The Coagglomeration of Innovation and Production*

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Abstract

This paper evaluates and quantifies the importance of production proximity for innovation efficiency. First, using a novel and comprehensive establishment-level dataset from the U.S. Census Bureau, I document that innovation and production activities are coagglomerated in the majority of manufacturing industries. The geographic concentration of innovation and production provides suggestive evidence on the importance of the two activities being colocated. Second, I develop an empirical model that allows for spillovers from local production to innovation and apply it to measure the private returns to R&D investment for a panel of U.S. R&D firms during 2002-2012. My estimates show that the proximity to production raises the returns to R&D, suggesting there are positive spillovers from the local manufacturing to innovation. Third, I evaluate the macroeconomic implications of my empirical findings in a multi-region production and trade model featuring the local spillovers from production to innovation. I find that the relocation of production workers due to the China trade shock leads to a moderate reduction in both process and product innovation. States with a larger decline in manufacturing employment experience a more substantial loss in innovation efficiency.

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1 Introduction

What factors can enhance innovation is a question of enormous interest, as creation of new technology is the key driver of long-run economic growth. There is a growing recognition that the transmission of knowledge plays an essential role in the development of new ideas (Cohen and Levinthal, 1989; Aghion and Jaravel, 2015). Going back to Marshall (1920), economists have argued that the transmission of knowledge is facilitated by geographic proximity. Geographic proximity not only improves the information flows across innovation activities, but also fosters the communications between the production workers and the researchers. While studies have focused on knowledge spillovers across innovation activities(Jaffe et al., 1993; Caragliu and Nijkamp, 2015), little attention has been paid to the potential spillovers from production to innovation. Understanding the role of production in fostering innovation is particularly relevant as the employment in U.S. manufacturing has shrunk by nearly 30 percent since the year 2000. In this paper, I evaluate and quantify the importance of production proximity for innovation efficiency.

First, I document the geographic concentration of innovation and production activities for U.S. manufacturing industries by using a novel and comprehensive plant-level data from the Census Bureau. To identify the innovation and production activities at the micro level, I link the Longitudinal Business Database (LBD) with the Business R&D and Innovation Survey (BRDIS). It enables me to measure the spatial distribution of these activities.

I quantify the concentration pattern of innovation and production activities from two aspects. I begin by using the Ellison and Glaeser (1997, hereafter EG) metric of agglomeration to measure the location pattern of innovation and production activities, respectively. Then I use the EG metric of coagglomeration to measure how colocated the innovation and production activities are within an industry. I find that (i) innovation is more agglomerated than production in the majority of industries; and ii) innovation and production activities are coagglomerated both in the absolute sense and relative to the coagglomeration of industrial production. The spatial distribution of innovation and production suggests that gains from geographic concentration are more significant for innovation than production (Capello and Lenzi, 2014; Buzard et al., 2015). More importantly, it highlights the importance of locating innovation and production facilities close to each other.

Second, motivated by the stylized facts, I develop and estimate an empirical model of production and innovation within a manufacturing firm to quantify the private returns to R&D, measured in terms of productivity gains generated by a marginal increase in R&D. The primary goal is to assess if the returns to R&D are higher when innovation plants are in regions with more production workers from their own industry. Building on the recent work by Aw et al. (2011), Doraszelski and Jaumandreu (2013) and Bøler et al. (2015), the model assumes that a plant's revenue is subject to the plant-specific performance which evolves according to a Markov process. The increment in plant performance depends on the R&D investment of the plant itself, the interaction between its R&D investment and the local manufacturing employment, as well as the transfer of technology from the other R&D plants within the same firm. A unique feature of my model is to consider spillovers from the local manufacturing to innovation explicitly. The inclusion of the spillovers allows for the possibility of learning from the production process. Local production workers are a source of knowledge that can enhance plants' R&D efficiency, which, in turn, has an impact on plant performance.

I construct a unique plant-level panel data on R&D investment and domestic production for U.S. R&D firms in the manufacturing sector from 2002-2012 for my estimation. These data allow me to observe the input and output for each production plant, and the R&D expenditures for each innovation plant.

My empirical results show that innovating plants obtain significantly higher returns to R&D if they are located in counties with more of their own industry production workers. It suggests that there are positive spillovers from the local production to innovation. All else equal, doubling the local own industry manufacturing employment increases the impact of a plant's own investment on its productivity by 21.4%. My analysis is informative for understanding the role of local manufacturing in enhancing efficiency of innovation plants. It supports the view put forth in Naghavi and Ottaviano (2009) that feedback from manufacturing plants is important for research labs.

Third, I evaluate the macroeconomic implications of my empirical findings by extending the multi-region production and trade model developed by Arkolakis et al. (2018)

with two key modifications: (i) allowing firms to increase productivity through R&D; and (ii) incorporating the spillovers from local manufacturing to innovation. Guided by my empirical findings, my model assumes that regions' capability in fostering innovation increases with their employment of production workers. Firms born in regions that are more capable of fostering innovation enjoy a higher return to R&D and spend more on innovation. New technologies created through R&D can be used in multi-region production (MP). Firms face a tradeoff between market proximity and production capability when choosing where to locate their production. Given the difference in regions' capability in innovation and production, the availability of MP leads some regions to specialize in production and others in innovation.

I take the model to the data in year 2012, and calibrate it to 48 states in the U.S. and the rest of the world (ROW). My quantitative analysis uses the China shock to evaluate the effects of production reallocation on the innovation efficiency. I model the rise of China as the productivity shocks to the ROW, and use the predicted changes in the U.S. imports from China during 1997-2012 to quantify the size of these productivity shocks. I find that the relocation of production workers due to the China trade shock leads to a moderate reduction in both process and product innovation. States with a larger decline in manufacturing employment experience a more substantial loss in innovation efficiency.

My analysis brings together three strands of the literature. First, it contributes to the literature on the agglomeration and coagglomeration of economic activities. Ellison and Glaeser (1997) and Duranton and Overman (2008) find that industrial production is geographically concentrated. The agglomeration of industrial production can be explained by the Marshall forces of labor pooling, input sharing and knowledge spillovers (Ellison et al., 2010; Faggio et al., 2017). Much less is known about the coagglomeration of innovation and production activities due to limitation in data availability (Audretsch and Feldman, 1996; Carlino and Kerr, 2015). I contribute to this line of research by using a novel micro level dataset to uncover the spatial distribution of innovation and production activities.

Second, my analysis is closely related to the work on R&D investment and plant productivity. Building on the knowledge capital model by Griliches et al. (1979), as well as more recent work by Aw et al. (2011), Doraszelski and Jaumandreu (2013), and Bøler et al. (2015), I evaluate the impact of R&D investment on plant productivity. The focus on multi-unit firms also relates my analysis to Bilir and Morales (2016), which allows for the intra-firm transfer of technology. My approach is novel in its explicit consideration of the local employment impact on innovation efficiency. The estimates support the theories proposed by Duranton and Puga (2001) and Naghavi and Ottaviano (2009) that production plays an important role in fostering innovation.

Third, my paper also contributes to the studies that seek to understand the consequences of trade shocks for innovation. The empirical evidence about the impact of trade shocks on innovation is mixed. While Bloom et al. (2016) finds that European firms facing higher levels of Chinese import competition create more patents, raise their IT intensity and increase their productivity, Dorn et al. (2016) shows that the foreign import competition reduces U.S. patent production. I propose a new channel to evaluate the impact of trade shocks on innovation. Trade shocks affect the local innovation through production reallocation. Innovation efficiency is enhanced by local manufacturing. The increased exposure to import competition leads to the decline of manufacturing, and thus reduces the local innovation efficiency. To quantify the impact of trade shocks on innovation through the new channel, I extend Arkolakis et al. (2018) by incorporating the local spillovers from the innovation and production.

The rest of this paper is organized as follows. Section 2 documents stylized facts about geographic concentration of innovation and production activities. Section 3 develops and estimates the empirical model to assess the spillovers from the local manufacturing to innovation. Section 4 extends the Arkolakis et al. (2018) model to evaluate the macroeconomic implications of my empirical findings. Section 5 concludes.

