{42}\rho_{23} & w_{43}\rho_{21} & 0 & w_{45}\rho_{22} \\ w_{51}\rho_{21} & 0 & w_{53}\rho_{21} & w_{54}\rho_{22} & 0 \end{pmatrix}.$$

This matrix now can be used to work with vectors $\boldsymbol{Z}_t$ and $\boldsymbol{Z}_{t-1}$, t=1, 2, ..., T as in calculations of impulse response functions.

Appendix B

MCMC estimation results

Table B.1: MCMC estimation results for models with county-specific temporal autoregressive coefficients.

Parameter	**County**	**Model 2.3**	**Model 2.6**	**Model 2.9**
g_1	Adair	1.0002	0.6807	0.9952
		(0.0022)	(0.0240)	(0.0896)
g_2	Andrew	0.9990	0.7202	0.6547
		(0.0022)	(0.0210)	(0.0570)
g_3	Atchison	0.9995	0.9064	0.9517
		(0.0022)	(0.0073)	(0.0790)
g_4	Audrain	0.9999	0.6750	0.9560
		(0.0022)	(0.0245)	(0.0951)
g_5	Barry	1.0002	0.7834	0.4121
		(0.0021)	(0.0166)	(0.1281)
g_6	Barton	1.0005	0.7401	0.3479
		(0.0023)	(0.0196)	(0.1030)
g_7	Bates	0.9996	0.7783	0.4902
		(0.0022)	(0.0168)	(0.1535)
g_8	Benton	1.0004	0.6683	0.4495
		(0.0023)	(0.0249)	(0.1015)
g_9	Bollinger	0.9999	0.6601	0.9102
		(0.0023)	(0.0256)	(0.0739)
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Parameter	County	Model 2.3	Model 2.6	Model 2.9
g_{10}	Boone	1.0005	0.6779	0.7773
		(0.0021)	(0.0242)	(0.0951)
g_{11}	Buchanan	1.0004	0.7880	1.0214
		(0.0022)	(0.0161)	(0.2324)
g_{12}	Butler	1.0009	0.7334	0.8607
		(0.0022)	(0.0203)	(0.0744)
g_{13}	Caldwell	1.0008	0.6655	0.5292
		(0.0023)	(0.0253)	(0.0559)
g_{14}	Callaway	1.0002	0.6770	0.8815
		(0.0022)	(0.0244)	(0.0595)
g_{15}	Camden	1.0004	0.6758	1.2953
		(0.0022)	(0.0245)	(0.3929)
g_{16}	Cape Girardeau	1.0004	0.7877	0.9710
		(0.0022)	(0.0162)	(0.0465)
g_{17}	Carroll	0.9991	0.6718	0.6231
		(0.0022)	(0.0247)	(0.0799)
g_{18}	Carter	0.9994	0.6732	0.7932
		(0.0022)	(0.0245)	(0.0690)
g_{19}	Cass	0.9998	0.7796	1.0920
		(0.0022)	(0.0167)	(0.1384)
g_{20}	Cedar	0.9995	0.6680	0.9586
		(0.0023)	(0.0250)	(0.0729)
g_{21}	Chariton	0.9990	0.6693	0.2798
		(0.0022)	(0.0249)	(0.0488)
g_{22}	Christian	1.0000	0.6722	0.6544
		(0.0022)	(0.0246)	(0.3307)
g_{23}	Clark	0.9994	0.8346	0.7903
		(0.0021)	(0.0126)	(0.0356)
g_{24}	Clay	0.9999	0.7446	1.2446
		(0.0021)	(0.0193)	(0.3514)
g_{25}	Clinton	0.9999	0.6633	0.72510
		(0.0022)	(0.0253)	(0.3664)
g_{26}	Cole	1.0007	0.6806	0.8298
		(0.0021)	(0.0242)	(0.0878)
g_{27}	Cooper	0.9997	0.6715	0.3316

