Spatial Development

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PRELIMINARY AND INCOMPLETE

April 20, 2009

Abstract

We present a theory of spatial development. A continuum of locations in a geographic area choose each period how much to innovate (if at all) in manufacturing and services. Locations can trade subject to transport costs and technology diffuses spatially across locations. The result is an endogenous growth theory that can shed light on the link between the evolution of economic activity over time and space. We apply the model to study the evolution of the U.S. economy in the last few decades and find that the model can generate the reduction in the employment share in manufacturing, the increase in service productivity in the second part of the 1990s, the increase in land rents in the same period, as well as several other spatial and temporal patterns.

1. INTRODUCTION

Economic development varies widely across space. It is a common observation, as stated in the 2009 World Development Report, that the location of people is the best predictor of their income. This is clearly true when we move across countries, but there is also significant

variation within. In the U.S. employment concentration and value added vary dramatically across counties, and so does the rate of growth (see, e.g., Desmet and Rossi-Hansberg, 2009). Even though a casual look at the spatial landscape makes these observations seem almost trivial, there has been little work incorporating space, and the economic structure implied by space, into modern endogenous growth theories. This paper addresses this shortcoming by presenting a dynamic theory of spatial development and contrasting its predictions with evidence on the spatial evolution of the U.S. in the last few decades.

The theory we present has four main components. First, it includes a continuum of locations that can produce in two industries, manufacturing and services. Production requires labor and land, with technologies being constant returns to scale in these two inputs. Since the amount of land at a given location is fixed, the actual technology experienced at a location exhibits decreasing returns to scale. This constitutes a congestion force. Second, locations can trade goods and services by incurring iceberg transport costs. Given these costs, national goods markets in both sectors clear in equilibrium. Labor is freely mobile and workers can relocate every period. As a result, all workers obtain a common utility level in equilibrium. Third, locations invest in innovation. Each location can decide to tax its residents and use the revenue to buy a probability of drawing a proportional shift in its technology from a given distribution. Hence, some locations may decide not to invest in technology, others may decide to invest but may be unlucky and do not get a draw, and still others will get a draw and innovate. The benefits from innovating for a location last for only one period, since in subsequent periods land and labor arbitrage the gains away. The more labor locates in a location before innovating, the more the investment costs can be shared, and thus the greater the incentives to improve the technology. The model therefore exhibits a local scale effect in innovation, implying that more dense locations innovate more. Fourth, technology diffuses spatially. Locations close to others with a high technology get access to that technology through diffusion. Each location will produce using the best technology it has access to.

We contrast the theory to U.S. macroeconomic and spatial data of the last two decades. A well known fact is that the employment share in manufacturing has declined over time

and, correspondingly, the employment share in services has increased. This shift has been accompanied by a decline in the relative price of manufactured goods (see, e.g., Buera and Kaboski, 2007). Pissarides and Ngai (2007) show that a faster increase in manufacturing productivity, relative to service productivity, together with CES preferences and an elasticity of substitution less than one, can yield these effects. Our model starts off with a similar story. Initial conditions are such that in the beginning only locations specializing in manufacturing innovate. This implies a reduction in the manufacturing share and a drop in the relative price of manufacturing goods, just as in Pissarides and Ngai (2007). However, where we differ is that in our model this reallocation of employment towards services at some point jump-starts innovation in some locations specialized in services. From then onwards service productivity increases together with manufacturing productivity, ultimately leading to a fairly constant growth path in both industries and the economy. This is consistent with the evidence on manufacturing and service productivity in Triplett and Bosworth (2004), who document an acceleration in service productivity growth starting around 1995, while manufacturing productivity keeps growing around 2% throughout.[1] Our model also generates a corresponding increase in land rents around that period, a prediction that is very clearly present in the data. Real wage growth exhibits a similar pattern, which is also corroborated by the data.

With respect to the spatial dimension, the theory predicts that, initially, when service productivity is stagnant, manufacturing is more concentrated than services. Once the service sector starts innovating, concentration in the service sector increases in terms of both employment and productivity, implying a positive link between employment density, innovation and productivity growth. These theoretical predictions are borne out in the data: over the last decades the service sector has become more concentrated, in terms of both employment and productivity, making it look increasingly similar to manufacturing along

[1] Table A-4 in Triplett and Bosworth (2004) shows that growth in value added per worker in goods-producing sectors went from 2.11% between 1987 and 1995 to 1.94% between 1995 and 2001. In contrast, in service-producing sectors the growth rate went from 0.78% to 2.49%. If we focus only on the contribution of TFP, the difference is smaller but still there: growth in TFP went from 0.75% to 1.29% in good-producing sectors and from 0.41% to 1.41% in service producing sectors. (Note that since our model does not include capital, the value added per worker measure is more appropriate than the TFP measure.)

this spatial dimension. This is consistent with the evidence in Desmet and Rossi-Hansberg (2009), who compare spatial growth in two different time periods, 1980-2000 and 1900-1920, and find that service growth at the end of the 20th century looked very similar to manufacturing growth at the beginning of the 20th century. Both industries, in very different time periods, exhibited increasing concentration for medium-sized locations.[2]

The existing literature on spatial dynamic models is fairly small. There is a successful literature in trade that has focused on dynamic models with several countries (see, amongst others, Grossman and Helpman, 1991, Eaton and Kortum, 1999, Young 1991, and Ventura, 1997).[3] The main difference with our work is that in these models there is no geography in the sense that locations are not ordered in space. In fact, most of these papers do not even introduce transport costs, let alone geography. In contrast, we introduce a continuum of locations on a line. Locations are therefore ordered geographically, and both transport costs and technology diffusion are affected by distance.

There is a set of recent papers, such as Quah (2002), Boucekkine et. al. (2009), and Brock and Xepapadeas (2008a,b), that introduces a continuum of locations with geography, as we do here. However, none of these papers has an active innovation decision, nor do they consider frameworks with transport costs, national good markets and factor mobility. Instead, these papers assume that each point in space is isolated, except for spatial spillovers or diffusion. The main difference, then, is that they do not need to calculate price functions across locations over time. Admittedly, some of these papers add physical capital and study the capital accumulation problem over time and the forward-looking problem this entails. We abstract from capital in this paper to focus on innovation. In contrast to these paper s, our analysis does not only focus on the mathematical characteristics of the framework, but also (and perhaps more importantly) on its ability to shed light on observed phenomena. Hence, we seek to connect the model with the data, both quantitatively and qualitatively, something none of these other papers attempts.

[2] However, Desmet and Rossi-Hansberg (2009) do not link their findings to the structural transformation and to other macroeconomic variables, which is the main focus of this paper.

[3] See also Baldwin and Martin (2004) for a survey of similar work within the 'New Economic geography' model.

To compute an equilibrium we have to clear factor and goods markets in a model with a continuum of locations each period, in the presence of transportation costs and factor mobility. To do so, we follow the method in Rossi-Hansberg (2005), that consists of clearing markets sequentially. In Desmet and Rossi-Hansberg (2009) we use a similar methodology to study the dynamics of manufacturing and service growth across U.S. counties in the 20th century. Although that model also analyzes the link between innovation and spatial growth, our current paper is different in two important ways. First, in contrast to Desmet and Rossi-Hansberg (2009), we explicitly model innovation as the outcome of a profit-maximizing problem, and in that sense, provide micro-foundations for why certain locations innovate more than others. Second, in Desmet and Rossi-Hansberg (2009) innovation in a given sector gets jump-started exogenously, thus making its timing *ad hoc* and independent of what is happening in the other sector. In our current paper innovation starts off endogenously as explained above.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 presents the data we use to empirically explore the theoretical predictions of the model. Section 4 presents some empirical simulations of the model and discusses the link between our results and the data in Section 3, in particular, the ability of the model to generate the increase in productivity growth in the mid-90s in the service sector and other related facts. Section 5 concludes.

2. THE MODEL

The economy consists of land and people located in the closed interval $[0, 1]$. Throughout we refer to a location as a point in this interval, and we let the density of land at each location ℓ be equal to one. Hence, the total mass of land in the economy is equal to 1. We divide space into regions or 'counties' (connected intervals in $[0, 1]$), each of which has a local government. For simplicity we make all counties of equal size. The total number of agents is given by $\overline{L}$, and each of them is endowed with one unit of time each period. Agents are infinitely lived.

2.1 Preferences

Agents live where they work and they derive utility from the consumption of two goods: manufactures and services. Labor is freely mobile across locations and sectors. Agents supply their unit of time inelastically in the labor market. They order consumption bundles according to an instantaneous utility function $U(c_M, c_S)$ with standard properties, where c_i denotes consumption of good $i \in \{M, S\}$. We also assume that $U(\cdot)$ is homogeneous of degree one. Agents hold a diversified portfolio of land in all locations. Apart from land, there is no other saving technology.

The problem of an agent at a particular location ℓ is given by

$$\max_{\{c_i(\ell,t)\}_0^\infty} E \sum_{t=0}^{\infty} \beta U(c_M(\ell,t), c_S(\ell,t)) \tag{1}$$

$$s.t. \qquad w(\ell,t) + \frac{\bar{R}(t)}{\bar{L}} = p_M(\ell,t)\, c_M(\ell,t) + p_S(\ell,t)\, c_S(\ell,t)$$

for all t and ℓ.

where $p_i(\ell,t)$ denotes the price of good i, $w(\ell,t)$ denotes the wage at location ℓ and time t, and $\bar{R}(t)$ denotes total land rents per unit of land, so that $\bar{R}(t)/\bar{L}$ is the dividend from land ownership (since $\bar{L}$ is total population size) given that agents hold a diversified portfolio of land in all locations. Free mobility implies that utilities equalize across regions, so we do not need to keep track of the path of locations of each worker to write (1). The first-order conditions of this problem yield $U_i(c_M(\ell,t), c_S(\ell,t)) = \lambda(\ell,t)\, p_i(\ell,t)$, for all $i \in \{M, S\}$, where $U_i(\cdot)$ is the marginal utility of consuming good i and $\lambda(\ell,t)$ is a location- and time-specific Lagrange multiplier. Denote by $\bar{U}(p_M(\ell), p_S(\ell), w(\ell) + R(\ell)/L(\ell))$ the indirect utility function of an agent at location ℓ. Because of free mobility of labor, it must be the case that

$$\bar{U}\left(p_M(\ell), p_S(\ell), w(\ell) + \bar{R}/\bar{L}\right) = \bar{u}, \text{ for all } \ell \in [0,1], \tag{2}$$

where $\bar{u}$ is determined in equilibrium. In the numerical examples in the next section we will

use a CES specification

$$U(c_M, c_S) = (h_M c_M^{\alpha} + h_S c_S^{\alpha})^{1/\alpha}$$

with $1/(1-\alpha) < 1$.

2.2 Technology

Each location can produce in both sectors or specialize in one of them. The inputs of production are land and labor. Production per unit of land in the manufacturing sector is given by

$$M\left(L_M\left(\ell,t\right)\right) = Z_M\left(\ell,t\right)^{\gamma} L_M\left(\ell,t\right)^{\mu},$$

and, similarly, in the service sector we have

$$S\left(L_S\left(\ell,t\right)\right) = Z_S\left(\ell,t\right)^{\gamma} L_S\left(\ell,t\right)^{\sigma},$$

where $Z_i\left(\ell,t\right)$ is TFP and $L_i\left(\ell,t\right)$ is the amount of labor per unit of land used at location ℓ and time t in sector i. We assume that a firm takes $Z_i\left(\ell,t\right)$ as given, so it does not take into account the effect of other producers on productivity. The problem of a firm in sector $i \in \{M, S\}$ at location ℓ is thus given by

$$\max_{L_i(\ell,t)} \left(1-\tau_i\left(\ell,t\right)\right)\left(p_i\left(\ell,t\right) Z_i\left(\ell,t\right)^{\gamma} L_i\left(\ell,t\right)^{\iota} - w\left(\ell,t\right) L_i\left(\ell,t\right)\right), \tag{3}$$

where $\iota \in \{\mu, \sigma\}$ and where $\tau_i\left(\ell,t\right)$ denotes taxes on profits charged by the government to firms in industry i. The maximum per unit land rent that firms in sector i are willing to pay, the bid rent, is then given by

$$R_i\left(\ell,t\right) = \left(p_i\left(\ell,t\right) Z_i\left(\ell,t\right)^{\gamma} \hat{L}_i\left(\ell,t\right)^{\iota} - w\left(\ell,t\right) \hat{L}_i\left(\ell,t\right)\right)\left(1-\tau\left(\ell,t\right)\right). \tag{4}$$

We assume that $\tau_i\left(\ell,t\right)$ is the same across industries.