2 The Location Pattern of Innovation and Production

Economic activities are geographically concentrated to utilize the advantages of proximity.[1] Activities with more substantial gains from proximity tend to be more closely located (Ellison and Glaeser, 1997; Ellison et al., 2010). Thus, the concentration patterns of

[1]According to Marshall (1920), economic activities are geographically concentrated to reduce the costs of obtaining inputs and supplying outputs, to share a broader labor market, and to enjoy intellectual or technology spillovers.

economic activities provide suggestive evidence on the importance of geographic proximity to these activities.

In this section, I use a novel plant-level dataset of innovation and production to establish two critical stylized facts of their agglomeration and coagglomeration patterns.

2.1 EG Metrics and Data

Measuring the spatial distribution of innovation and production activities has long been recognized as extremely difficult due to the lack of data (Audretsch and Feldman, 1996; Carlino and Kerr, 2015). In this section, I exploit detailed and comprehensive establishment-level data from two Census Bureau surveys —the Longitudinal Business Database (LBD) and the Business R&D and Innovation Survey (BRDIS)—to document the geographic concentration of innovation and production activities for manufacturing industries. The LBD covers the universe of establishments in the U.S. and contains annual data on their size, industry, geographic location, and legal form of organization. The BRDIS is a confidential firm-level survey conducted annually by the U.S. Census Bureau in partnership with the National Science Foundation (NSF). It collects detailed information on firms' R&D activities including R&D-related employment, R&D expenditure, and the geographic location of domestic and foreign R&D performance. Linking the LBD with the BRDIS allows me to identify the innovation and production activities at the establishment level. Thus, it enables me to document the geographic concentration of innovation and production activities for manufacturing industries.

I measure the industry-level geographic concentration of innovation and production activities by using Ellison and Glaeser (1997) metrics. The EG metrics are derived from a sequential profit-maximizing plant location choice model. It compares the degree of spatial concentration of economic activities in an industry with what would arise if these activities were randomly distributed across locations. I will focus on the four-digit manufacturing industries of the 2002 North American Industry Classification System (NAICS) and measure the concentration of these activities at the county level for the sample period 2008-2012.

I quantify the concentration pattern of innovation and production activities in two ways. First, I use the EG metric of agglomeration to measure the location pattern of innovation and production activities, respectively. The EG agglomeration measure for economic activity A in industry k is

$$\gamma_k^A \equiv \frac{\sum_l \left(s_{lk}^A - x_l\right)^2 - \left(1 - \sum_l x_l^2\right) H_k^A}{\left(1 - \sum_l x_l^2\right)\left(1 - H_k^A\right)} \tag{1}$$

where $A \in \{P, I\}$ denotes the type of economics activities. $A = P$ when measuring the agglomeration pattern for production activities and $A = I$ for innovation ones. s_{lk}^A is the production (innovation) employment share in industry k at county l and x_l is county l's share of total population. H_k^A is the Herfindahl index of the industry k's production (innovation) plant size distribution[2].

The EG metric of agglomeration measures the tendency for production (innovation) activities to be closely located. $\gamma_k^A = 0$ is a no-agglomeration benchmark such that production (innovation) activities are randomly located. $\gamma_k^A = 1$ indicates that production (innovation) activities are perfectly agglomerated with all the production (innovation) employment in a single county.

Second, I use the EG metric of coagglomeration to quantify how collocated the innovation and production activities are within an industry.[3] The EG coagglomeration measure of innovation and production for industry k takes the form:

$$\gamma_k^c \equiv \frac{\sum_l \left(s_{lk}^P - x_l\right)\left(s_{lk}^I - x_l\right)}{1 - \sum_l x_l^2} \tag{2}$$

where s_{lk}^P is the production employment share in industry k at county l, s_{lk}^I is the innovation employment share in industry k, and x_l is the population share of county l.

The EG coagglomeration measure captures the tendency for innovation activities to locate near production ones. It is closely related to the covariance of the county's employment shares in innovation and production. Negative values of the coagglomeration measure arise when innovation and production activities are agglomerated in different areas. The coagglomeration measure is zero when the production and production ac-

[2]The subtraction of H_k^A is a adjustment that accounts for the fact that $\sum_l \left(s_{lk}^A - x_l\right)^2$ measure is expected to be larger in industries consisting of fewer larger plants if locations were chosen completely at random.

[3]The EG coagglomeration metric takes a simpler form when applied to measure the concentration of two activities. See appendix for the relationships between EG coagglomeration measure for two economic activities and for a group of activities.

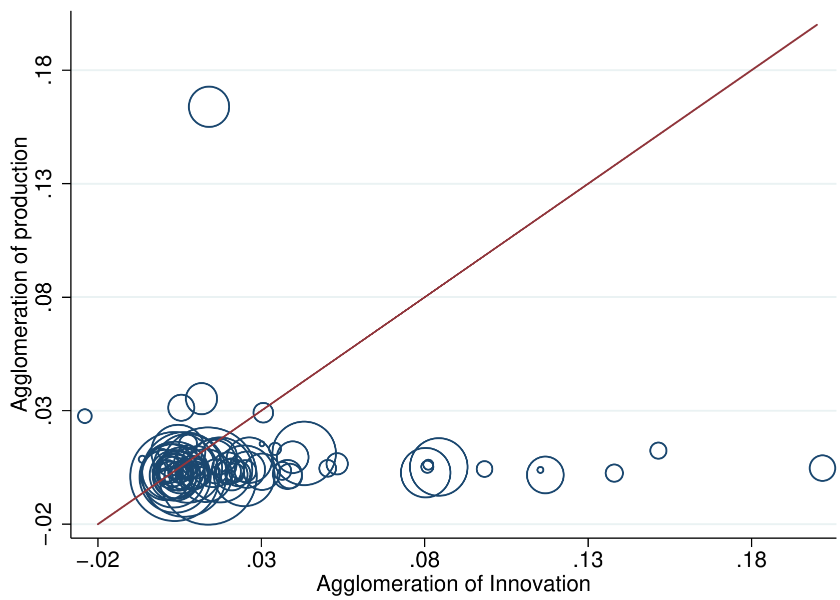
tivities are randomly located.

2.2 Two Facts on the Spatial Distribution of Innovation and Production

Fact 1: Innovation activities are more agglomerated than production ones in the majority of manufacturing industries.

Figure 1 plots the agglomeration of innovation in each manufacturing industry against that of its production. Each circle represents a four-digit NAICS industry, and the size of the circle reflects the size of the industry. The x-axis measures the agglomeration pattern of innovation activities, and the y-axis measures that of production ones. The solid line is the 45-degree line. Most of the circles lie under the 45-degree line, implying that innovation activities are geographically more concentrated than production ones in the majority of manufacturing industries. This pattern suggests that the gains from concentration are more significant for innovation than production activities.

Figure 1: Agglomeration Indices of Innovation and Production



Notes: The figure plots the agglomeration of innovation in each manufacturing industry against that of its production. Each circle represents a four-digit NAICS manufacturing industry, and the size of the circle reflects the size of the industry. The solid line is the 45-degree line.

Fact 2: Innovation and production activities are coagglomerated in the majority of manufacturing industries.

Figure 2 plots the coagglomeration measure of innovation and production for each industry against the max coagglomeration measure of its production with other industries. The x-axis measures the coagglomeration of innovation and production for each manufacturing industry. The majority of coagglomeration measures are greater than 0, implying that innovation tends to locate closely with production in most manufacturing industries.