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Parameter	County	Model 2.3	Model 2.6	Model 2.9
		(0.0023)	(0.0248)	(0.0471)
g_{28}	Crawford	0.9999	0.6643	0.7658
		(0.0021)	(0.0253)	(0.0789)
g_{29}	Dade	0.9994	0.6596	0.0893
		(0.0023)	(0.0257)	(0.0988)
g_{30}	Dallas	0.9996	0.6635	0.1384
		(0.0023)	(0.0253)	(0.0903)
g_{31}	Daviess	1.0003	0.6661	0.5290
		(0.0023)	(0.0251)	(0.0557)
g_{32}	DeKalb	0.9998	0.6717	0.47020
		(0.0022)	(0.0247)	(0.3541)
g_{33}	Dent	0.9997	0.6687	0.7901
		(0.0022)	(0.0249)	(0.0700)
g_{34}	Douglas	0.9987	0.6642	0.7940
		(0.0022)	(0.0252)	(0.1071)
g_{35}	Dunklin	1.0008	0.8362	1.0068
		(0.0022)	(0.0126)	(0.0762)
g_{36}	Franklin	1.0002	0.6730	0.8404
		(0.0021)	(0.0246)	(0.1037)
g_{37}	Gasconade	1.0002	0.6699	0.9021
		(0.0023)	(0.0249)	(0.0527)
g_{38}	Gentry	0.9998	0.6727	0.7519
		(0.0022)	(0.0246)	(0.0812)
g_{39}	Greene	1.0004	0.6886	0.9076
		(0.0021)	(0.0235)	(0.0676)
g_{40}	Grundy	1.0002	0.6770	0.6668
		(0.0022)	(0.0244)	(0.0841)
g_{41}	Harrison	1.0001	0.7657	0.6785
		(0.0024)	(0.0178)	(0.0504)
g_{42}	Henry	1.0003	0.6748	0.3319
		(0.0022)	(0.0245)	(0.1547)
g_{43}	Hickory	0.9996	0.6643	0.3307
		(0.0024)	(0.0252)	(0.1056)
g_{44}	Holt	0.9998	0.8363	0.8753
		(0.0022)	(0.0125)	(0.0501)