2.3 Diffusion and Timing

Technology diffuses locally between time periods. This type of diffusion is assumed to be local and to decline exponentially with distance. In particular, if $Z\left(r,t-1\right)$ is the

technology in location r which was used for production in period $t-1$, next period t location ℓ has access to (but does not necessarily need to use) technology

$$e^{-d|\ell-r|} Z_i(r, t-1).$$

Hence, before the innovation decision, location ℓ has access to

$$Z_i(\ell, t+1) = \max_{r \in [0,1]} e^{-\delta|\ell-r|} Z_i(r, t) \tag{5}$$

which of course includes its own technology. This type of diffusion is the only exogenous source of agglomeration in the model. There is an endogenous source of agglomeration that results from trade. As we describe below, locations that experience high prices of a given good have more incentives to innovate. High levels of innovation leads to agglomeration in the sector.

The timing of the problem is key. Figure 1 illustrates the assumed timing.

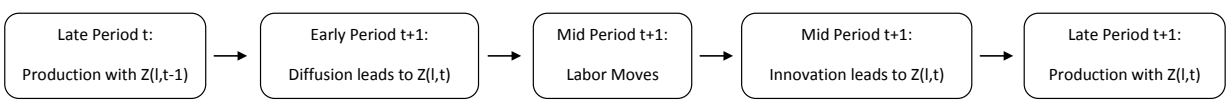


Figure 1: Timing

During the night, technology diffuses locally as described above. This leads to a level of technology $Z_i(\ell, t)$. Labor moves according to this technology and the wage determined by it. After labor moves, localities invest in innovation by taxing local firms as we describe in the next subsections. Innovation is then realized and leads to the level of technology used in production. Note that we are assuming that the number of people that come to the location $L(\ell, t)$ react to $Z_i(\ell, t)$ before the results of innovation are realized (that is, they move at the beginning of the period so the innovation has no contemporaneous labor mobility effect). The key is that, because labor cannot move to a location immediately as a result of a successful innovation, there are rents that can cover the fixed costs of innovation.

2.4 Idea Generation

The government of a 'county' can decide to innovate by taxing firms to buy an opportunity to innovate. In particular, the 'county' buys a probability $\phi \leq 1$ of innovating at cost $\psi(\phi)$ per unit of land in a particular industry i. Thus, if the measure of a county is I, the total fixed cost is $I\psi(\phi)$.[4] This implies that with probability ϕ the county obtains an innovation and with probability $(1-\phi)$ its technology is not affected by the investment in innovation.[5]

If a county innovates, all firms (in all locations) in the 'county' have access to the new technology. A county that obtains the chance to innovate draws a technology multiplier z_i from a Pareto distribution (with lower bound 1), leading to an improved technology level, $z_i Z_i(\ell, t)$, where

$$\Pr[z < z_i] = \left(\frac{1}{z}\right)^a$$

Thus, conditional on innovation, the average technology becomes

$$E\left(Z_i(\ell, t+1) \,|\, Z_i(\ell, t), Innovation\right) = \frac{a}{a-1} Z_i(\ell, t) \text{ for } a > 1. \tag{6}$$

Note that the average technology for a given ϕ, not conditional on innovating, is

$$\begin{aligned} E\left(Z_i(\ell, t+1) \,|\, Z_i(\ell, t)\right) &= \left(\frac{\phi a}{a-1} + (1-\phi)\right) Z_i(\ell, t) \\ &= \left(\frac{\phi + a - 1}{a-1}\right) Z_i(\ell, t). \end{aligned}$$

2.5 Innovation and Government Budget

The government of a county taxes profits of its firms to invest in innovation. We assume a balanced budget: if total investment in innovation in industry i in a county of measure I that includes location ℓ is $I\psi(\phi_i(\ell, t))$, the government taxes its firms exactly this amount. A county of size I that pays $I\psi(\phi_i(\ell, t))$, obtains in expectations a technology $\frac{\phi+a-1}{a-1}$ times

[4] Note that all counties have the same measure.

[5] Instead we could assume that a county buys a realization of a Poisson distribution for a number of opportunities to innovate. In this case, we need to calculate the expectation of the maximum draw out of N realizations, which is distributed Fréchet, as discussed in Eaton and Kortum (2002).

greater than its current technology. Local governments maximize total output gains minus fixed costs. Hence, the local government maximizes

$$\max_{\phi_i(\ell,t)} \int_{C_I} \left(\left(\frac{\phi_i(\ell,t) + a - 1}{a-1} \right)^{\gamma} - 1 \right) Z_i(\ell,t)^{\gamma} p_i(\ell,t) L_i(\ell,t)^{\iota} d\ell - I\psi(\phi) \tag{7}$$

$$= \max_{\phi_i(\ell,t)} \frac{(\phi_i(\ell,t) + a - 1)^{\gamma} - (a-1)^{\gamma}}{(a-1)^{\gamma}} \int_{C_I} Z_i(\ell,t)^{\gamma} p_i(\ell,t) L_i(\ell,t)^{\iota} d\ell - I\psi(\phi)$$

where i denotes the industry in which the location is producing. The benefits of the extra production last only for one period since a county is small (an assumption) and so it has no power to affect (in expectation) the level of technology if diffusion lasts one period. Furthermore, after a period new people move to the county and equalize utility across locations (people cannot be excluded after one period).

Note from (7) that the benefits of increasing ϕ are concave for $\gamma < 1$. Suppose the cost of a draw satisfies

$$\begin{aligned} \psi'(\phi) &> 0, \\ \psi''(\phi) &\geq 0. \end{aligned}$$

A ready example would be

$$\psi(\phi) = \psi_1 + \psi_2 \phi \text{ for } \psi_1, \psi_2 > 0.$$

Given the fixed costs to invest we need

$$\int_{C_I} \left(\left(\frac{\phi_i(\ell,t) + a - 1}{a-1} \right)^{\gamma} - 1 \right) Z_i(\ell,t)^{\gamma} p_i(\ell,t) L_i(\ell,t)^{\iota} d\ell > I\psi(\phi_i(\ell,t))$$

for some $\phi_i(\ell,t) \in [0,1]$. We also need to satisfy the first order condition (note that if $\psi(\cdot)$ is linear the second order condition is satisfied since $\gamma < 1$). The FOC is given by

$$I\psi_2 = \frac{(\phi_i^*(\ell,t) + a - 1)^{\gamma-1}}{(a-1)^{\gamma}} \int_{C_I} Z_i(\ell,t)^{\gamma} p_i(\ell,t) L_i(\ell,t)^{\iota} d\ell.$$

So let

$$\phi_i^*(\ell,t) = \left(\frac{\frac{\gamma}{I} \int_{C_I} Z_i(\ell,t)^{\gamma} p_i(\ell,t) L_i(\ell,t)^{\iota} d\ell}{\psi_2 (a-1)^{\gamma}} \right)^{\frac{1}{1-\gamma}} - a + 1,$$

then in the linear cost case

$$\phi_i(\ell,t)=\begin{cases} 0 & \text{if } \psi(\phi_i^*(\ell,t)) \geq \frac{(\phi_i^*(\ell,t)+a-1)^\gamma-(a-1)^\gamma}{(a-1)^\gamma I}\int_{C_I} Z_i(\ell,t)^\gamma p_i(\ell,t) L_i(\ell,t)^\iota d\ell \\ & \text{and/or } \phi_i^*(\ell,t)\leq 0 \\ \phi_i^*(\ell,t) & \text{if } \psi(\phi_i^*(\ell,t)) < \frac{(\phi_i^*(\ell,t)+a-1)^\gamma-(a-1)^\gamma}{(a-1)^\gamma I}\int_{C_I} Z_i(\ell,t)^\gamma p_i(\ell,t) L_i(\ell,t)^\iota d\ell \\ & \text{and } \phi_i^*(\ell,t)>0 \\ 1 & \text{if } \psi(\phi_i^*(\ell,t)) < \frac{(\phi_i^*(\ell,t)+a-1)^\gamma-(a-1)^\gamma}{(a-1)^\gamma I}\int_{C_I} Z_i(\ell,t)^\gamma p_i(\ell,t) L_i(\ell,t)^\iota d\ell \\ & \text{and } \phi_i^*(\ell,t)\geq 1 \end{cases}.$$

Note that a few results are immediate from these equations. Since $0<\gamma<1$, investment is weakly increasing in total industry output (or output per unit of land). This scale effect is consistent with the evidence presented by Carlino et al. (2007). They show that in the U.S. a doubling of employment density leads to a 20% increase in patents per capita.

We can also let

$$\psi(\phi)=\psi_1+\psi_2\frac{1}{1-\phi} \text{ for } \psi_1,\psi_2>0. \tag{8}$$

The advantage of this cost function is that is has an asymptote at 1. This prevents us from dealing with corner solutions at 1. For simplicity let $\gamma=1$ (in order to solve the FOC in closed form). Then the FOC is given by

$$I\frac{\psi_2}{(1-\phi)^2}=\frac{1}{a-1}\int_{C_I} Z_i(\ell,t)\, p_i(\ell,t)\, L_i(\ell,t)^\iota\, d\ell,$$

which implies that

$$\phi_i^*(\ell,t)=1-\left(\frac{\psi_2(a-1)}{\frac{1}{I}\int_{C_I} Z_i(\ell,t)\, p_i(\ell,t)\, L_i(\ell,t)^\iota\, d\ell}\right)^{\frac{1}{2}}.$$

Then

$$\phi_i(\ell,t)=\begin{cases} 0 & \text{if } \psi(\phi_i^*(\ell,t)) \geq \frac{\phi_i^*(\ell,t)}{(a-1)I}\int_{C_I} Z_i(\ell,t)\, p_i(\ell,t)\, L_i(\ell,t)^\iota\, d\ell \\ & \text{and/or } \phi_i^*(\ell,t)\leq 0 \\ \phi_i^*(\ell,t) & \text{if } \psi(\phi_i^*(\ell,t)) < \frac{\phi_i^*(\ell,t)}{(a-1)I}\int_{C_I} Z_i(\ell,t)\, p_i(\ell,t)\, L_i(\ell,t)^\iota\, d\ell \\ & \text{and } \phi_i^*(\ell,t)>0 \end{cases}. \tag{9}$$

In order to finance $I\psi(\phi_i(\ell,t))$ the government in location ℓ levies a tax $\tau_i(\ell,t)$ on firms in industry i such that

$$\psi(\phi_i(\ell,t)) = \frac{\tau(\ell,t)}{I}\int_{C_I}(Z_i(\ell,t)^{\gamma}p_i(\ell,t)L_i(\ell,t)^{\iota} - w(\ell,t)L_i(\ell,t))d\ell \tag{10}$$

each period, where $\phi_i(\ell,t)$ is given by the expression above. Note the timing. Taxes are set after the innovation is realized to cover its costs. So in (10), $\frac{1}{I}\int_{C_I} Z_i(\ell,t)^{\gamma}p_i(\ell,t)L_i(\ell,t)^{\iota}\,d\ell$ is actual average production per unit of land in the county in that industry.

Note that so far we have assumed that each county only invests in one industry. We do not need to restrict this. We can have a county invest in both industries and tax firms in each industry separately. (In the simulations we use the same tax rate for the moment).

In general we will also make $\psi(\cdot)$ proportional to wages in each location. Hence if an economy grows (and therefore wages increase) the cost of investment in innovation grows accordingly. Then, the model is such that –with enough locations so that the law of large numbers applies– the economy converges to a balanced growth path. Of course, for a finite number of locations, there will be fluctuations around this balanced growth path even in the long run. Note also that, even if the law of large numbers holds, individual locations' employment, specialization, trade, etc. will keep changing.

2.6 Land, Goods, and Labor Markets

Trade allows locations to specialize in one industry.[6] Goods are costly to transport. For simplicity we assume iceberg transportation costs that are identical in manufacturing and services. This is without loss of generality, given that the equilibrium depends only on the sum of transport costs in both industries. If one unit of any of the goods is transported from ℓ to r, only $e^{-\kappa|\ell-r|}$ units of the good arrive in r. Since the technology to transport goods is freely available, the price of good i produced in location ℓ and consumed in location r has to satisfy

$$p_i(r,t) = e^{\kappa|\ell-r|}p_i(\ell,t).$$

[6] Counties are potentially formed by many locations and so do not need to specialize. Since counties are the ones that invest in innovation, we allow for the possibility of having one county invest in innovation in both industries.

Land is assigned to its highest value. Hence, land rents are such that

$$R(\ell, t) = \max\{R_M(\ell, t), R_S(\ell, t)\}.$$

Denote by $\theta_i(\ell)$ the fraction of land at location ℓ used in the production of good i. If $R(\ell, t) = R_i(\ell, t)$, then $\theta_i(\ell, t) > 0$. Of course, with complete specialization this condition becomes $\theta_i(\ell, t) = 1$.