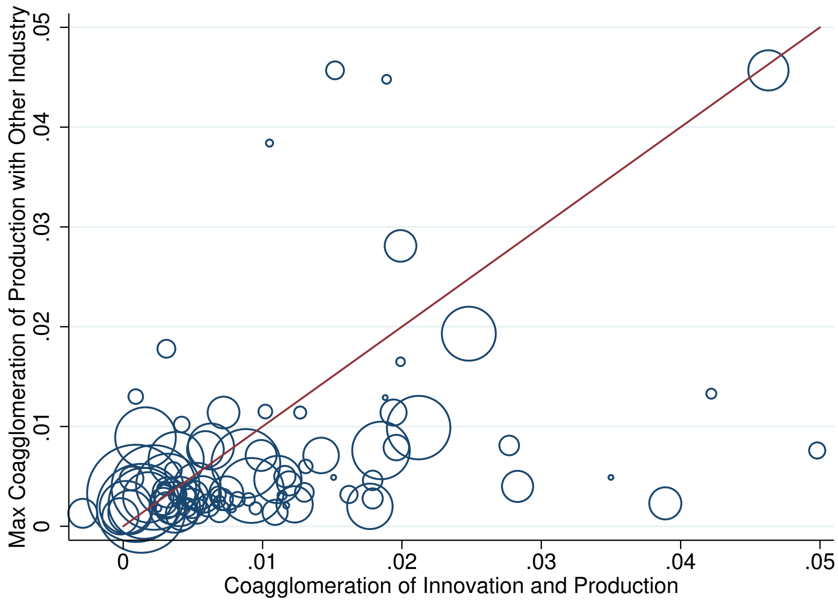
To evaluate the strength of the coagglomeration between innovation and production within each industry, I compare it with the coagglomeration of cross-industry production. Production activities are known to be closely colocated across industries (Ellison et al., 2010; Duranton and Overman, 2008; Faggio et al., 2017),[4] and therefore, the coagglomeration of cross-industry production serves as a good benchmark. For each industry, I compute the pairwise coagglomeration measures for its production with other manufacturing industries' production. Table X in the Data Appendix summarizes the mean, 25th percentile, median, 75th percentile, and max coagglomeration indices of the cross-industry production for each manufacturing industry. The mean and median coagglomeration of cross-industry production are centered at zero and skewed towards positive values. The y-axis in Figure 2 reports max coagglomeration index of the cross-industry production for each manufacturing industry. Most industries lie under the 45-degree line in Figure 2, suggesting that locating production close to its own industry innovation is more important than locating it close to any other industry's production.

3 The Returns to R&D When Innovation Collocated with Production

The coagglomeration of innovation and production provides suggestive evidence on the importance of the two activities being closely located. This section provides econometric evidence on the importance of proximity to production on innovation efficiency.

[4] Ellison et al. (2010) finds that the coagglomeration of the industry's production can be explained by the Marshallian forces of input sharing, labor pooling, and knowledge spillovers.

Figure 2: Coagglomeration of Innovation and Production vs. Max Coagglomeration of Production with Other Industry



Notes: The figure plots the coagglomeration measure of innovation and production for each industry against the max coagglomeration measure of its production with other industries. Each circle represents a four-digit NAICS manufacturing industry, and the size of the circle reflects the size of the industry. The solid line is the 45-degree line.

3.1 Empirical Model

I develop and estimate an empirical model of production and innovation within the manufacturing firm to quantify the returns to R&D, primarily to assess if the returns are higher when innovation plants are located in places with more own industry production workers. The empirical model considers a manufacturing firm i with a set of active plants $j \in J_{i,t}$.[5] In each period, it determines the optimal levels of variable inputs, capital investment, R&D expenditures, and output prices for each of its plants to maximize the firm-level profits. As my focus is on exploring the spillovers from the local production to innovation, I restrict attention here to the R&D investment decisions and

[5] Plants within a manufacturing firm can be one of the following functional forms: innovation plants, production ones, and the mixed ones that both innovate and produce. For simplicity, in this paper, innovation plants refer to these that conduct R&D. It can either be a plant only conducts R&D or a mixed one. The same applies to production plants.

process of plant performance evolution and abstract from the innovation plants' decision to enter or exit. In the subsections below, I will first model the revenue functions for these production plants within the firm, then model the evolution of the plants' performance, and finally define the firms' maximization problem.

3.1.1 Revenue Function

Assume plant j locates at l and operates in industry k.[6] Following Aw et al. (2011) and Bøler et al. (2015), I model its short-run marginal cost function at period t as [7]

$$\ln c_{jt} = \beta_0 + \beta_k \ln k_{jt} + \beta_w \ln w_{j_k t} - \psi_{jt}, \tag{3}$$

where k_{jt} is the capital stock of plant j at period t, $w_{j_k t}$ is the wage common to all plants in industry k, and ψ_{jt} is the plant-specific productivity. The marginal costs of production are lower for plants with higher productivities. Labor is a variable input, whereas capital is determined by the investment and capital stock in the previous period.

The product market is characterized by monopolistic competition, and the demand faced by plant j in industry k is

$$q_{jt} = Q_{j_k t} \left(p_{jt}/P_{j_k t}\right)^{-\sigma} exp\left[\zeta_{jt}\left(\sigma - 1\right)\right], \tag{4}$$

where $\sigma > 1$ is the constant elasticity of substitution, p_{jt} is the output price of plant j, and ζ_{jt} is a plant-specific demand shifter. The variable $Q_{j_k t}$ and $P_{j_k t}$ are the industry-level demand and price index.

Given the cost and demand function described above, firm i sets the optimal price p_{jt} to maximize the plant j's profits. The log revenue of plant j depends on the aggregate market conditions, the capital stock and the plant-specific performance,

$$\ln Rev_{jt} = \gamma_0 + \ln\left(Q_{j_k t} P^{\sigma}_{j_k t}\right) + (1-\sigma)\,\beta_w \ln w_{j_k t} + (1-\sigma)\left(\beta_k \ln k_{jt} - z_{jt}\right) + u_{jt}, \tag{5}$$

[6] In this section, I write k and l as the subscript of j to indicate the industry and location of plant j.

[7] The marginal cost function here only considers the marginal cost of production. The R&D investment decisions and the cost of innovation will be modeled in the Section 3.1.2.

where $\gamma_0 \equiv (1-\sigma)ln(\frac{\sigma}{\sigma-1}) + (1-\sigma)\beta_0$, and u_{jt} is the measurement error. Denote $z_{jt} = \psi_{jt} + \zeta_{jt}$ as the plant performance. It is an endogenous state variable that captures two sources of heterogeneity: plant-specific productivity ψ_{jt} and plant-specific demand shock ζ_{jt}. R&D investment can boost plant performance through raising its productivity or product quality. Plants with higher performance z_{jt} obtain a higher revenue.

3.1.2 The Impact of Innovation on Plant Performance

The performance of plant j evolves as a Markov process that depends on its own investment in R&D, the transfer of technology from other plants in the same firm and a random shock,[8]

$$z_{jt} = \alpha_0 + \alpha_1 z_{jt-1} + \alpha_2 z_{jt-1}^2 + V_{j_{lk}t} + \sum_{j' \in J_t} \gamma_{jj'} V_{j'_{l'k'}t} + \eta_{jt}, \tag{6}$$

where $V_{j_{lk}t}$ captures the increase in plant performance through its own investment in R&D. Following Aw et al. (2011), Doraszelski and Jaumandreu (2013) and Bøler et al. (2015), I assume that the increment in plant performance at period t depends on its investment in R&D in the previous period. To explore and quantify the spillovers from the local production, I assume it also depends on the interaction between R&D investment $\ln r_{jt-1}$ and the employment of local production workers in its own industry $\ln(emp_{j_{lk}t-1})$. The increment in plant performance $V_{j_{lk}t}$ is written as

$$V_{j_{lk}t} = \beta_1 \ln r_{jt-1} + \beta_2 \ln r_{jt-1} \ln(emp_{j_{lk}t-1}). \tag{7}$$

The inclusion of $\ln r_{jt-1} \ln(emp_{j_{lk}t-1})$ allows for the possibility of spillover from production to innovation within the same industry.[9] The rationale is that the local employment of its industrial production workers is a source of knowledge that can enhance

[8] The main focus of this paper is to explore and quantify the spillovers from the local manufacturing to innovation. Thus, I restrict my attention to the existing innovation plants and look at a subset of predetermined innovation plants. Tecu (2013) estimate an R&D location choice model to assess the importance of manufacturing on firms' innovation location choice. She finds that manufacturing plays an important role in determining innovation location, and both the internal and external linkages between innovation and production are important for the innovation plants.

[9] The spillover from local production to innovation considers both the internal feedbacks from its own local factories but also the manufacturing know-how learned from the other firms.

plant innovation, through which it affects the plant's future performance. The empirical analysis also includes an alternative specification with discrete R&D expenditure (R&D dummy).