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Parameter	**County**	**Model 2.3**	**Model 2.6**	**Model 2.9**
g_{45}	Howard	0.9993	0.6635	1.0169
		(0.0023)	(0.0253)	(0.0663)
g_{46}	Howell	0.9998	0.7212	0.8077
		(0.0023)	(0.0210)	(0.0638)
g_{47}	Iron	0.9995	0.6837	0.7764
		(0.0022)	(0.0238)	(0.0765)
g_{48}	Jackson	1.0007	0.7770	0.9847
		(0.0021)	(0.0169)	(0.1092)
g_{49}	Jasper	1.0004	0.7886	0.9689
		(0.0021)	(0.0160)	(0.0461)
g_{50}	Jefferson	0.9998	0.7256	0.9071
		(0.0021)	(0.0208)	(0.3243)
g_{51}	Johnson	1.0000	0.6732	0.9867
		(0.0021)	(0.0246)	(0.1815)
g_{52}	Knox	0.9997	0.6664	0.4474
		(0.0022)	(0.0251)	(0.0541)
g_{53}	Laclede	0.9999	0.6756	0.3693
		(0.0021)	(0.0245)	(0.1616)
g_{54}	Lafayette	1.0000	0.6661	0.3982
		(0.0021)	(0.0252)	(0.0873)
g_{55}	Lawrence	0.9995	0.6681	0.8530
		(0.0022)	(0.0250)	(0.1038)
g_{56}	Lewis	1.0001	0.7816	1.1172
		(0.0023)	(0.0165)	(0.0618)
g_{57}	Lincoln	1.0006	0.7336	0.6392
		(0.0022)	(0.0202)	(0.1177)
g_{58}	Linn	1.0003	0.6739	0.5186
		(0.0022)	(0.0246)	(0.0875)
g_{59}	Livingston	1.0001	0.6806	1.0601
		(0.0022)	(0.0240)	(0.0781)
g_{60}	McDonald	1.0000	0.8662	0.7398
		(0.0023)	(0.0104)	(0.0414)
g_{61}	Macon	0.9998	0.6698	1.0790
		(0.0021)	(0.0249)	(0.0728)
g_{62}	Madison	0.9994	0.6684	0.8299
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Parameter	**County**	**Model 2.3**	**Model 2.6**	**Model 2.9**
		(0.0022)	(0.0250)	(0.0806)
g_{63}	Maries	0.9981	0.6579	0.8397
		(0.0023)	(0.0256)	(0.0921)
g_{64}	Marion	1.0002	0.7856	1.1241
		(0.0021)	(0.0163)	(0.0613)
g_{65}	Mercer	1.0001	0.7792	0.8727
		(0.0023)	(0.0167)	(0.0630)
g_{66}	Miller	0.9999	0.6714	0.3246
		(0.0023)	(0.0249)	(0.1405)
g_{67}	Mississippi	1.0014	0.9055	0.8188
		(0.0021)	(0.0074)	(0.0203)
g_{68}	Moniteau	0.9994	0.6667	0.95887
		(0.0022)	(0.0251)	(0.0650)
g_{69}	Monroe	1.0002	0.6692	0.3246
		(0.0022)	(0.0249)	(0.0472)
g_{70}	Montgomery	1.0002	0.6675	0.3457
		(0.0022)	(0.0250)	(0.0548)
g_{71}	Morgan	0.9998	0.6658	0.3184
		(0.0023)	(0.0252)	(0.0900)
g_{72}	New Madrid	1.0018	0.7726	0.6149
		(0.0022)	(0.0174)	(0.0471)
g_{73}	Newton	1.0002	0.7843	0.8763
		(0.0022)	(0.0164)	(0.0514)
g_{74}	Nodaway	1.0002	0.7696	0.8252
		(0.0022)	(0.0175)	(0.0582)
g_{75}	Oregon	0.9997	0.8111	0.85607
		(0.0022)	(0.0143)	(0.0562)
g_{76}	Osage	0.9996	0.6675	0.6969
		(0.0022)	(0.0251)	(0.0749)
g_{77}	Ozark	0.9994	0.8309	0.5417
		(0.0022)	(0.0128)	(0.1319)
g_{78}	Pemiscot	1.0011	0.8682	0.5609
		(0.0022)	(0.0102)	(0.1475)
g_{79}	Perry	1.0007	0.7965	0.3753
		(0.0021)	(0.0155)	(0.0724)
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Parameter	**County**	**Model 2.3**	**Model 2.6**	**Model 2.9**
g_{80}	Pettis	1.0003	0.6783	1.2790
		(0.0021)	(0.0241)	(0.1218)
g_{81}	Phelps	1.0001	0.6789	0.4910
		(0.0022)	(0.0242)	(0.1315)
g_{82}	Pike	0.9988	0.7822	0.5756
		(0.0022)	(0.0164)	(0.1230)
g_{83}	Platte	0.9998	0.8421	0.4306
		(0.0020)	(0.0120)	(0.2901)
g_{84}	Polk	1.0002	0.6734	0.9714
		(0.0023)	(0.0246)	(0.0575)
g_{85}	Pulaski	1.0011	0.6872	0.9260
		(0.0022)	(0.0235)	(0.1995)
g_{86}	Putnam	0.9987	0.7779	0.4506
		(0.0023)	(0.0168)	(0.0615)
g_{87}	Ralls	1.0006	0.7380	0.5477
		(0.0022)	(0.0198)	(0.0586)
g_{88}	Randolph	0.9998	0.6788	0.9597
		(0.0022)	(0.0241)	(0.0542)
g_{89}	Ray	0.9999	0.6635	0.3908
		(0.0023)	(0.0253)	(0.0959)
g_{90}	Reynolds	0.9996	0.6772	0.6504
		(0.0022)	(0.0243)	(0.1103)
g_{91}	Ripley	0.9995	0.8002	0.8734
		(0.0022)	(0.0151)	(0.0424)
g_{92}	St. Charles	1.0003	0.8159	1.0713
		(0.0020)	(0.0141)	(0.1906)
g_{93}	St. Clair	0.9989	0.8159	1.0250
		(0.0022)	(0.0250)	(0.1017)
g_{94}	Ste. Genevieve	0.9996	0.8043	0.9531
		(0.0022)	(0.0148)	(0.0753)
g_{95}	St. Francois	1.0001	0.6712	0.8356
		(0.0021)	(0.0248)	(0.0718)
g_{96}	St. Louis	1.0007	0.8175	0.8918
		(0.0021)	(0.0138)	(0.1009)
g_{97}	Saline	1.0003	0.6756	0.5475
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Parameter	County	Model 2.3	Model 2.6	Model 2.9
		(0.0022)	(0.0244)	(0.0606)
g_{98}	Schuyler	0.9988	0.7981	1.1486
		(0.0024)	(0.0153)	(0.0569)
g_{99}	Scotland	0.9999	0.7814	0.6231
		(0.0023)	(0.0165)	(0.0328)
g_{100}	Scott	1.0006	0.7400	1.0437
		(0.0021)	(0.0197)	(0.0676)
g_{101}	Shannon	0.9996	0.6662	0.7673
		(0.0024)	(0.0252)	(0.0782)
g_{102}	Shelby	1.0004	0.6697	0.3679
		(0.0021)	(0.0249)	(0.0617)
g_{103}	Stoddard	1.0013	0.6719	0.1407
		(0.0022)	(0.0247)	(0.0755)
g_{104}	Stone	1.0001	0.7354	0.7536
		(0.0022)	(0.0200)	(0.3028)
g_{105}	Sullivan	1.0008	0.6691	0.4786
		(0.0022)	(0.0249)	(0.1051)
g_{106}	Taney	1.0007	0.8176	0.8253
		(0.0021)	(0.0139)	(0.2115)
g_{107}	Texas	1.0000	0.6683	0.7940
		(0.0023)	(0.0250)	(0.0670)
g_{108}	Vernon	1.0005	0.8170	1.1440
		(0.0022)	(0.0138)	(0.1483)
g_{109}	Warren	0.9999	0.6731	0.2959
		(0.0021)	(0.0246)	(0.1086)
g_{110}	Washington	0.9987	0.6696	0.7703
		(0.0022)	(0.0248)	(0.0851)
g_{111}	Wayne	0.9996	0.6647	0.8405
		(0.0022)	(0.0252)	(0.0589)
g_{112}	Webster	0.9996	0.6711	0.8552
		(0.0023)	(0..0247)	(0.0649)
g_{113}	Worth	0.9989	0.7974	0.8465
		(0.0023)	(0.0153)	(0.0600)
g_{114}	Wright	0.9999	0.6711	0.7814
		(0.0023)	(0.0249)	(0.0711)