In order to guarantee equilibrium in product markets, we need to take into account that some of the goods are lost in transportation. To do this, let $H_i(\ell, t)$ denote the stock of excess supply of product i between locations 0 and ℓ. Define $H_i(\ell, t)$ by $H_i(0, t) = 0$ and by the differential equation

$$\frac{\partial H_i(\ell, t)}{\partial \ell} = \theta_i(\ell, t) x_i(\ell, t) - c_i(\ell, t)\left(\sum_i \theta_i(\ell, t)\hat{L}_i(\ell, t)\right) - \kappa |H_i(\ell, t)|, \tag{11}$$

where $x_M(\ell, t) = M\left(\hat{L}_M(\ell, t)\right)$ and $x_S(\ell, t) = S\left(\hat{L}_S(\ell, t)\right)$ denote the equilibrium production of good i at location r per unit of land. That is, at each location we add to the stock of excess supply the amount of good i produced and we subtract the consumption of good i by all residents of r. We then need to adjust for the fact that if $H_i(\ell, t)$ is positive and we increase r, we have to ship the stock of excess supply a longer distance. This implies a cost in terms of goods and services given by κ. The equilibrium conditions in the goods markets are then $H_i(1, t) = 0$ for all i.

We impose trade balance location by location. The value of the goods shipped to location ℓ must thus be identical to the value of the goods shipped from location ℓ, so that

$$p_M(\ell, t) H_M(\ell, t) + p_S(\ell, t) H_S(\ell, t) = 0 \text{ for all } \ell \text{ and } t. \tag{12}$$

The trade balance condition says that the value of goods produced and consumed at ℓ is equal, once transport costs in terms of goods are covered.

In equilibrium labor markets clear. Given free mobility, we have to guarantee that the total amount of labor demanded in the economy is equal to the total supply $\overline{L}$. The labor market equilibrium condition is therefore

$$\int_0^1 \sum_i \theta_i(\ell, t)\hat{L}_i(\ell, t)\, d\ell = \overline{L}. \tag{13}$$

2.7 Definition of Equilibrium

An equilibrium in this economy is a set of real functions $(c_i, \hat{L}_i, \theta_i, H_i, p_i, R_i, w, Z_i, \phi_i, \tau_i)$ of locations $\ell \in [0,1]$ and time $t = 1, ...,$ for $i \in \{M, S\}$, such that:

- Agents choose consumption, c_i, by solving the problem in (1)
- Agents locate optimally, so w, p_i, R_i and L_i satisfy (2)
- Firms maximize profits by choosing the number of workers per unit of land, $\hat{L}_i$, that solves (3), and by choosing the land bid rent, R_i, that solves (4)
- Land is assigned to its highest value, so if $\max\{R_M(\ell,t), R_S(\ell,t)\} = R_i(\ell,t)$, then $\theta_i(\ell,t) = 1$
- Goods markets clear, so H_i is given by (11) and $H_i(1) = 0$
- Trade is balanced location by location, so (12) is satisfied
- The labor market clears, so θ_i and $\hat{L}_i$ satisfy (13)
- The government budget is balanced each period, so ϕ_i and τ_i satisfy (10) and investment in innovation ϕ_i satisfies (7)
- Technology Z_i satisfies the innovation process that leads to (6) and the diffusion process given by (5)

3. EMPIRICAL EVIDENCE

In this section we present a number of stylized facts about the industrial sector and the service sector in the United States since the beginning of the 1970s, and empirically explore some of the theoretical predictions of our model.

3.1 Stylized Facts

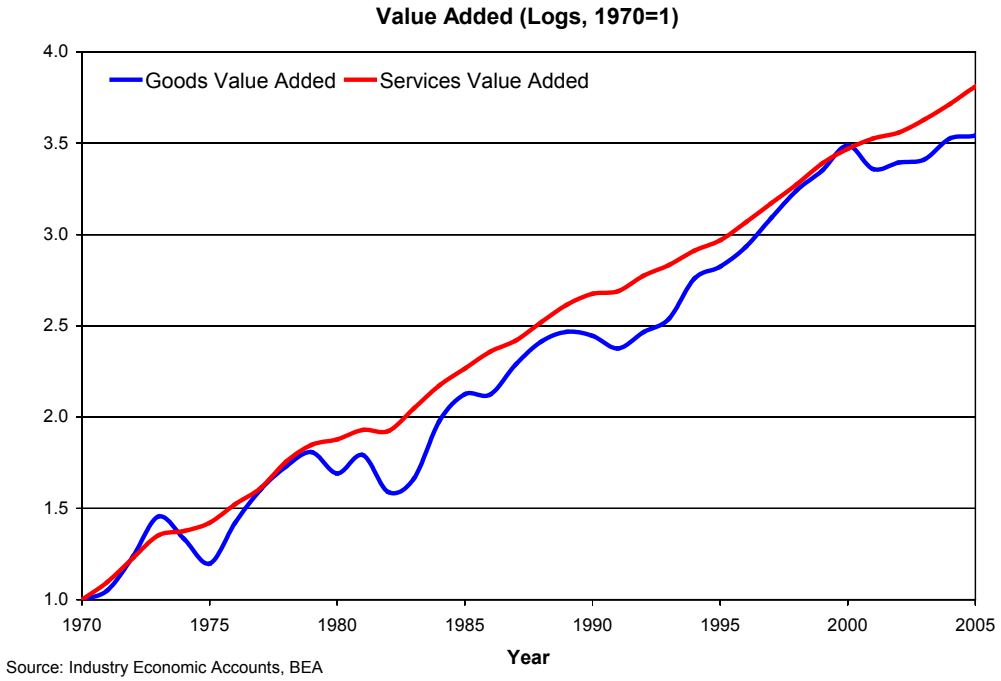
Although many of the stylized facts will appear familiar from the literature on the structural transformation (see, e.g., Ngai and Pissarides, 2007, and Buera and Kaboski, 2006),

we will also emphasize two less well known aspects. First, in the last fifteen years, compared to the 1970s and the 1980s, many of those familiar facts have witnessed significant changes. Second, we will present evidence on the spatial dimension, an aspect generally ignored in this literature.

In terms of quantities produced, Figure 2.1 (where .1 refers to the upper panel and .2 to the bottom panel) shows that both the goods sector and service sector have been steadily growing, at similar rates. At the same time, employment has been moving out of goods into services, as can be seen in Figure 2.2. The start of this shift dates back to the 1930s, and has continued to the present day. However, since the 1990s this shift has clearly been slowing down. In fact, in the last 10 years the share of service employment has increased by a mere 2 percentage points, compared to around 6 percent both in the 1970s and the 1980s. The decrease in the price of goods, relative to services, typically associated with the structural transformation, has also been slowing down since the 1990s, compared to the 1980s. This trend is reported in Figure 3.1. As can be seen, in the last 5 years there is even a slight reversal, with the relative price of goods increasing. The mid 1990s also marks a breakpoint for wages. Figure 3.2 shows how real hourly wages of production workers started to increase significantly around 1995, after two decades of decline.[7]

When looking at the evidence on productivity, Figure 4.1 shows how in the 1970s and the 1980s services productivity growth, as measured by value added per worker, was falling behind that of goods, a well known phenomenon described by Baumol (1967), who argued that it was inherently more difficult to innovate in services than in goods. That same widening gap is also apparent in Figure 4.2, which reports the log of value added per worker in both goods and services. However, since the 1990s services productivity growth has clearly been catching up. On some accounts, since 1995 it has even surpassed productivity growth in the goods producing sector (Triplett and Bosworth, 2004).

[7] For purposes of comparison with the numerical section, to obtain real wages we deflate by the services price index used in the *Industry Economic Accounts* of the BEA.



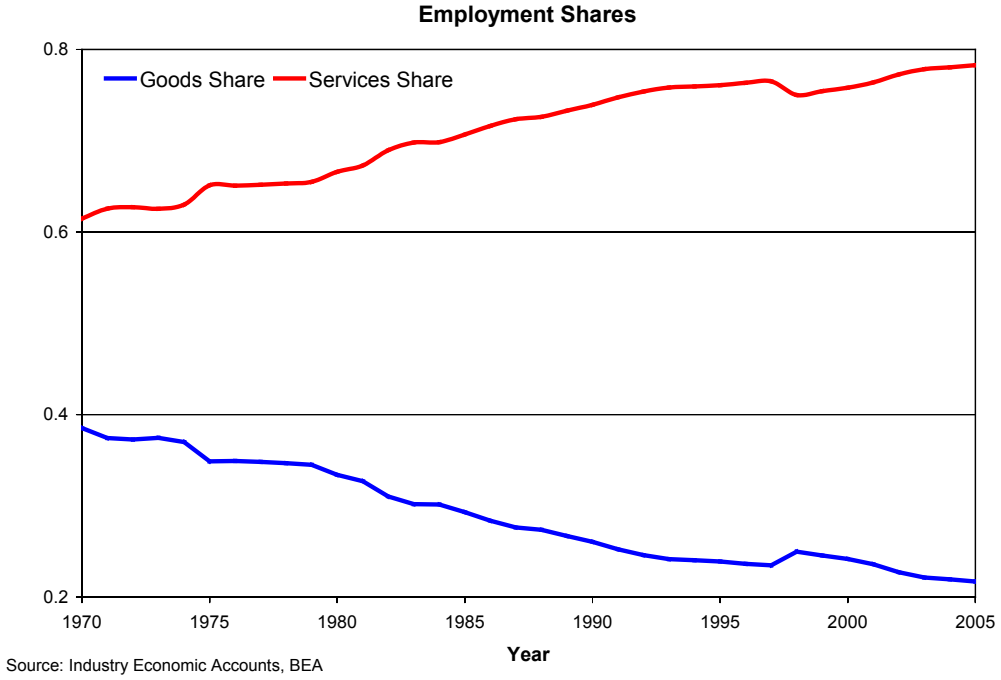
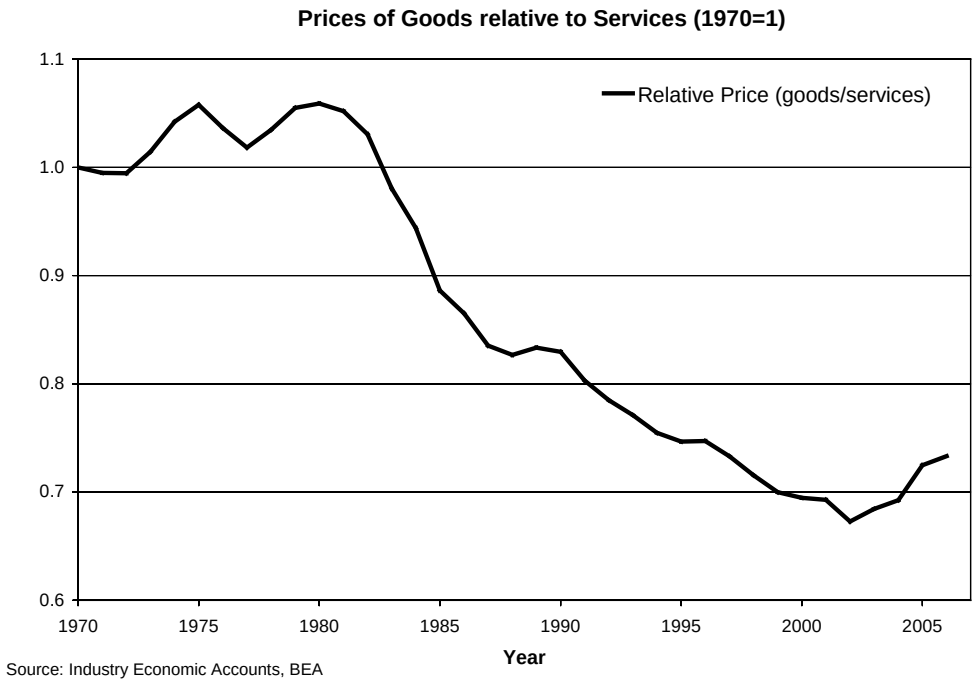