The term $\sum_{j' \in J_t} \gamma_{jj'} V_{j'_{l'k'}t}$ in Equation (7) captures intrafirm impact of R&D investment. Bilir and Morales (2016) shows that technological improvements developed in a plant can be shared with other plants within the same firm. I incorporate the sharing of proprietary technology in my empirical model by allowing the intra-firm transfer of proprietary technology across plants in the same industry.[10] $\tau_{jj'}$ captures the knowledge communication frictions when transferring technology from plant j' to plant j. Assume the decay of technology is a function of distance between plant j and j' as follows

$$\sum_{j' \in J_t} \tau_{jj'} V_{j'_{l'k'}t} = \sum_{j' \in J_t} \left[\beta_4 + \beta_5 \ln \beta \left(dist_{jj'}\right)\right] V_{j'_{l'k'}t}. \tag{8}$$

The term η_{jt} in Equation (6) represents shocks to the performance of plant j at time t that are not anticipated at $t-1$.

3.1.3 Firm Optimization Problem

In each period t, firm i determines the optimal levels of labor $\mathbf{L_{it}}$, capital investment $\mathbf{I_{it}}$, R&D investment $\mathbf{R_{it}}$, and output prices $\mathbf{P_{it}}$ for each of its plants j active at time t, as well as the set of plants that will be active at $t+1$, $J_{i,t+1}$. These decisions are made based on the state vector $\mathbf{S_{it}}$ that firm i faces.

The state vector for plant j is

$$S_{ijt} = \left(z_{jt}, k_{jt-1}, w_{jt}, P_{j_k t}, Q_{j_k t}, p^k_{jt}, \ln\left(emp_{j_{lk}t-1}\right), F_{jt}\right), \tag{9}$$

where p^k_{jt} is the price of capital and F_{jt} is a fixed cost of operating plant j.

Decisions at period t regarding plant j's investment and employment depend on z_{jt}.

[10] In the case when the innovation-only plants conduct R&D to improve the performance of the production and the mixed plants, the spillovers are from the industry to which it provides technology. For example, if the innovation plant invests in R&D to improve the performance of the auto manufacturing plants, then the local production workers in the auto industry will be sources of expertise that can enhance the innovation plant R&D efficiency. My data sample includes firms that run businesses in more than one 3-digit NAICS industries. In this case, I restrict the transfer of technology to be only within the plants in the same 3-digit NAICS industry.

Labor is a variable input, whereas capital is fixed in the short run. It's determined by the investment and capital stock in period $t-1$, according to the law of motion $k_{jt} = (1-\delta_k)k_{jt-1} + i_{jt-1}$. Decisions on plant j's investment in R&D also depend on the local employment of its own industry production workers $\ln(emp_{j_{lk}t-1})$.

If plant j is active at period t, the profit function of plant j is

$$\Pi(s_{jt}, i_{jt}, l_{jt}, p_{jt}, r_{jt}) = \frac{1}{\sigma} Rev\left(Z_{jt}, k_{jt}, P_{j_k t}, Q_{j_k t}, w_{jt}\right) - r_{jt} - C_k\left(i_{jt}, p^k_{jt}, k_{jt}\right) - F_{jt}, \tag{10}$$

where $C_k(\cdot)$ is the cost function of investment in capital.

The firm i's optimization problem is

$$V(\mathbf{S_{it}}) = max_{\mathbf{X_{it}}}\left[\sum_{j\in J_{it}} \Pi\left(s_{ijt}, i_{ijt}, n_{ijt}, p_{ijt}, r_{ijt}\right) + \delta E\left(V\left(\mathbf{S_{it+1}}\right)|\mathbf{S_{it}}, \mathbf{I_{it}}, \mathbf{R_{it}}, J_{it+1}\right)\right], \tag{11}$$

where $\mathbf{X_{it}} = (J_{it+1}, \mathbf{L_{it}}, \mathbf{M_{it}}, \mathbf{I_{it}}, \mathbf{R_{it}}, \mathbf{P_{it}})$ is a vector of control variables, $V(\cdot)$ is the value function, $\Pi(\cdot)$ is the profit function and δ is the discount factor.

3.2 Estimation

To estimate the impact of local manufacturing on the returns to R&D, I proceed in two steps. First, I estimate the revenue function in Equation (5). Second, I estimate the Markov process governing the evolution of firm performance in Equation (6).

Step 1 Estimating Revenue Function Plant performance z_{jt} is likely to affect its demand for labor and capital. Therefore, OLS estimates of the revenue function suffer from the simultaneity bias. I utilize the insights from Olley and Pakes (1996) and Levinsohn and Petrin (2003) and rewrite the unobserved performance in terms of some observed variables that are correlated with it. In general, plants' usages of materials, electricity and energy depend on the level of its performance. Therefore, I rewrite the level of productivity, conditional on the capital stock, as a function of the variable input levels, i.e. $z_{jt}(k_{jt}, m_{jt}, n_{jt}, e_{jt})$. This allows me to use the expenditures on materials m_{jt}, electricity e_{jt} and energy n_{it} by the firm to control for the productivity in Equation (5).

The Equation (5) can be rewritten as

$$\ln Rev_{jt} = \gamma_0 + d_{j_k t} + h\left(k_{jt}, m_{jt}, n_{jt}, e_{jt}\right) + u_{jt}, \tag{12}$$

where the function $h\left(k_{jt}, m_{jt}, n_{jt}, e_{jt}\right) = (1-\sigma)\left(\beta_k \ln k_{jt} - z_{jt}\left(k_{jt}, m_{jt}, n_{jt}, e_{jt}\right)\right)$ captures the combined effects of capital and plant performance on revenue and $d_{j_k t} = \ln\left(Q_{j_k t} P_{j_k t}^{\sigma}\right) + (1-\sigma)\beta_w \ln w_{j_k t}$ is a set of industry-time dummies capturing industry-wide demand and cost trends. I specify $h(\cdot)$ as a cubic function of its arguments and estimate Equation (12) by OLS.

Step 2 Estimating Performance Evolution Function In the second step, I rewrite the plant performance z_{jt} in terms of predicted $\hat{h}_{jt}$ from the first stage

$$z_{jt} = -\frac{1}{1-\sigma}\hat{h}_{jt} + \beta_k \ln k_{jt}. \tag{13}$$

Substituting the z_{jt} into Equation (6) for the performance evolution gives the estimation equation

$$\begin{aligned}
\hat{h}_{jt} &= -\alpha_0^* + \beta_k^* \ln k_{jt} + \alpha_1\left(\hat{h}_{jt-1} - \beta_k^* \ln k_{jt-1}\right) - \alpha_2^*\left(\hat{h}_{jt-1} - \beta_k^* \ln k_{jt-1}\right)^2 \\
&\quad - \left(\beta_1^* \ln r_{j,t-1} + \beta_2^* \ln r_{j,t-1} \ln\left(emp_{j_{lk}t-1}\right)\right) \\
&\quad - \sum_{j'}\left(\beta_3 + \beta_4 \ln\left(dist_{jj'}\right)\right)\left(\beta_1^* \ln r_{j',t-1} + \beta_2^* \ln r_{j',t-1} \ln\left(emp_{j_{lk}t-1}\right)\right) - \eta_{jt}^*,
\end{aligned} \tag{14}$$

where the superscript $*$ denotes that the coefficient is multiplied by $1-\sigma$.[11]

The second stage estimation equation relates the predicted revenue to the current and lagged capital stock, the lagged predicted revenue, lagged R&D expenditure of its own, and that of other plants in the same firm, as well as the lagged local production employment of its industry.

I estimate the second stage equation with the generalized method of moments (GMM). The identification of the parameters depends on the timing assumptions. η_{jt} are the shocks to plant performance between $t-1$ and t that are unanticipated by the firm. By

[11] Except for α_2^*, $\alpha_2^* = \frac{\alpha_2}{1-\sigma}$.

construction, the shocks are not correlated with the predetermined variables k_{jt-1},r_{jt-1}, $r_{j't-1}$, $\ln(emp_{jt-1})$, $\ln(emp_{j't-1})$ and $\ln(dist_{jj't-1})$. I allow the constant in the Markov process to vary by industry by including industry fixed effects (3-digit NAICS). In total, it gives me 31 moment conditions with 28 unknown.

The α and β can be backed out given an estimate of σ. The demand elasticity σ is estimated from total variable cost function. Given the CES demand, the total variable cost TC_{jt} can be written as a function of its total revenue Rev_{jt}:

$$TC_{jt} = (1 - \frac{1}{\sigma})Rev_{jt} + \epsilon_{jt}, \tag{15}$$

where the error term ϵ_{ijt} is the measurement error in total cost.