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Parameter	**County**	**Model 2.3**	**Model 2.6**	**Model 2.9**
g_{115}	St. Louis (City)	1.0008	0.8923	0.9183
		(0.0020)	(0.0085)	(0.0322)
σ_ϵ^2		0.0133	0.0127	0.0126
DIC		3423.02	3408.62	3265.76

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VITA

First 20 years of my life I lived in the USSR – 13 years in Soviet Kazakhstan and the rest in Soviet Ukraine. When in 1991 Ukraine declared its independence I was a student at Technical National University of Oil and Gas studying economics and engineering in oil and gas industry. The country was slowly transforming from a Soviet Socialist Republic to a sovereign country with a market economy, and there was a shortage of economists with a good understanding of what a market economy is. So my undergraduate education, though done in economics, did not include any microeconomics or macroeconomics courses.

After graduating from the university for 3 years I worked for tax authorities but decided that I would like to pursue an academic career. I have spent 3 years at a university teaching and doing research which ended up with realization that my PhD diploma would worth as much as a diploma of a person who would literally purchase it. This broken system of awarding degrees in Ukraine made me think of getting a degree abroad, in a country where degrees are awarded for doing research and not for paying money. I have applied for a scholarship from the U.S. Department of State. That's how I ended up at Mizzou pursuing Master's degree in economics and that's when I got introduced to 'real' economics.

After getting the Master's degree I went back to Ukraine and taught student at a private university in my hometown Ivano-Frankivsk. I tried to teach them values of a free society along with principles of a free-market economy.

In 2006 I came back to Mizzou to continue my education and pursue PhD degree in economics. So here I am – making my dreams come true.