Figure 2: Value Added and Employment Shares



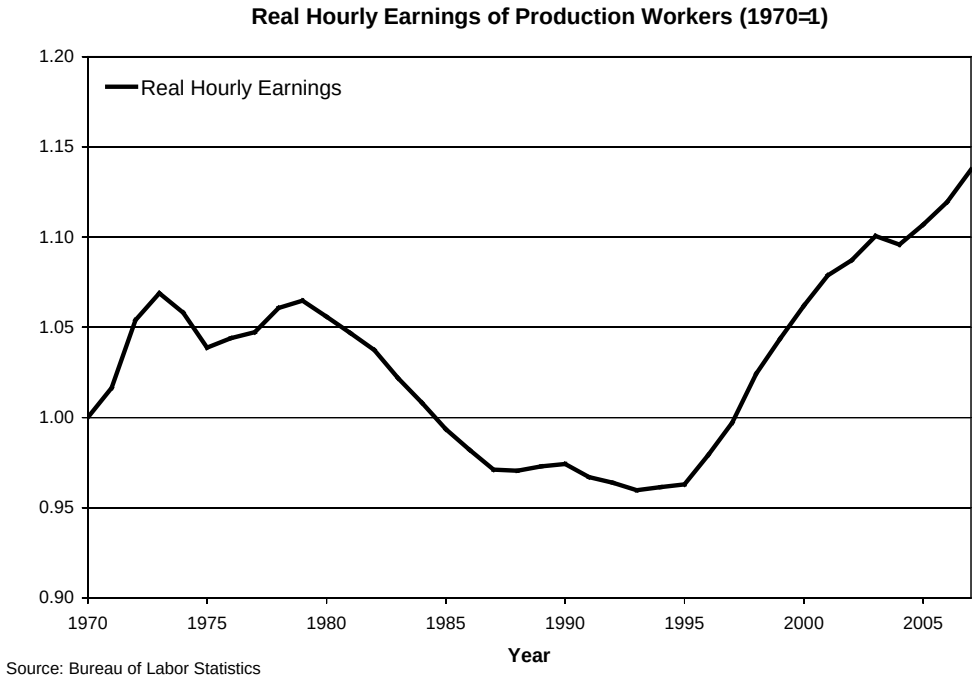


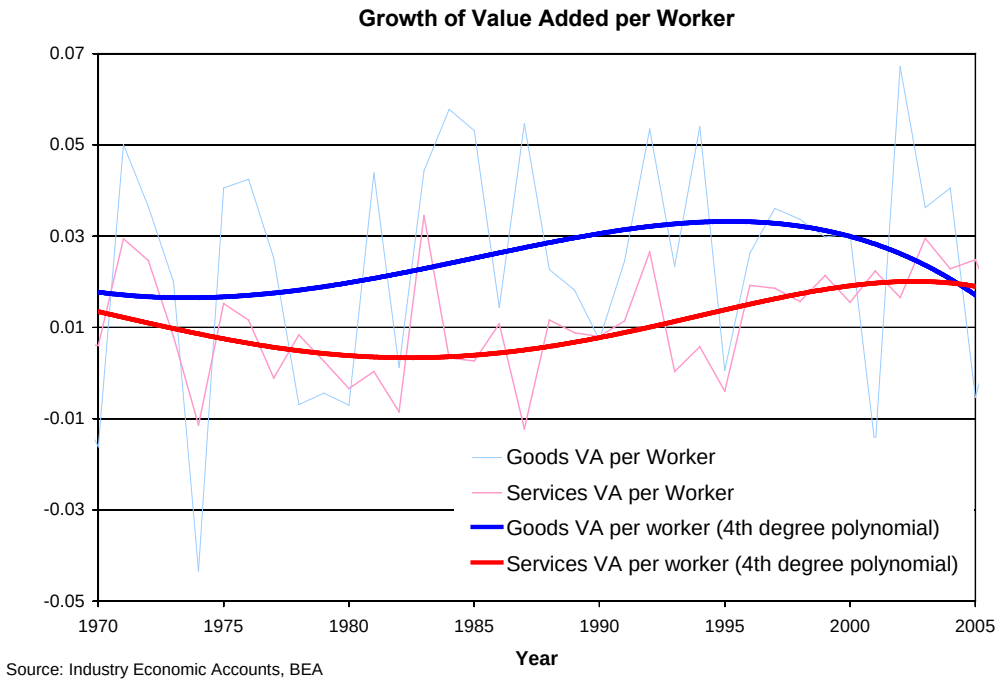
Figure 3: Relative Prices and Wages

The post-1995 period also witnessed significant changes in a number of other variables. Figure 5 shows sharp increases in the real values of land and housing. Of course part of this dramatic increase is disappearing as a result of the current housing crisis, but it remains to be seen whether values will return to their pre-1995 levels in real terms.[8]

As for the spatial dimension, the industrial sector has become more dispersed, and the service sector more concentrated over time. Figure 6.1 shows the distribution of industrial employment density (in logs) across U.S. counties in 1970 and 2000. The distribution has become tighter over time, indicating increased dispersion. Indeed, the tightening distribution implies counties becoming more alike in terms of manufacturing employment density. The service sector behaves very differently. Figure 6.2 shows services becoming more concentrated. Note, furthermore, that services started off being more dispersed, compared to goods. A similar picture emerges when computing the standard deviation of log employment for both sectors. In the case of the industrial sector, the standard deviation decreases (implying sigma-convergence), whereas in services the standard deviation increases (implying sigma-divergence).

The increased spatial concentration in services also shows up when analyzing labor productivity. Figure 7 shows the distribution of earnings per worker (in logs) in both sectors across U.S. counties in 1970 and 2000. To facilitate the comparison between 1970 and 2000, the mean growth rate has been taken out. As can be seen in Figure 7, the distribution of earnings per worker in the industrial sector did not change significantly over time. In contrast, in the service sector, earnings per worker have become more unequal across counties, as reflected by the widening distribution. In other words, labor productivity across counties has become increasingly different. As in the case of employment, productivity in services started off being more equal across space than productivity in manufacturing. Over time these differences have becomes mitigated.

[8] Once again, we deflate by the services price index used in the *Industry Economic Accounts* of the BEA.



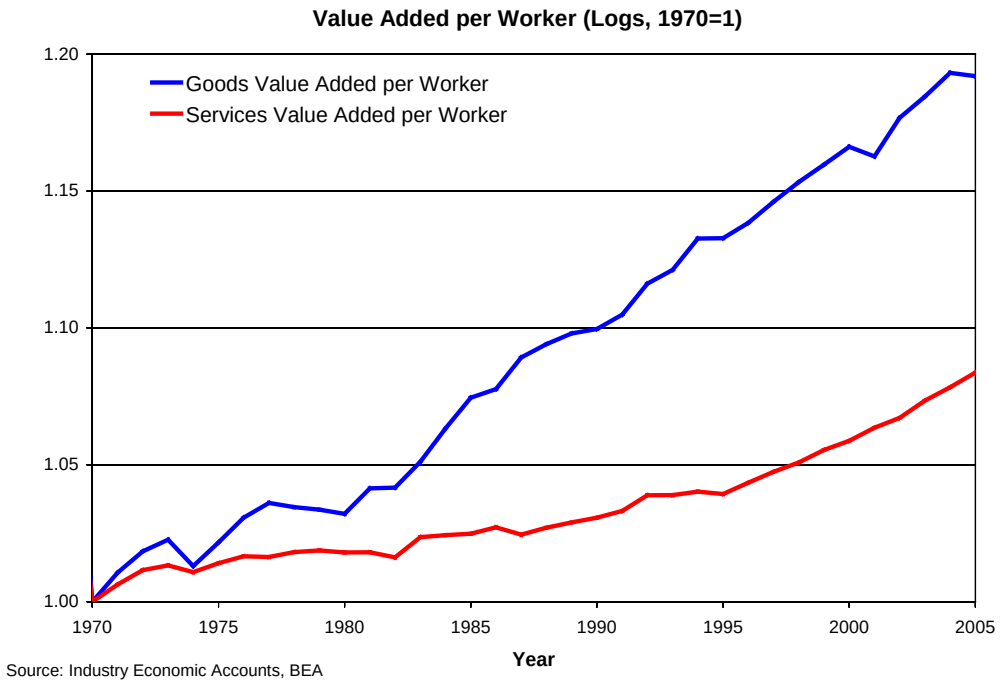
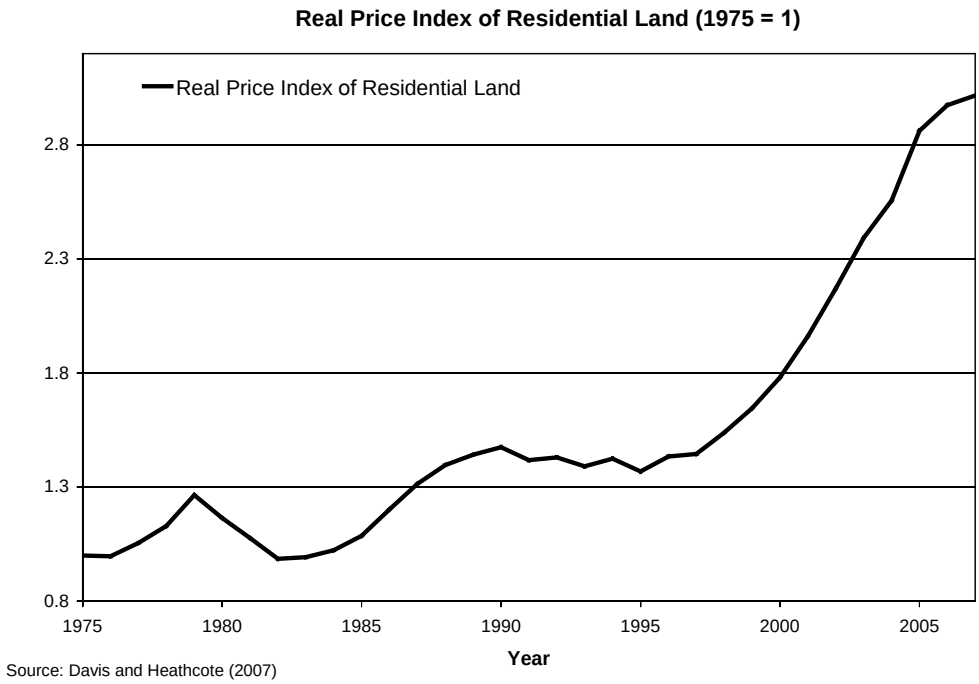


Figure 4: Value Added per Worker



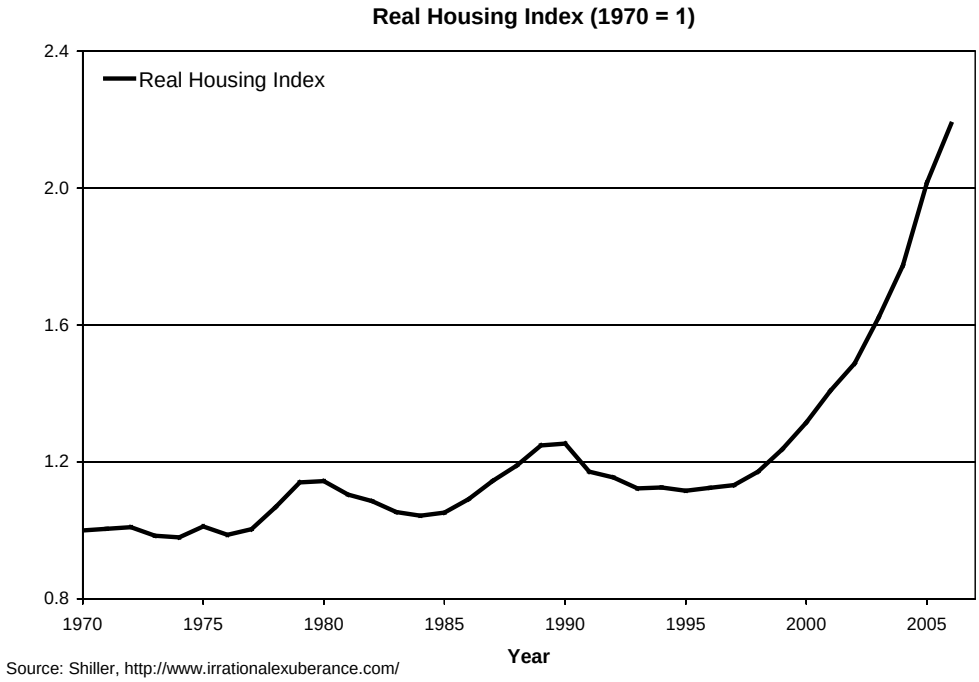
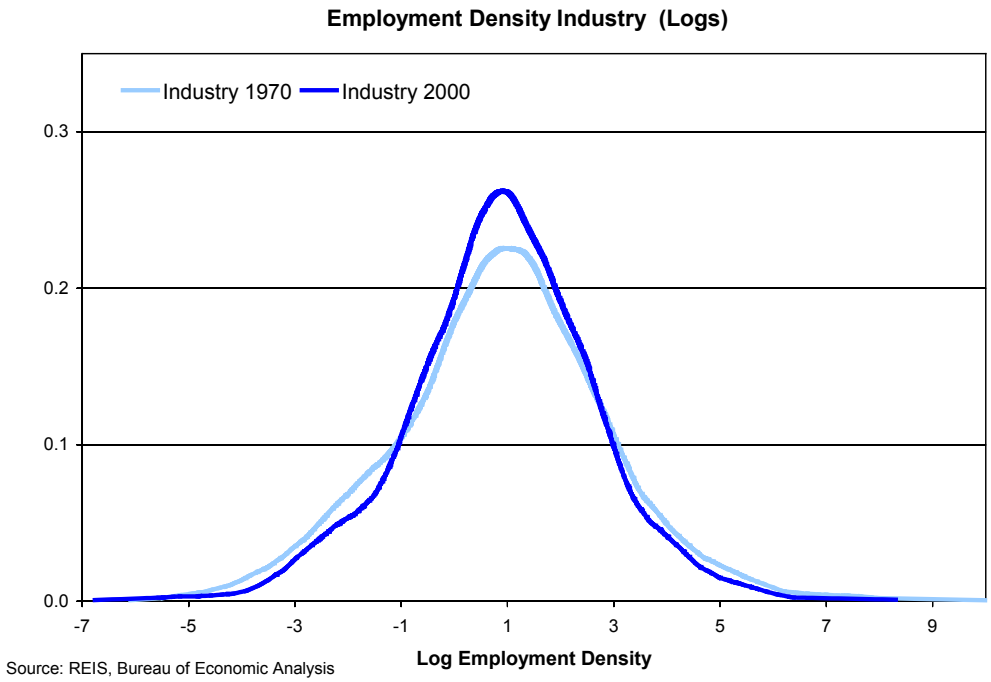