3.3 Data

Estimating the impact of local manufacturing on the plant innovation efficiency requires data on R&D expenditure for each innovation plant, input and output for each production plant, as well as the local employment of manufacturing industries. By combining several confidential datasets from the Census Bureau, I create a plant-level panel data on R&D investment and domestic production for U.S. R&D firms in the manufacturing sector from 2002-2012. Details regarding data construction are documented in Data Appendix.

Firm-level data on R&D investment are available between 1972 and 2015 from the BRDIS.[12] The BRDIS utilizes a stratified sample frame and samples firms proportionally within each strata to their known R&D activity, or to their payroll if R&D activity is unknown. It surveys about 45,000 firms each year and includes a certainty component for firms with payroll or R&D expenditures above a certain threshold. My data sample is mainly composed of these large firms which are consistently surveyed by the BRDIS. The BRDIS asks respondents to report the total domestic R&D expenditure as well as the allocation of their spending across states.[13] The firm-level information on geographic

[12] This survey was known as the Survey of Industrial Research Development (SIRD) from 1972 through 2007. The SIRD is the predecessor of the BRDIS.

[13] In the BRDIS survey, R&D is defined as planned, creative work aimed at discovering new knowledge or developing new or significantly improved goods and services. This includes 1) activities aimed at acquiring new knowledge or understanding without specific immediate commercial application or use (basic research); 2)activities aimed at solving a specific problem or meeting a specific commercial objective

location of domestic R&D activities allows me to identify innovation plants and their R&D expenditure within an R&D-performing firm when supplemented by the plants location information from the LBD. In my empirical model, the innovation plants are predetermined, thus I define an establishment as an innovation plant if it has ever done R&D during the period pre-sample 1972-2001.

Plant-level production data are from the Census of Manufacturers (CMF) for years ending in 2 and 7, and from Annual Survey of Manufacturers (ASM) in other years.[14] The CMF/ASM collects production data for manufacturing establishments on their value of shipments, employment and payroll, cost of inputs, number of products, and capital. The local manufacturing employment is constructed by using data from the LBD. It's measured at the county level and on the 4-digit NAICS manufacturing industries.

In total, my data sample includes 1,500 R&D firms. Table 1 provides the summary statistics of the R&D firms. Within an R&D firm, the average number of innovation sites is 3.3, and the median is 2. These innovation sites locate in about 1200 counties and 400 commuting zones. The average number of production sites is 9.7, with the median of 4. On average, the innovation sites spend 12,860 thousand dollars on R&D each year.

3.4 Empirical Results

3.4.1 Baseline Estimates

The estimates of the empirical model described above are reported in Table 2. The upper panel presents the estimates of structural parameters in Equation (14). The lower panel evaluates the mean plant performance elasticities with respect to its own R&D investment, other plants' R&D investment, and the distance between the technology receiving and providing plants by using estimated structural parameters in the upper panel. Columns (a) and (b) use a discrete measure of R&D, while (c) and (d) use a continuous measure.

(applied research) 3) systematic use of research and practical experience to produce new or significantly improved goods, services, or processes (development). Thus costs for routine product testing, quality control, and technical services are not included in the R&D expenditure.

[14]The ASM is a sample survey of approximately 50,000 establishments. For sample efficiency and cost consideration, the big and important establishments in each industry are overrepresented. A number of establishments are included in the sample with certainty and the remaining establishments are sampled at a probability that is consistent with their relative importance in the industry or other key aggregations. Further details on the ASM are provided in the Data Appendix.

Table 1: Summary Statistics of the R&D Firms

Number of R&D firms	$1500^{\dagger}$
Average number of innovation plants within a firm	3.3
Median number of innovation plants within a firm	2
Average number of production plants within a firm	9.7
Median number of production plants within a firm	4
Average R&D expenditure at innovation plants (thousands)	$12,860^{\dagger}$
Number of innovation counties	$1200^{\dagger}$
Number of innovation commuting zones	$450^{\dagger}$

Notes: This table reports the summary statistics of the R&D firms in the data sample. † indicates number are rounded to thousands or hundreds to meet the Census disclosure requirements.

In columns (a) and (c), I first evaluate the influence of R&D investment on plant performance in a specification that does not allow the spillovers from the local manufacturing to innovation. The benchmark estimates show that a plant's performance increases in R&D investment. The results qualitatively match the recent estimates by Aw et al. (2011), Doraszelski and Jaumandreu (2013), Bøler et al. (2015) and Bilir and Morales (2016). The performance impact of a plant's own R&D investment is economically significant, and that of other plants' R&D investment is positive yet not precisely estimated.

In columns (b) and (d), I include the interaction between R&D investment and local manufacturing employment. The estimates of β_2 are positive and statistically significant, evidencing that innovating plants obtain significantly higher gains if they are located in counties with more of their own industry production workers. It suggests that there are positive spillovers from the local manufacturing to innovation. All else equal, the estimates in column (b) indicate that doubling the local own industry manufacturing employment increases the impact of a plant's own investment on its performance by 21.4%. The empirical results contribute to our understanding of the role of local manufacturing in enhancing efficiency of innovation plants and it support the view put forth in Naghavi and Ottaviano (2009) that feedback from manufacturing plants is important for research labs. The complementarity between innovation and manufacturing that I find in columns (b) and (d) is also of importance from the innovation policy perspective.

The capital coefficient β_k is negative and statistically significant across all specifications. It implies that with higher capital stock, the marginal costs are lower and revenue is higher for firms. The coefficients α_1 and α_2 measure the impact of lagged productivity on current productivity. The estimates are strong and precisely estimated, indicating impact of R&D on plant performance is persistent. The coefficients β_3 and β_4 quantify knowledge communication frictions when transferring technology within the firm across plants, and the lower panel calculates the mean performance elasticity with respect to distance. The estimates show that the longer the distance between the technology receiving and providing plants, the larger the performance losses will be. I check the validity of the instruments with an overidentification test and the p-values from the test are listed below the estimates in each column.

To retrieve the structural parameter α and β, I estimate σ from Equation (15). The estimates of $1 - \frac{1}{\sigma}$ is 0.6618 with the standard error of 0.0111.

3.4.2 Instrumenting Local Manufacturing Employment with Predicted Employment

A potential concern is the local employment might be positively correlated with the unobserved shocks to plant performance. To address this concern, I instrument the local manufacturing employment with a predicted one. The predicted local employment is constructed by interacting the initial local employment shares with national growth of industry employment *a la* Bartik (1991).

Using the pre-sample year 1997 as the base year, I predict the local manufacturing employment for each 4-digit NAICS manufacturing industry by interacting the initial shares of 6-digits NAICS subindustry in year 1997 with the national growth of the 6-digits NAICS subindustry employment. The formula is as follows

$$pemp_{lk_{4d}t} = \sum_{k_{6d} \in k_{4d}} s_{lk_{6d},1997} \times g_{k_{6d},t}, \tag{16}$$

where $pemp_{lk_{4d}t}$ is the predicted manufacturing employment at county l in 4-digit NAICS industry k at time t, $s_{lk_{6d},1997}$ is the initial share of each 6-digit NAICS subindustry within

Table 2: GMM Estimates: Baseline

		Continuous R&D		Discrete R&D	
		(a)	(b)	(c)	(d)
β_k	Log(capital)	-0.4073***	-0.4087***	-0.4073***	-0.4083***
		(0.0043)	(0.0043)	(0.0043)	(0.0042)
α_1	Performance$_{t-1}$	0.9088***	0.9120***	0.9093***	0.9114***
		(0.0112)	(0.0115)	(0.0112)	(0.0114)
α_2	Performance$^2_{t-1}$	0.0969***	0.0979***	0.0972***	0.0979***
		(0.0084)	(0.0085)	(0.0083)	(0.0084)
β_1	Log(R&D$_{t-1}$)	0.0014***	-0.0005	0.0118***	-0.0086*
		(0.0002)	(0.0005)	(0.0021)	(0.0045)
β_2	Log(R&D$_{t-1}$)$\times$ Log(Emp$_{t-1}$)		0.0003 ***		0.0031***
			(0.0001)		(0.0008)
β_3	Constant	0.3216	0.2804	0.379	0.2187
		(0.2567)	(0.2464)	(0.2628)	(0.2467)
β_4	Log(Dist.)	-0.0763*	-0.0783**	-0.0788*	-0.0631*
		(0.0398)	(0.0375)	(0.0407)	(0.0375)
Own Plant R&D Elasticity		0.0014***	0.0014***	0.0118***	0.0124***
		(0.0002)	(0.0002)	(0.0021)	(0.0019)
Other Plant R&D Elasticity		0.0001	0.0000	0.0016	-0.0000
		(0.0002)	(0.0001)	(0.0016)	(0.0011)
Distance Elasticity		-0.0002*	-0.0002**	-0.0014*	-0.0009*
		(0.0001)	(0.0001)	(0.0007)	(0.0006)
Overidentification Test (p value)		0.81	0.31	0.82	0.34
Observations		106,000	106,000	106,000	106,000
Industry Effects		Yes	Yes	Yes	Yes

Notes: The upper panel reports the GMM estimates of structural parameters in Equation (14). Columns (a) and (c) presents the estimates of the benchmark specification. Robust standard errors in parentheses are clustered by county. Each specification reports the p-value for the overidentification restrictions test (Hansen, 1982). The lower panel evaluates the mean plant performance elasticities by using estimated structural parameters in the upper panel. R&D is measured as log(1+R&D) in columns (a) and (b), and a binary variable in columns (c) and (d). *** denotes 1% significance, ** 5%, and * 10%.

the 4-digit NAICS industry k at county l in year 1997 and the $g_{k_{6d},t}$ is the national growth rate of each 6-digit NAICS subindustry between year 1997 and time t.

Table 3 reports the estimates when instrumenting local manufacturing employment with a predicted one. It gives similar estimates on the structural parameters as our baseline estimation in Table 2. The impact of local manufacturing on innovation efficiency β_2 is slightly lower.

3.4.3 Robustness Checks

Spillovers from the Local R&D A potential concern is that other than the spillovers from the local manufacturing to the plant innovation, there are also spillovers from the local R&D activities of the other firms. As a robustness check, I estimate a specification that controls the spillovers from the local innovation. The increment in plant performance in Equation (7) is written as

$$V_{j_{lk}t} = \beta_1 \ln r_{jt-1} + \beta_2 \ln r_{jt-1} \ln\left(emp_{j_{lk}t-1}\right) + \beta_5 \ln r_{jt-1} \ln(rdemp_{j_l t-1}). \tag{17}$$

where $\ln(rdemp_{j_l t-1})$ is the local R&D employment. Due to the data availability, I measure the local R&D employment at the commuting zone level.[15] Local R&D employment is measured as the total employment in the NAICS 5417 *Scientific Research and Development Services* industry.

Table 4 reports the estimates for the robustness check. The inclusion of the spillovers from the R&D activities to the plants' innovation has a negligible impact on my results. The estimated coefficient β_5 for the spillovers from local R&D is not significantly different from zero. Thus, there is no evidence suggesting the spillovers from local R&D to plant innovation.

The Direct Impact of Local Employment on Plant Performance Another concern is that the local employment might have a direct impact on plant performance. To account

[15]The plant-level data on R&D employment from the BRDIS is highly correlated with the R&D expenditure. Since the R&D investment is lumpy, local R&D employment measured by data from the BRDIS is lumpy as well. Instead, I measure the local R&D employment by using data from the LBD and measured it as the employment in the *Scientific Research and Development Services* industry. The county-level R&D employment is limited, and thus I measure the local R&D employment at the county level.

Table 3: GMM Estimates: Instrumenting Local Employment with Predicted Emp.

	Continuous R&D		Discrete R&D	
	(a)	(b)	(c)	(d)
β_k Log(capital)	-0.4073***	-0.4088***	-0.4073***	-0.4083***
	(0.0043)	(0.0042)	(0.0043)	(0.0042)
α_1 Performance$_{t-1}$	0.9088***	0.9125***	0.9093***	0.9118***
	(0.0112)	(0.0115)	(0.0112)	(0.0113)
α_2 Performance$^2_{t-1}$	0.0969***	0.0986***	0.0972***	0.0985***
	(0.0084)	(0.0084)	(0.0083)	(0.0084)
β_1 Log(R&D$_{t-1}$)	0.0014***	-0.0001	0.0118***	-0.0051
	(0.0002)	(0.0005)	(0.0021)	(0.0044)
β_2 Log(R&D$_{t-1}$)$\times$ Log(Emp$_{t-1}$)		0.0002**		0.0025***
		(-0.0001)		(0.0008)
β_3 Constant	0.3216	0.3638	0.379	0.3016
	(0.2567)	(0.2546)	(0.2628)	(0.2600)
β_4 Log(Dist.)	-0.0763*	-0.0905**	-0.0788*	-0.0758*
	(0.0398)	(0.0392)	(0.0407)	(0.0398)
Own Plant R&D Elasticity	0.0014***	0.0013***	0.0118***	0.0118***
	(0.0002)	(0.0002)	(0.0021)	(0.0019)
Other Plant R&D Elasticity	0.0001	0.0001	0.0016	0.0004
	(0.0002)	(0.0001)	(0.0016)	(0.0012)
Distance Elasticity	-0.0002*	-0.0002**	-0.0014*	-0.0011*
	(0.0001)	(0.0001)	(0.0007)	(0.0006)
Overidentification Test (p value)	0.81	0.25	0.82	0.34
Observations	106,000	106,000	106,000	106,000
Industry Effects	Yes	Yes	Yes	Yes

Notes: The upper panel reports the GMM estimates of structural parameters in Equation (14), instrumenting local employment with the predicted one. Columns (a) and (c) presents the estimates of the benchmark specification. Robust standard errors in parentheses are clustered by county. Each specification reports the p-value for the overidentification restrictions test (Hansen, 1982). The lower panel evaluates the mean plant performance elasticities by using estimated structural parameters in the upper panel. R&D is measured as log(1+R&D) in columns (a) and (b), and a binary variable in columns (c) and (d). *** denotes 1% significance, ** 5%, and * 10%.

for this possibility, I consider a specification that includes the employment levels in the performance increment function as follows,

$$V_{j_{lk}t} = \beta_1 \ln r_{jt-1} + \beta_2 \ln r_{jt-1} \ln \left(emp_{j_{lk}t-1} \right) + \beta_6 \ln \left(emp_{j_{lk}t-1} \right). \tag{18}$$

Accounting for the direct effect of local manufacturing employment does not change the conclusions from my baseline estimation. The local manufacturing employment has no direct impact on the plant performance, and it only affects the plant performance through interacting with the R&D investment.

4 A Model of Innovation and Production

Motivated by the facts presented in section 2 and the empirical evidence on the positive spillovers from local manufacturing to innovation in section 3, I extend the trade and multi-region production model developed by Arkolakis et al. (2018) with two key modifications: (i) allowing firms to increase productivity through R&D; and (ii) incorporating the spillovers from local manufacturing to innovation.

4.1 Setup

Consider an economy with $n = 1 \cdots N$ regions. There are $\bar{L}_n$ workers in region n. Workers with CES preferences consume a continuum of goods indexed by $\omega \in \Omega$:

$$U_n = \left(\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}. \tag{19}$$

There are two activities in the economy: innovation and production. Workers possess heterogeneous abilities in these activities. Some are good at production while others are good at research. Their abilities in these two activities are characterized by the efficiency units of labor with which they are endowed, $\boldsymbol{E} = (E^e, E^p)$. E^e denotes the endowment of efficiency units of labor which can be supplied to innovation activities, and E^p denotes the endowment that can be supplied to production. Assume that $E^e = u_e / \Gamma\left(1 - 1/\kappa\right)$ and $E^p = u_p / \Gamma\left(1 - 1/\kappa\right)$, with u_e and u_p drawn independently from the distribution $F(u) = \exp\left[-u^{-\kappa}\right]$, where $\kappa > 1$ and $\Gamma\left(\cdot\right)$ is the Gamma function.