Figure 5: The Value of Land



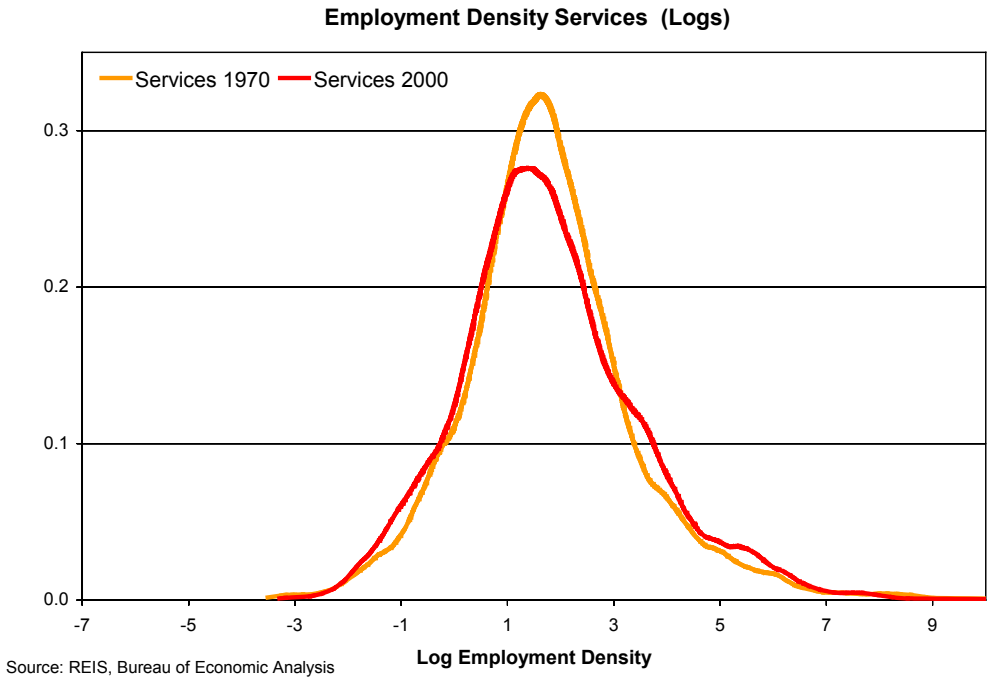
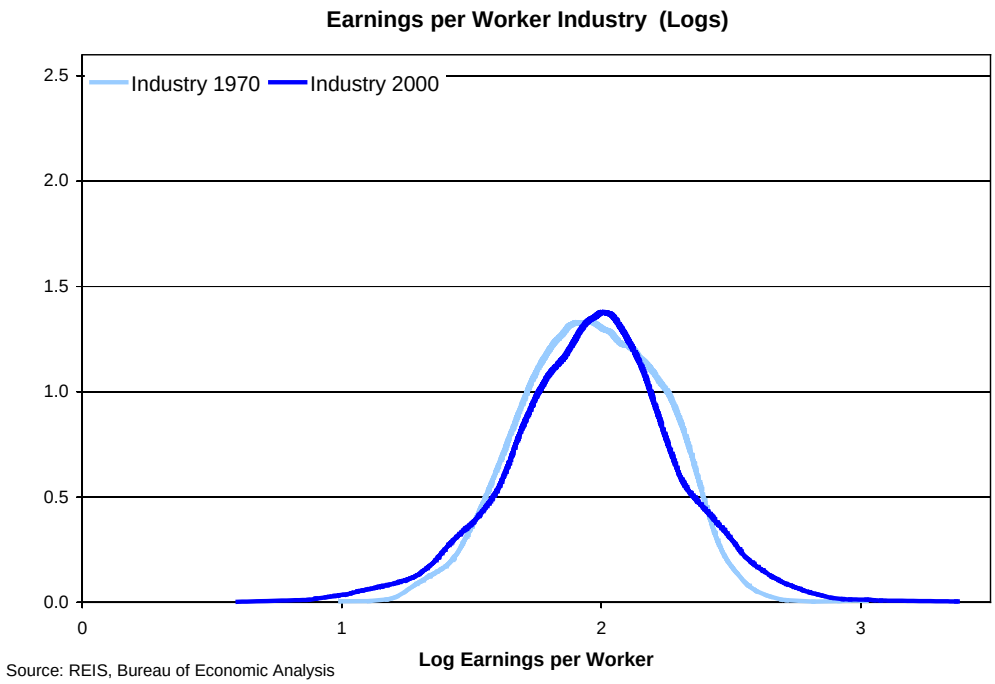


Figure 6: Distribution of Employment across Counties



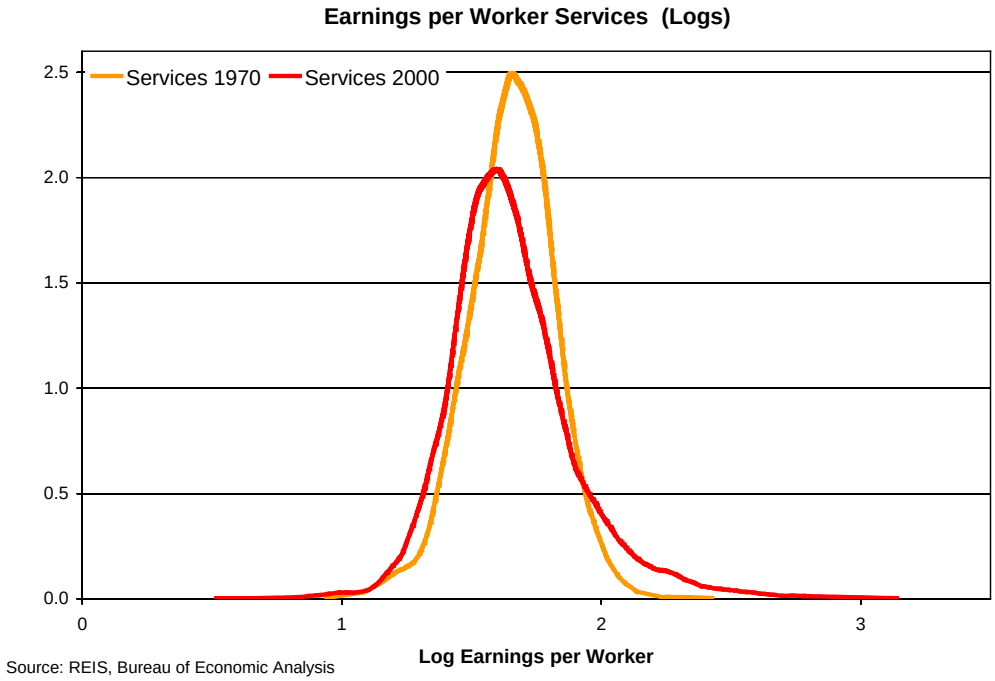


Figure 7: Distribution of Productivity across Counties

3.2 Evidence on Spatial Growth

Our theoretical model predicts that locations will grow faster in a given sector if they are geographically close to other locations specialized in that same sector (a 'spillover effect') and if they are close to locations that have excess demand for the goods produced by that sector (a 'trade effect'). That is, service growth in a given location will benefit from proximity to both service-producing clusters and service-importing locations. Since in our two-sector model service-importing locations are specialized in manufacturing, this implies that proximity to both service clusters and manufacturing clusters may be beneficial for growth in services. However, the first channel works through spillovers, whereas the second channel works through trade. Note also that since high productivity locations attract a higher fraction of workers in a given sector, the relevant variable to consider is growth in output (value added).

To explore these theoretical predictions, we first construct two kernels to measure the 'spillover effect' and the 'trade effect'. We use US county data for the period 1980-2000 from the Bureau of Economic Analysis. For each county, the first kernel sums earnings in a particular sector (as a measure of value added) over all other counties, exponentially discounted by distance. The second kernel is constructed in the same way, but sums imports in a particular sector, instead of earnings.[9] This measures the excess demand experienced by a county in a particular sector. We then run the following regression:

$$\log Earn^i_\ell(t+1) - \log Earn^i_\ell(t) = \alpha + \beta_1 \log Earn^i_\ell(t) + \beta_2 \log(EarnK^i_\ell(t)) + \beta_3 \log(ImpK^i_\ell(t))$$

where $Earn^i_\ell(t)$ denotes earnings, $EarnK^i_\ell(t)$ the earnings kernel, and $ImpK^i_\ell(t)$ the imports kernel, for sector i, county ℓ and period t.[10]

[9] Imports in a given sector is the difference between a county's consumption and production in that sector. A county's consumption in a given sector is obtained by multiplying the national share of earnings in that sector by the county's total earnings. A county's production in a given sector is simply measured by its earnings in that sector.

[10] Since the import kernel measures a discounted sum of imports in a given sector, this measure may be positive or negative. In the regression we use the natural logarithm of the kernel when the kernel is positive and minus the natural logarithm of the absolute value of the kernel when it is negative. Also, since we include the log of earnings in county ℓ as a separate regressor, the earnings kernel does not include employment in county ℓ, whereas the import kernel does include imports by county ℓ.

Decay Earnings Kernel:				0.1 (half life 7 km)				
Decay Import Kernel:	0.07	0.08	0.09	0.10	0.11	0.12	0.13	0.14
Half-Life Import Kernel (km):	9.9	8.7	7.7	6.9	6.3	5.8	5.3	5.0
Dependent variable: Log(Service Earnings 2000)-Log(Service Earnings 1990)								
Log(Serv. Earnings 1990)	0.0248	0.02517	0.02539	0.02564	0.02563	0.02573	0.02582	0.02587
	[7.17]***	[7.29]***	[7.36]***	[7.44]***	[7.44]***	[7.47]***	[7.51]***	[7.52]***
Log(Serv. Earnings Kernel 1990)	0.01312	0.01272	0.01243	0.01218	0.01208	0.01197	0.01185	0.01177
	[6.19]***	[6.01]***	[5.88]***	[5.76]***	[5.71]***	[5.67]***	[5.61]***	[5.57]***
Log(Serv. Imp. Kernel 1990)	0.00166	0.00225	0.00269	0.00308	0.00319	0.00335	0.00356	0.0037
	[2.87]***	[3.84]***	[4.55]***	[5.17]***	[5.33]***	[5.57]***	[5.90]***	[6.12]***
Constant	0.14154	0.1395	0.1386	0.13708	0.13775	0.13725	0.13695	0.13676
	[3.80]***	[3.75]***	[3.73]***	[3.69]***	[3.72]***	[3.70]***	[3.70]***	[3.69]***
Observations	2972	2972	2972	2972	2972	2972	2972	2972
R-squared	0.0508	0.0529	0.0548	0.0567	0.0572	0.058	0.0592	0.06
Dependent variable: Log(Service Earnings 1990)-Log(Service Earnings 1980)								
Log(Serv. Earnings 1980)	0.03713	0.03731	0.03763	0.03778	0.03776	0.03775	0.03773	0.03763
	[9.98]***	[10.04]***	[10.13]***	[10.19]***	[10.19]***	[10.20]***	[10.20]***	[10.17]***
Log(Serv. Earnings Kernel 1980)	0.0172	0.0169	0.01662	0.01643	0.01634	0.01625	0.01625	0.01632
	[7.82]***	[7.70]***	[7.57]***	[7.50]***	[7.46]***	[7.43]***	[7.43]***	[7.47]***
Log(Serv. Imp. Kernel 1980)	0.00274	0.00328	0.00376	0.00411	0.00435	0.00459	0.00468	0.0046
	[4.50]***	[5.33]***	[6.06]***	[6.60]***	[6.96]***	[7.32]***	[7.45]***	[7.31]***
Constant	0.05781	0.05816	0.05694	0.0568	0.058	0.05889	0.05918	0.05976
	[1.49]	[1.50]	[1.47]	[1.47]	[1.50]	[1.53]	[1.54]	[1.55]
Observations	2972	2972	2972	2972	2972	2972	2972	2972
R-squared	0.0839	0.0864	0.0889	0.0909	0.0924	0.094	0.0945	0.0939
Dependent variable: Log(Industry Earnings 2000)-Log(Industry Earnings 1990)								
Log(Ind. Earnings 1990)	0.00581	0.00662	0.00744	0.00789	0.00838	0.00869	0.00907	0.00932
	[0.94]	[1.07]	[1.20]	[1.27]	[1.35]	[1.40]	[1.46]	[1.50]
Log(Ind. Earnings Kernel 1990)	0.02256	0.02276	0.02291	0.02282	0.02292	0.02288	0.02289	0.02277
	[5.00]***	[5.06]***	[5.10]***	[5.08]***	[5.11]***	[5.10]***	[5.11]***	[5.08]***
Log(Ind. Imp. Kernel 1990)	0.00643	0.00685	0.00722	0.00735	0.00749	0.00756	0.00768	0.00765
	[6.36]***	[6.70]***	[7.00]***	[7.08]***	[7.15]***	[7.19]***	[7.28]***	[7.23]***
Constant	0.1408	0.13084	0.12136	0.11723	0.11128	0.10831	0.10412	0.10226
	[2.36]**	[2.19]**	[2.03]**	[1.95]*	[1.85]*	[1.80]*	[1.73]*	[1.69]*
Observations	2816	2816	2816	2816	2816	2816	2816	2816
R-squared	0.0217	0.0232	0.0246	0.025	0.0254	0.0255	0.026	0.0257
Dependent variable: Log(Industry Earnings 1990)-Log(Industry Earnings 1980)								
Log(Ind. Earnings 1980)	-0.04799	-0.04774	-0.04754	-0.04742	-0.0471	-0.04683	-0.04658	-0.04629
	[8.57]***	[8.50]***	[8.46]***	[8.43]***	[8.35]***	[8.28]***	[8.22]***	[8.16]***
Log(Ind. Earnings Kernel 1980)	0.05618	0.05621	0.05632	0.0563	0.05638	0.05642	0.05648	0.05654
	[13.74]***	[13.77]***	[13.80]***	[13.81]***	[13.85]***	[13.88]***	[13.91]***	[13.94]***
Log(Ind. Imp. Kernel 1980)	0.00137	0.00147	0.00164	0.00168	0.00186	0.00198	0.00212	0.00228
	[1.45]	[1.54]	[1.70]*	[1.73]*	[1.90]*	[2.02]**	[2.16]**	[2.31]**
Constant	0.50405	0.5012	0.49821	0.49698	0.49293	0.48986	0.4867	0.48315
	[9.27]***	[9.17]***	[9.10]***	[9.06]***	[8.95]***	[8.87]***	[8.80]***	[8.71]***
Observations	2816	2816	2816	2816	2816	2816	2816	2816
R-squared	0.0657	0.0658	0.0659	0.066	0.0662	0.0663	0.0665	0.0667