Workers are immobile across different regions but mobile across innovation and pro-

Table 4: GMM Estimates: Robustness

		Continuous R&D		Discrete R&D	
		(a)	(b)	(c)	(d)
β_k	Log(capital)	-0.4085***	-0.4087***	-0.4081***	-0.4083***
		-0.0043	-0.0042	-0.0042	-0.0042
α_1	Performance$_{t-1}$	0.9115***	0.9123***	0.9110***	0.9117***
		-0.0114	-0.0114	-0.0113	-0.0113
α_2	Performance$^2_{t-1}$	0.0977***	0.0985***	0.0977***	0.0985***
		-0.0084	-0.0084	-0.0084	-0.0084
β_1	Log(R&D$_{t-1}$)	-0.0002	-0.0002	-0.0055	-0.006
		-0.0006	-0.0006	-0.0052	-0.0051
β_2	Log(R&D$_{t-1}$)$\times$ Log(Emp$_{t-1}$)	0.0003***	0.0002**	0.0034***	0.0022***
		-0.0001	-0.0001	-0.0008	-0.0003
β_5	Log(R&D$_{t-1}$)$\times$ Log(RDemp$_{t-1}$)	-0.0001		-0.0008	
		-0.0001		-0.0007	
β_6	Log(Emp$_{t-1}$)		0.0001		0.0004
			-0.0002		-0.0003
β_3	Constant	0.2889	0.3574	0.2296	0.2791
		-0.2339	-0.2436	-0.2349	-0.2303
β_4	Log(Dist.)	-0.0793**	-0.0872**	-0.0644*	-0.0684*
		-0.036	-0.038	-0.036	-0.0357
Overidentification Test (p value)		0.32	0.25	0.35	0.34
Observations		106,000	106,000	106,000	106,000
Industry Effects		Yes	Yes	Yes	Yes

Notes: This table reports GMM estimates corresponding to variants of Equation (14). Columns (a) and (c) allow for spillovers from the local R&D activities to innovation. Columns (b) and (d) incorporate the direct impact of local manufacturing employment on plant performance. Robust standard errors in parentheses are clustered by county. Each specification reports the p-value for the overidentification restrictions test (Hansen, 1982). R&D is measured as log(1+R&D) in columns (a) and (b), and a binary variable in columns (c) and (d). *** denotes 1% significance, ** 5%, and * 10%.

duction activities within each region.[16] Wage per efficiency unit of innovation labor is w_n^e, and per efficiency unit of production labor is w_n^p. Workers will choose to work in innovation activities if $E^e w_n^e \geq E^p w_n^p$, otherwise they will choose to work in production. Given the wages w_n^e and w_n^p, the supply of labor units to innovation and production activities in region i are given by

$$L_n^e = \bar{L}_n \left[1 + \left(\frac{w_n^e}{w_n^p} \right)^{-\kappa} \right]^{1/\kappa - 1}, \tag{20}$$

and

$$L_n^p = \bar{L}_n \left[1 + \left(\frac{w_n^p}{w_n^e} \right)^{-\kappa} \right]^{1/\kappa - 1}. \tag{21}$$

Labor units supplied to innovation and production activities depend on the relative wage $\frac{w_n^e}{w_n^p}$. With a finite κ, workers are heterogeneous in their productivity across activities. The change of relative wage will lead to the expansion of one activity and the contraction of the other. With $\kappa \to \infty$, workers are homogeneous and perfectly mobile across activities. There is no mobility across activities when $\kappa \to 1$.

4.2 The R&D Firm's Problem

A firm born in region i only conducts R&D in its birth region.[17] New technologies created through R&D can be used in multi-region production (MP). MP occurs when the technology from region i is used for production in region l. The firm's productivity in region l is denoted as z_l. Engaging in MP incurs a productivity loss γ_{il} due to the transfer of technology. γ_{il} is an iceberg cost, with $\gamma_{il} > 1$ and $\gamma_{ll} = 1$. There is a fixed cost F_n in units of labor and an iceberg trade cost τ_{ln} when selling a variety produced in l to n. Labor is the only input of production, and therefore the marginal cost of a variety from i produced in region l to serve market n is $c_{iln} = \frac{\gamma_{il} w_l^p \tau_{ln}}{z_l}$. Given the CES preference, firms will set the prices $p_{iln} = \tilde{\sigma} c_{iln}$, where $\tilde{\sigma} = \frac{\sigma}{\sigma - 1}$ is the markup over the marginal cost. To enter

[16] There is limited empirical evidence of geographic mobility. Caliendo et al. (2015) find that only 2% of the U.S. population moves across states in a year. Autor et al. (2013) find that trade shocks induced only small population shifts across regions in the US. In the appendix, I consider an extension of the benchmark model where workers can move across regions.

[17] For the origin-production-market triplet below, I use index i to denote the source of idea, index l to denote the location of production and index n to denote the product market.

market n, the variable profits earned in market n should be able to cover the fixed cost $w_n F_n$, and thus the unit cost of production needs to be lower than $c_n^* = \left(\frac{\sigma w_n^p F_n}{X_n}\right)^{1/(1-\sigma)} \frac{P_n}{\tilde{\sigma}}$, where X_n is the total expenditure in region n and $P_n = \left(\int_{\omega \in \Omega} p_n^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$ is the aggregate price index in region n.

4.2.1 Innovation

An R&D firm at region l can invest $\bar{f}_i$ efficiency units of innovation labor to come up with a new variety (product innovation).[18] The new variety can be produced in regions different from where it is created. Assume that the vector of productivity at each potential production site $\mathbf{z} = (z_1, z_2, \ldots, z_N)$ is randomly drawn from the multivariate Pareto distribution

$$G_i(z_1, \ldots, z_N) = 1 - \left(\sum_{l=1}^{N} \left[\left(\bar{T}_i^e v\right) T_l^p z_l^{-\theta}\right]^{\frac{1}{1-\rho}}\right)^{1-\rho} \tag{22}$$

with support $z_l \geq \sum_l \left[T_{il}^{1/(1-\rho)}\right]^{\frac{1-\rho}{\theta}}$, $\theta > max(1, \sigma - 1)$ and $\rho \in [0, 1)$.[19] The shape parameter θ controls the heterogeneity across realizations of different productivity vectors, and the correlation parameter ρ controls the correlation of the elements within the productivity vector.

The scale parameter $\left(\bar{T}_i^e v\right) T_l^p$ determines the average productivity of varieties created in i and produced in l. T_l^p is the productivity in production at region l. $\left(\bar{T}_i^e v\right)$ determines the quality of ideas created in region i, and can be thought of as the productivity in innovation. $\bar{T}_i^e$ is the fundamental productivity in innovation at location i. The R&D firm can also invest in R&D to increase productivity, and thus lower the marginal cost of production (process innovation). v is the level of process innovation chosen by the firm.

To achieve v level of process innovation, the R&D firm incurs a cost of v^{β_i} ($\beta_i > 1$) efficiency units of innovation labor. The region-specific parameter β_i reflects the capability of a region in fostering innovation. A lower β_i indicates that region i is better at fostering innovation. In this case, the marginal cost of process innovation will be lower

[18] To line up with my empirical model, innovation site within an R&D firm is predetermined.

[19] See Arkolakis et al. (2017) for detail information of the distribution properties and boundary conditions.

and the returns to R&D are higher. In section 3, I find that returns to R&D are higher when innovation plants are located in a region with more manufacturing employment. In other words, regions with a higher employment in production are better at fostering innovation. Thus, I impose the following assumption on the region-specific parameter β_i.

Assumption: $\beta_i = \frac{1}{g\left(L_i^p\right)}$ is an decreasing function in L_i^p.

Regions with a higher level of employment in production are better at fostering innovation. In this case, the cost of process innovation $v^{\frac{1}{g\left(L_i^p\right)}}$ is lower. Denote $T_i^e = \bar{T}_i^e v$ as the post process innovation productivity. With a higher T_i^e, the new varieties created in region i will have higher productivity at all potential production sites.

4.2.2 Production

The R&D firm from region i faces a tradeoff between market proximity and production capability when choosing where to produce for market n. It can either locate in a region closer to the market (a smaller τ_{ln}) or in a region with lower production cost (a lower $\frac{w_l^p \gamma_{il}}{z_l}$). Given the multivariate Pareto distribution of the productivity vector, the probability that a variety created from i serving market n through region l is

$$\psi_{iln} \equiv Pr\left(argmin_l C_{iln} = l | min_l C_{iln} \le c_n^*\right) = \frac{\left(T_l^p \left(\gamma_{il} w_l^p \tau_{ln}\right)^{-\theta}\right)^{1/(1-\rho)}}{\sum_m \left(T_m^p \left(\gamma_{im} w_m^p \tau_{mn}\right)^{-\theta}\right)^{1/(1-\rho)}}. \tag{23}$$

The probability depends on the production capacities of region l relative to other regions. The numerator represents a region's production capacity, which depends on the region's productivity in production T_l^p, the proximity to technology γ_{il} and market τ_{ln}, and the wage of production labor w_l^p. The denominator in equation is the sum of all potential production sites' capacities, and can be thought of as the access to production for firms from region i.