Absolute value of t statistics in brackets
** significant at 10%; ** significant at 5%; *** significant at 1%*

Table 1: The Effect of Earnings and Import Kernels on US County Earnings Growth Rates

Table 1 reports the results of this regression. The discount rate for the earnings kernel is set to 0.1, implying the effect declines by half every 7 km, whereas the discount rate for imports varies between 0.07 and 0.014, implying the effect declines by half every 5 to 10 km. The top panel reports the results for the service sector for the decade 1990-2000. As expected, both the earnings kernel and the imports kernel have positive effects on earnings growth. All effects have the expected sign and are statistically significant at the 1% level. Taking a decay parameter for the import kernel of 0.1, we find that a 1% increase in the earnings kernel leads to a 0.012% increase in earnings growth. With respect to the import kernel, a 1% increase leads to a 0.003% increase in earnings growth over the period 1990-2000. As can be seen, the coefficients are fairly robust to changes in the decay parameter. The second panel reports the results for the 1980-1990 decade. Once again, all coefficients have the expected sign and are statistically highly significant.

The last two panels present the regressions for the industrial sector (manufacturing plus construction). These regressions confirm our previous findings. There is one difference between industry and services though. Whereas in services initial earnings always have a positive and statistically significant effect on earnings growth, in industry the effect is either statistically insignificant (for the 1990-2000 decade) or negative (for the 1980-1900 decade). This reflects the facts reported in Figure 7: the service sector is becoming spatially more concentrated, whereas this is not the case for the industrial sector.

4. NUMERICAL SIMULATIONS

In this section we simulate using the cost function in equation (8). Throughout the section we let $\psi_2 = -\psi_1 > 0$ so there are no fixed costs of investment. We present a basic parametrization and several deviations to illustrate numerically the comparative statics of the model. We plan to calibrate the model using the data presented in Section 3 in future drafts of the paper. For the moment we present some exercises that replicate, mostly qualitatively, the patterns in the data. To compute the model we need to specify initial productivity functions for both manufacturing and services. We let $Z_S(\cdot, 0) = 1$ and $Z_M(\cdot, 0) = 0.8 + 0.4\ell$.

The key characteristic of the initial productivity functions is that service productivity is initially larger for locations close to the left border and manufacturing productivity is larger close to the right border. Furthermore, the locations with the highest manufacturing productivity (namely the right border) have a 20% larger productivity than the locations with the highest service productivity. The result of these initial productivity functions is that, as we show below, we can have three different configurations of productivity growth in both industries. Either the economy starts innovating in manufacturing but not in services, or it does the same in both industries (innovate or not). What these initial conditions rule out is service innovation starting before manufacturing innovation.

The elasticity of substitution between manufacturing and services, $1/(1-\alpha)$, is important for the results. A key mechanism in the model is that as productivity in one sector increases, relative to the other sector, the relative price of goods in that sector decreases and so does its employment share. This is only the case if the elasticity of substitution is less than 1. The literature has estimated this elasticity to be substantially below 1. Stockman and Tesar (1995), for example, estimate it to be 0.44 for a set of 30 countries. Given this evidence, we set $\alpha = -1$, so the elasticity of substitution is $1/(1-\alpha) = 1/2$. With an elasticity below 1, when a sector's relative productivity grows and employment in the sector declines, the increase in employment in the other sector increases the incentives for innovation in that slow-growing sector. Eventually, enough people switch to the slow producing sector for innovation to start there. In that sense, the economy self regulates. Indeed, as more people move out of the fast growing sector, thus tending to lower overall growth, the other sector starts innovating as well, thus tending to increase overall growth. As we show in the examples, the aggregate trend converges to a balanced growth path (apart from small deviations).

In order to gauge the effect of the main mechanisms in the theory, we make both sectors identical apart from their initial productivities. We set the share of labor in both sectors to $\mu = \sigma = 0.6$ and the share of expenditure in each sector to one half, so $h_S = h_M = 1$. We think of a period in the model as a year, so we let $\beta = 0.95$. In all simulations we let the model run for 100 periods and we use 500 locations.

We vary all other parameters to understand their effect. In the benchmark case we let $\psi_2 = 0.003851$. As Figure 8 illustrates, this value yields no innovation in services for the first 42 periods. We set the parameter of the Pareto distribution, a, equal to 35. This value yields aggregate productivity that grows by roughly 5% per period in manufacturing. When service innovation starts, the growth rate in service productivity is about the same. This can be seen in the second figure of the first row of Figure 8 (from now on Figure 8.1.2, where 1.2 stands for row 1 column 2). Note, furthermore, that in all figures services are red, and manufacturing is blue.

Aggregate productivity growth rates are also determined by technological diffusion. We set the exponential diffusion rate of technology, d, equal to 20. This results in employment shares in services that rise from about 0.5 to about 0.75. (as shown in Figure 8.3.1). We set the transport cost parameter $\kappa = 0.005$. This level of transport costs in general yields two main specialization areas, one for services in the left side of the line and one for manufacturing. This cost has important effects on the timing of the start of service innovation, as well as on the total decline in average manufacturing prices. Here, manufacturing prices decline by about 90% during the period, too much relative to the evidence in Section 3.

For all numerical simulations we present similar graphs, consisting of nine subplots. Subplots 1.1 in Figures 8 to 13 present the coefficient of variation of employment over space in both industries. The pattern here is always similar. Since our initial productivity function has some variation in manufacturing but not in services, this value starts off always higher in manufacturing. After the start of service productivity growth the coefficient of variation in services catches up with that of manufacturing. This indicates services becoming more concentrated in space. In many cases the coefficient of variation in services ends up surpassing that in manufacturing, as locations close to the left boundary continue to have little employment, compared to locations specialized in services, which are close to the manufacturing clusters. This is consistent with the data on U.S. counties in Figure 6. The distribution of employment across counties is becoming more similar between manufacturing and services, with services becoming geographically more concentrated, as reflected by its distribution becoming less tight.

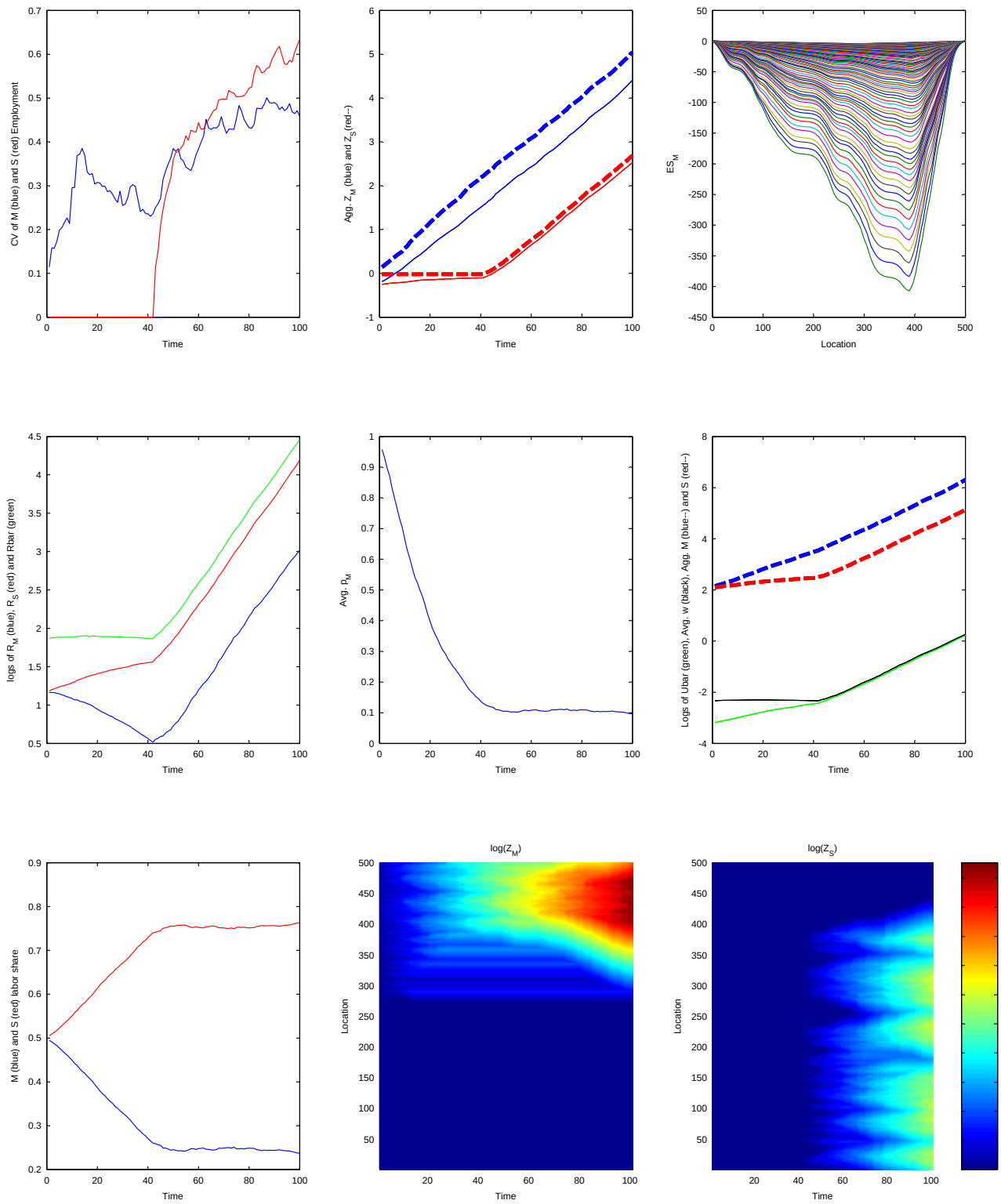


Figure 8: Simulation Results for Benchmark Parameterization

Subplots 1.2 in all figures present aggregate productivity calculated in two different ways. The solid curves present aggregate productivity as

$$Agg_1 Z_i(t) = \frac{\int_0^1 x_i(\ell,t)\,\theta_i(\ell,t)\,d\ell}{\left(\int_0^1 \hat{L}_i(\ell,t)\,\theta_i(\ell,t)\,d\ell\right)^{\iota}},$$

the dashed curves present an alternative statistic, namely,

$$Agg_2 Z_i(t) = \frac{\int_0^1 x_i(\ell,t)\,\theta_i(\ell,t)\,d\ell}{\int_0^1 \left(\hat{L}_i(\ell,t)\,\theta_i(\ell,t)\right)^{\iota} d\ell}.$$

Given that there are decreasing returns to scale in labor at each location, it is not clear that one of them is preferred. $Agg_1 Z_i(t)$ is the equivalent of a Solow residual, but a shift in $Agg_2 Z_i(t)$ increases aggregate output by exactly the same amount.

Subplots 1.3 present the stock of excess supply, $H_M(\ell,t)$. $H_M(\cdot,t)$ declines when locations specialize in services and it grows when locations specialize in manufacturing. It is a good way of tracking changes in specialization over space. A parameter that is key to determine the number of areas of specialization is the diffusion parameter d. An increase in d implies that diffusion dies out fast and so locations benefit little from it. Figure 9 presents a simulation with $d = 100$. Compared to Figure 8.1.3, we can see in Figure 9.13 that the slope of the stock of excess supply changes slope many times, indicating several switches in land use specialization. The reason is clear: when diffusion is local, being close to other regions producing the same good does not provide any advantage. The increase in d also reduces aggregate productivity growth to about 2.5% per year whenever there is innovation.

Subplots 2.1 present the value of land over time. It shows the value of the diverse portfolio of land held by all agents, as well as the value of land specialized in each sector. Note from Figures 8.2.1 and 9.2.1 how the value of manufacturing land decreases as technology in manufacturing improves and service technology remains constant. This happens because the decline in the value of manufacturing goods more than compensates the increase in productivity. The value of service land, on the other hand, increases throughout. Once innovation in the service sector starts, both the value of the portfolio of land and manufacturing land rents start increasing. This is very clear in the U.S. data presented in Figure 5,

and the timing coincides with the increase in service productivity shown in the top panel of Figure 4. Note that both in the model and in the data we deflate by the price of service goods.

Subplots 2.2 present the price of manufacturing goods relative to services. The initial increase in manufacturing productivity, together with an elasticity of substitution less than 1, implies that the relative price of manufactured goods declines over time. Once service productivity starts to increase, the price stabilizes and stays more or less constant. The magnitude of the decline in the price from its starting level around 1 depends on the number of periods without service productivity growth. In Figure 10, for example, we let $d = 10$. In that case, diffusion has a wide scope, which implies larger growth rates (about 6% per year). This leads to a shorter time period during which only manufacturing grows. As a result, the relative price now falls only 50%, closer to the drop we observe in Figure 3.

Subplots 2.3 present the evolution of utility, wages and aggregate real output in both industries. Note that wages do not increase significantly until service productivity starts growing. This is again consistent with the evidence in Figure 3, where wage growth in terms of service goods increases dramatically starting around 1995. Utility grows throughout, since productivity growth in any industry always increases welfare independently of the relative price and labor reallocation effects. This is particularly clear in Figures 1.1 and 1.2. In Figure 1.1 we present a case for which $\psi_2 = 0.003$ and in Figure 1.2 a case for which $\psi_2 = 0.005$. When the costs of innovation are low, both sectors innovate in some locations from the start. The result is that relative prices vary little and in random directions. Furthermore, both utility and wages grow throughout, as do both real output series. Employment dispersion in Figure 11.1.1 is also similar in both industries as is aggregate productivity in Figure 11.1.2. In contrast, Figure 12 shows a case where the cost of innovation is so large that service employment growth does not start in the 100 periods we compute. As a result, wages stay mostly flat, with a small decline given that we normalize by service prices. Utility grows, but at a much slower level. The real output series show that output in both sectors increases. Clearly, the increase in service output is just the result of employment reallocation.

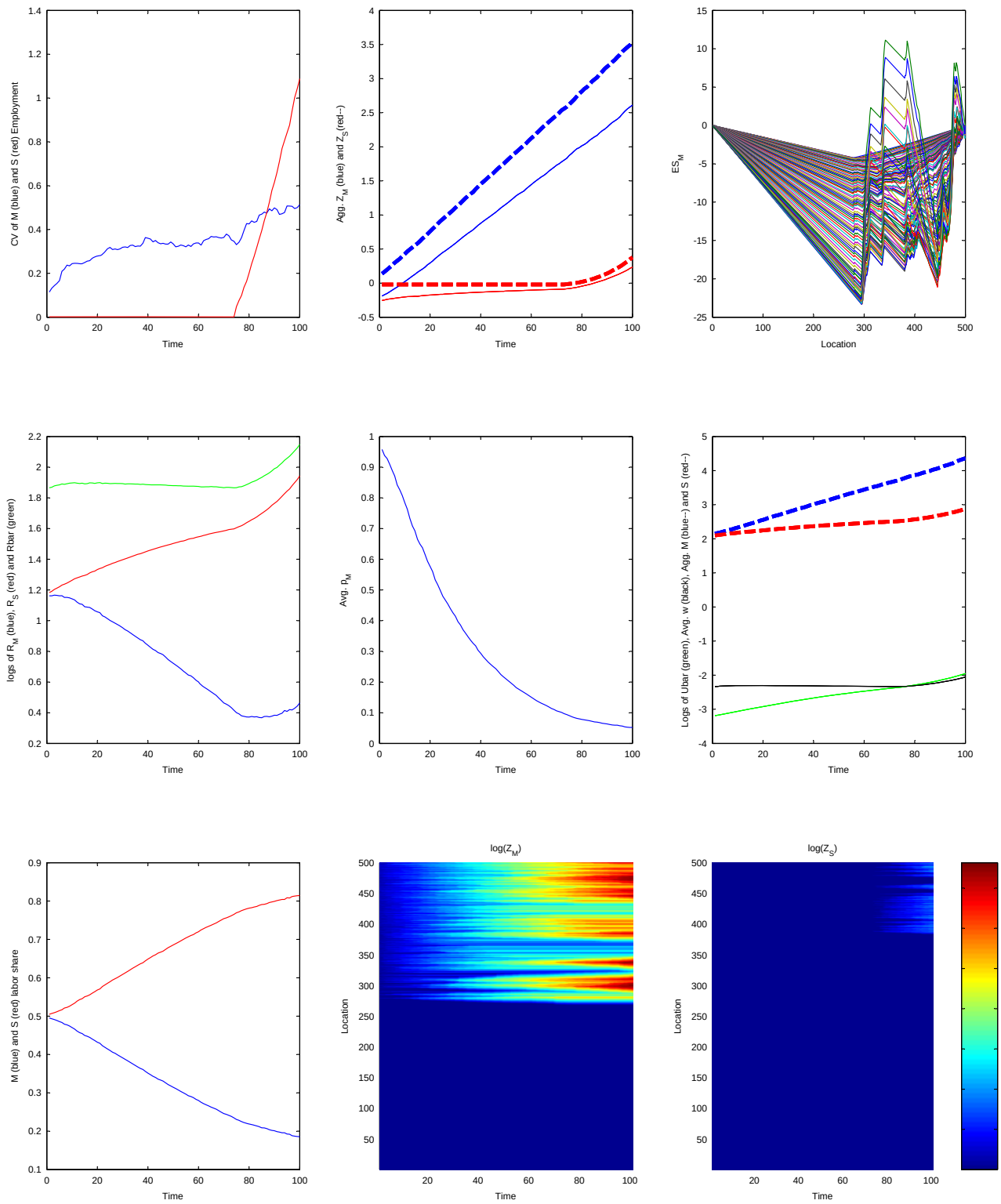


Figure 9: Simulation Results with $d = 100$

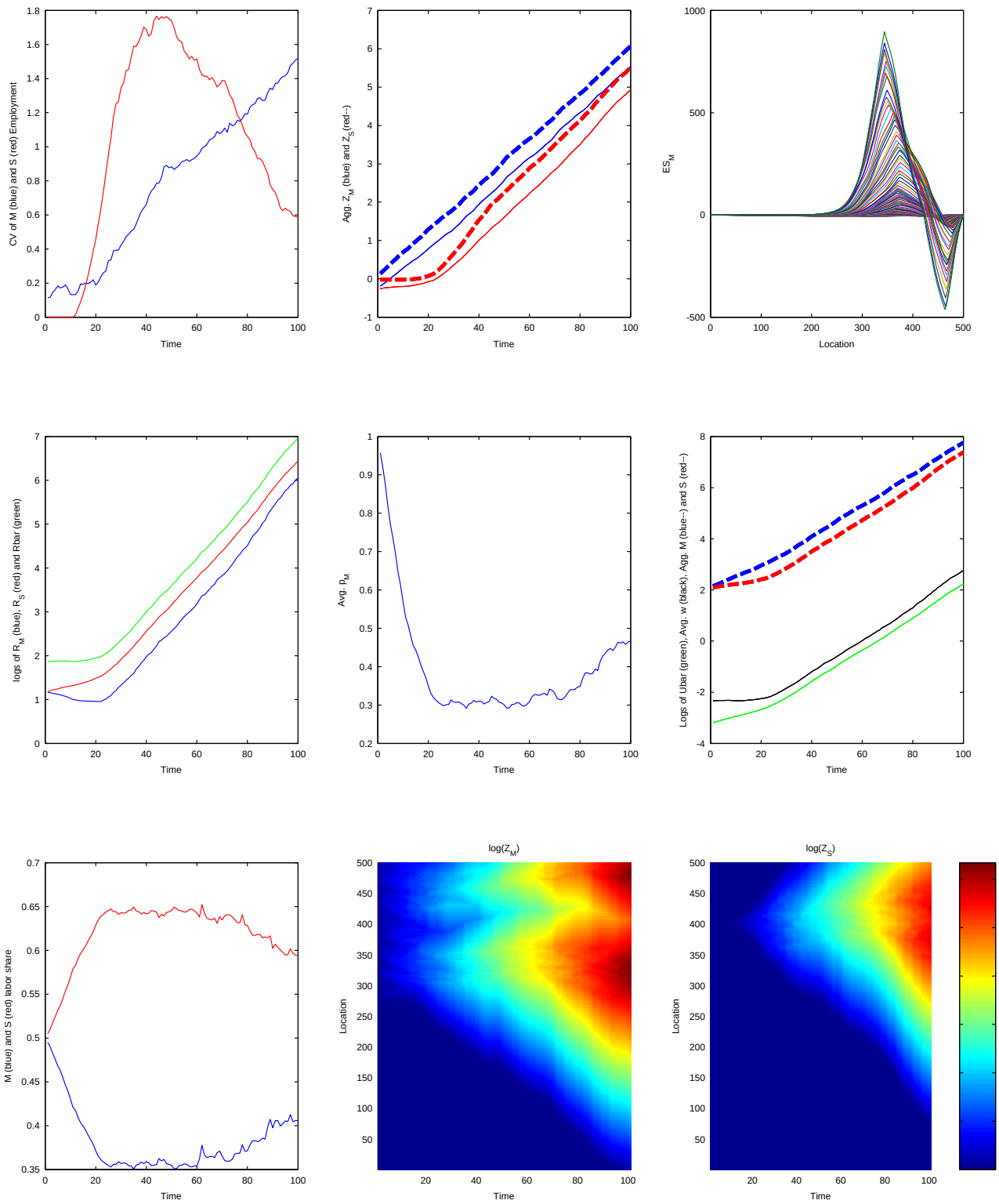


Figure 10: Simulation Results with $d = 10$

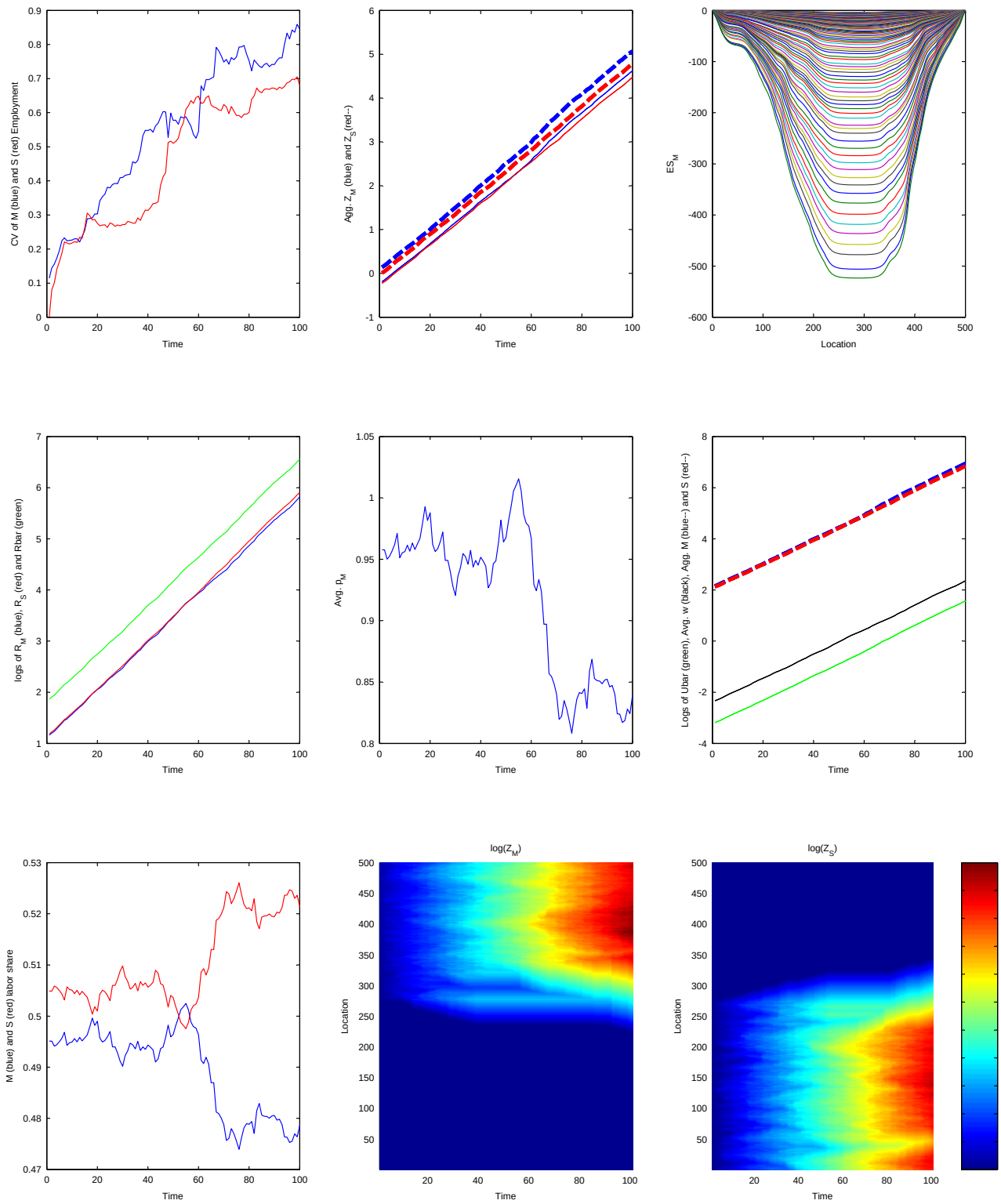


Figure 11: Simulation Results with $\psi_2 = -\psi_1 = 0.003$

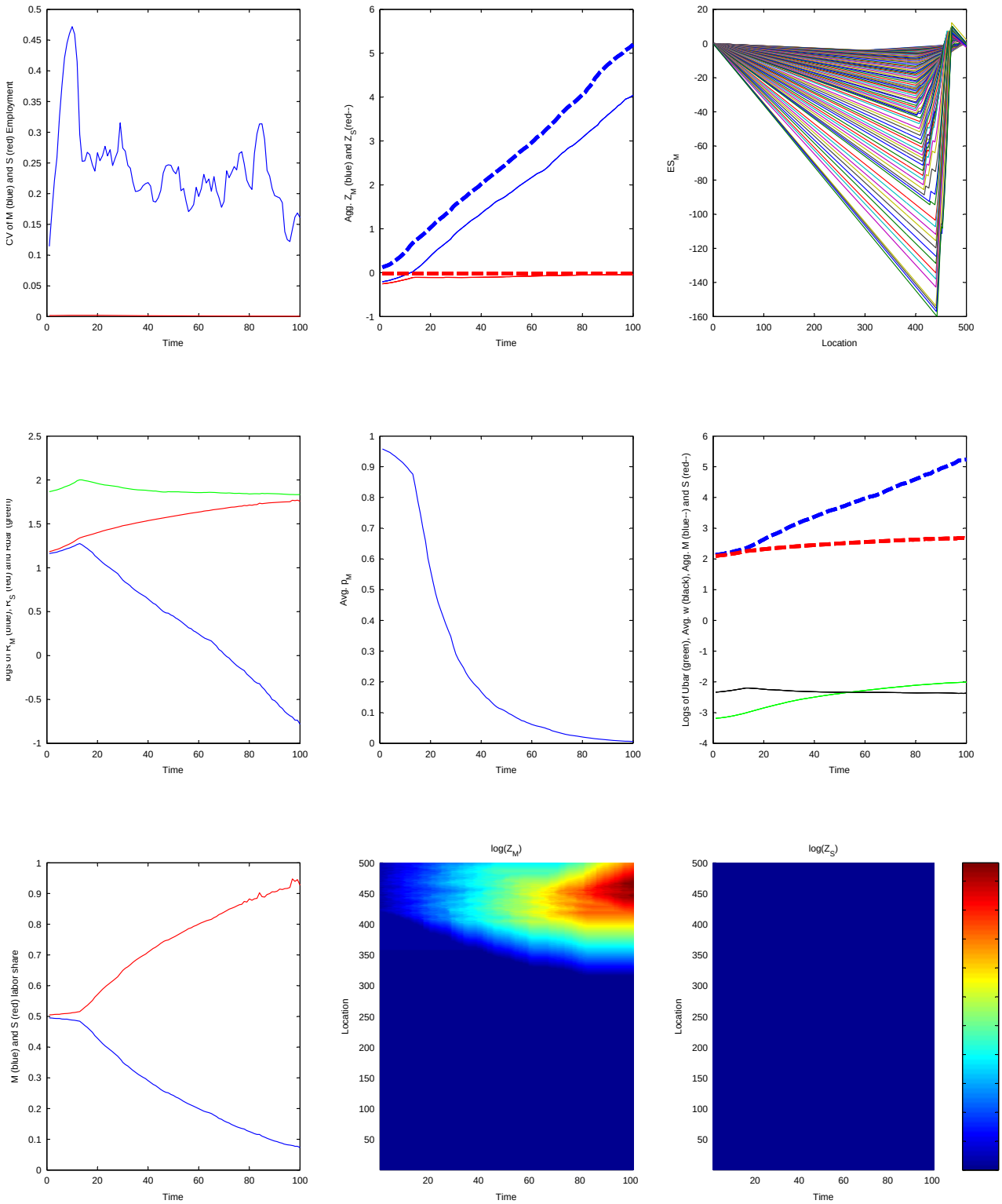


Figure 12: Simulation Results with $\psi_2 = -\psi_1 = 0.005$

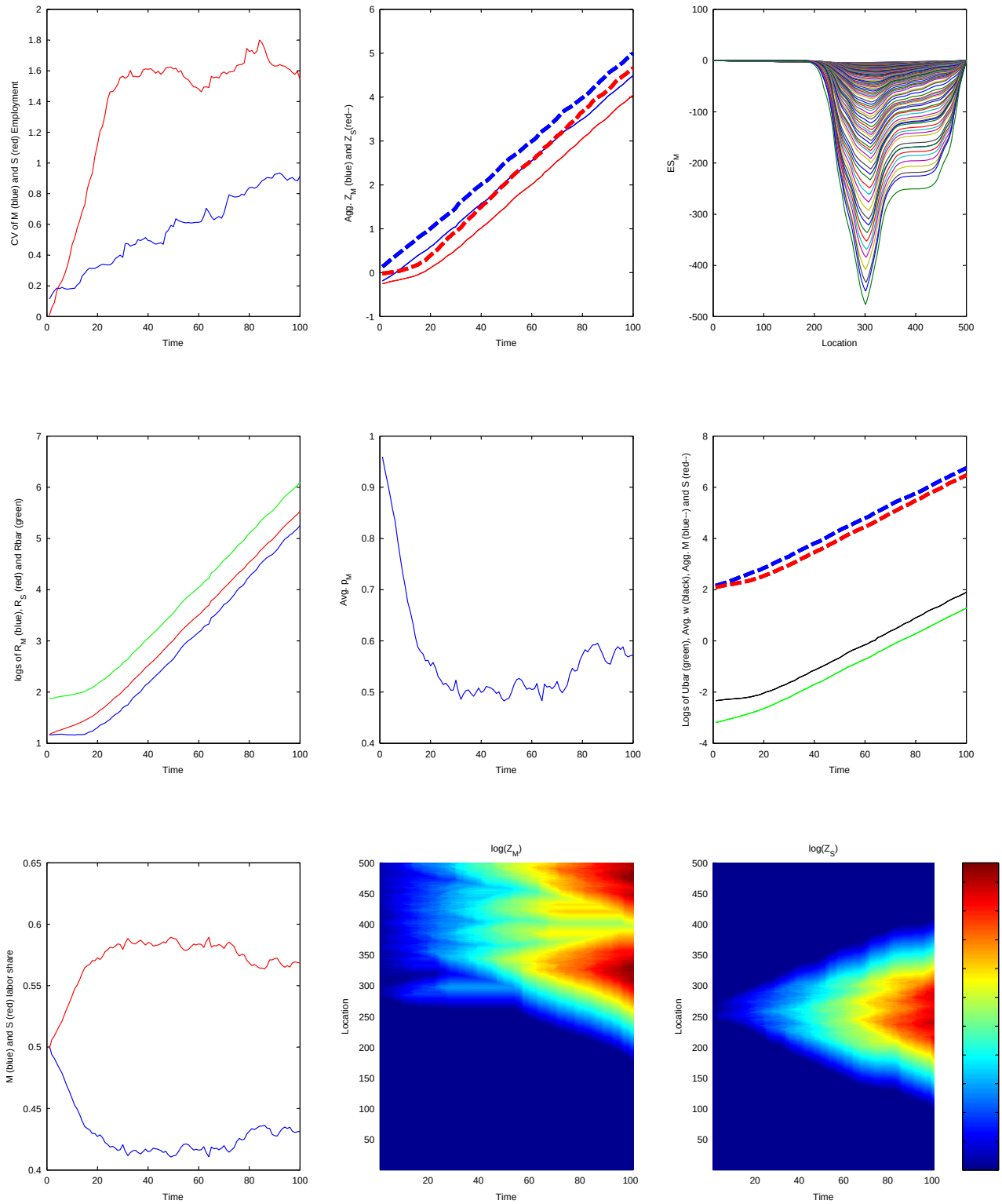


Figure 13: Simulation Results with $\kappa = 0.02$

Subplots 3.1 show employment shares in both sectors. As there is no unemployment in this economy, one is the mirror image of the other (subject to some small computation error in some cases). Note how in Figure 12, where the cost of innovation is very high and we never observe innovation in the service sector, the share of labor in services goes up to 90% percent and the price of goods is almost zero. Still the cost is so high that no one innovates in the service sector. Eventually, as the price falls even further and the share of labor in manufacturing goes to zero, some locations will start innovating in services, although this may take a long time. In contrast, in Figure 11, with small innovation costs, Figure 11.3.1 shows that employment shares vary little, as both sectors are innovating at a similar aggregate rate (of course there is a significant, and growing, regional variation, as is evident in Figure 11.1.2).

Finally Subplots 3.2 and 3.3 present the evolution of productivity over time and space. As this is a three-dimensional object, we present colored contour plots. Blue (darker) areas represent low productivity and lighter and then red areas represent higher productivity levels. These figures are helpful to identify the areas in which innovation is happening and how clusters of innovation are created and destroyed over time. As can be seen, once services start innovating, this happens in a limited number of locations. In other words, service productivity, which started off being homogeneous across space, is becoming increasingly different across locations. This is consistent with the evidence for the U.S. in Figure 7. There we see how the productivity distribution in services across counties is becoming less tight, indicating that counties are becoming increasingly different in terms of service productivity.

In Figure 13 we present an example with large transport costs in which we set $\kappa = 0.02$. The result of the increase in transport costs is that service production and innovation now clusters around manufacturing areas instead of all over the left region. Because relative prices of service goods decline as we move away from manufacturing clusters (goods have to be transported and are therefore more expensive), the service producing locations close to manufacturing clusters benefit more from innovation and are therefore the first to start innovating. As can be seen in Figure 13.3.3 only a few locations innovate initially and the main service cluster grows over time. Perhaps surprisingly, in contrast to Figure 8,

higher transport costs lead to faster innovation in the service sector, and therefore, faster growth in wages and welfare (see Figure 13.1.2 and 13.2.3). The static loses from higher transport costs are outweighed by the higher incentives to innovate in certain areas. This is an example in which having a rich spatial dimension leads to some novel economic effects. It is the dispersion in service employment in space, caused by transport costs via price differences across locations, that creates this dynamic effect.

5. CONCLUSION

In this paper we have presented a spatial dynamic growth model in which locations choose how much to invest in innovation, if at all, in each sector. We find that employment relocation is crucial in balancing innovation across sectors. As innovation in one sector increases relative to the other sector, employment in the sector decreases and this increases incentives for innovation in the other sector that is gaining employment, especially in those locations near the growing sectors' clusters. These effects balance the value of sectors in the economy and lead to a balanced growth path in which aggregate growth in the economy eventually stabilizes. A fairly stable aggregate path hides increasing activity in employment reallocation across locations. Regional activity sees local clusters grow and disappear as the economy grows. The pattern of clusters is related to the costs of innovation, transport costs and the spatial scope of diffusion, as we document numerically. We argue that this process of innovation and employment reallocation helps rationalize many observed phenomena in the U.S. during the last few decades.

In the current draft of the paper we have only compared the outcome of the model with data in a fairly informal way. In the future we hope to calibrate the model to the data presented in Section 3. The exercises we have presented so far suggest that the model is rich enough to capture the observed patterns. It also suggests many interesting links between development and the distribution of economic activity in space.

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