Given the access to production, the probability of R&D firm from i serving market n at a cost lower than c, for $c \le c_n^*$, is

$$Pr\left(min_l C_{iln} \leq c\right) = T_i^e \left[\left(\sum_m T_m^p \left(\gamma_{im} w_m^p \tau_{mn}\right)^{-\theta} \right)^{1/(1-\rho)} \right]^{1-\rho} \theta c^{\theta-1}. \tag{24}$$

Denote $\Phi_{in}(v) = \left(\bar{T}_i^e v\right) \left[\left(\sum_m T_m^p \left(\gamma_{im} w_m^p \tau_{mn}\right)^{-\theta} \right)^{1/(1-\rho)} \right]^{1-\rho}$ as the market potential of firms from region i in serving market n. With higher productivity in innovation and greater access to production, firms from i gain a higher market potential in n.

4.2.3 Optimal Level of Process Innovation

The R&D firms choose the optimal level of process innovation to maximize their profits. Given the probability of serving market n by firms from i in Equation 24 and the probability of producing in region l in Equation (23), the expected sales of a firm from i serving market n through region l can be written as

$$E(x_{iln}) = \phi_{iln} \Phi_{in}(v) X_n \tilde{\sigma}^{1-\sigma} P_n^{\sigma-1} \int_0^{c_n^*} \theta c^{\theta-\sigma} dc, \tag{25}$$

and the total expected profits net of innovation costs for a firm innovating in i and conducting v level of process innovation is

$$E\left[\pi_i(v)\right] = \frac{\sigma-1}{\theta-\sigma+1} \sum_n \Phi_{in}(v) \left(\frac{X_n P_n^{\sigma-1}}{w_n^p F_n} \frac{\sigma}{\tilde{\sigma}^{1-\sigma}} \right)^{\frac{\theta}{\sigma-1}} w_n^p F_n - w_i^e \bar{f}_i - w_i^e v^\beta. \tag{26}$$

The first-order condition for the choice of the optimal level of process innovation and the zero expected profit condition due to the free entry yields $v = \left(\frac{1}{1-g(L_i^p)} \bar{f}_i \right)^{g(L_i^p)}$. The optimal level of process innovation is an increasing function in its production labor L_i^p. R&D firms locating in regions with higher employment in production will choose a higher level of process innovation.

4.3 Aggregation

The R&D firm from region i will spend f_i efficiency units of labor on innovation, which is the sum of its expenditures on product innovation $\bar{f}_i$ and process innovation $\frac{1}{g\left(L_i^p\right)} \bar{f}_i$. In region i, L_i^e efficiency units of labor are allocated to innovation and the measure of varieties created in region i is $M_i = \frac{L_i^e}{f_i}$. The total sales of varieties created in i serving the market n through region l can be written as

$$X_{iln} = M_i x_{iln} = \phi_{iln} \frac{M_i \Phi_{in}}{\sum_k M_k \Phi_{kn}} X_n. \tag{27}$$

Given the aggregate trilateral technology and trade flows X_{iln}, the total value of varieties produced in region l is denoted as $Y_l \equiv \sum_{i,n} X_{iln}$ and the total expenditure in region n is $X_n \equiv \sum_{i,l} X_{iln}$. X_{iln} can be used to construct three sets of aggregate bilateral shares:

the expenditure shares

$$\lambda_{in}^E \equiv \frac{\sum_l X_{iln}}{X_n} = \frac{M_i \Phi_{in}}{\sum_k M_k \Phi_{kn}}, \tag{28}$$

the trade shares

$$\lambda_{ln}^T \equiv \frac{\sum_i X_{iln}}{X_n} = \sum_i \phi_{iln} \lambda_{in}^E, \tag{29}$$

and the MP shares

$$\lambda_{il}^M \equiv \frac{\sum_n X_{iln}}{Y_l} = \frac{\sum_n \phi_{iln} \lambda_{in}^E X_n}{Y_l}. \tag{30}$$

4.4 Equilibrium

Given the measure of varieties created in region i and the profits earned by the R&D firm in Equation (26), the total profits earned by firms from region i can be written as $\Pi_i = M_i \pi_i = \eta \sum_n \lambda_{in}^E X_n - w_i^e L_i^e$, where $\eta = \frac{\sigma - 1}{\theta \sigma}$. Zero profit condition implies that labor market clearing condition for innovation workers can be written as follows,

$$\sum_n \lambda_{in}^E X_n = w_i^e L_i^e. \tag{31}$$

The labor demand for production in region l equals the total output Y_l minus the profits associated with the output $\frac{Y_l}{\sigma}$, which gives $\frac{\sum_n \lambda_{ln}^T X_n}{\tilde{\sigma}}$. The labor demand for serving the market (entry) is $(1 - \eta - \frac{1}{\tilde{\sigma}}) X_l$, which depends on the total consumption in region l. The labor marketing clearing condition for innovation workers can be written as follows,

$$\frac{\sum_n \lambda_{ln}^T X_n}{\tilde{\sigma}} + (1 - \eta - \frac{1}{\tilde{\sigma}}) X_l = w_l^p L_l^p. \tag{32}$$

Following Dekle et al. (2007), this model allows for aggregate trade and MP imbalances via exogenous cross region transfer Δ_i with $\sum_i \Delta_i = 0$. The budget balance condition can then be written as:

$$w_i^p L_i^p + w_i^e L_i^e + \Delta_i = X_i. \tag{33}$$

Equations (31) and (32) can be written in terms of wages by substituting L_i^e and L_i^p using Equations (20) and (21), and X_i using Equation (33). Equilibrium wages can be obtained by solving a system of $2N$ equations.

4.5 Calibration

I take the model to the data in year 2012, and restrict my analysis to 48 states in the U.S. and the rest of the world (ROW) for which I have good data for trade, output and multi-region production.[20] The parameters to be calibrated in the model are the multivariate Pareto distribution parametrs ρ and θ; the Frechet distribution parameter κ; the elasticity of substitution σ; the entry cost of innovation f_i; the parameters that determine bilateral trade and MP cost τ_{ln} and γ_{il}; the productivity parameters T_i^e and T_l^p; and regions' capability in fostering innovation $g(L_i^p)$.

To calibrate these parameters, I construct data on the bilateral trade and MP flows, the number of varieties in each region and the endowment of equipped labor in each region. For domestic trade, I aggregate the firm-level manufacturing trade flow data from the Commodity Flow Survey (CFS) to the state level to get the bilateral trade flows between the 48 states. I get the trade flows between each state and the ROW from Longitudinal Firm Trade Transaction Database (LFTTD). For the trade flows within the ROW $X_{row,row}$, I take it from the World Input-Output Database. With these data, I construct the 49×49 matrix of trade shares λ_{ln}^T, a vector of aggregate expenditure on manufacturing goods $X_n = \sum_l X_{ln}$, and a vector of aggregate output in manufacturing $Y_l = \sum_n X_{ln}$.

The empirical counterpart of bilateral MP flows from region i to region l is defined as the output in region l that is using the technology from region i. To construct the domestic MP flows, I link the BRDIS with Census of Manufactures (CMF). The data from the BRDIS allow me to identify the origin state of technology within a firm and the data

[20]Alaska, Hawaii and D.C. are excluded from my data sample.

from the CMF provide me with the information of output. I measure the outward MP flows from the U.S. to the ROW as the output of the R&D firms' foreign affiliates. To measure the inward MP flows from the ROW to each state, I link the Survey of Business Owners (SBO) with CMF to identify the foreign firms' operations in each state. I take the MP flows from ROW to ROW from Arkolakis et al. (2018). In this way, I obtain the 49×49 matrix of trade shares λ_{il}^{M}.

The number of varieties created in each state and the ROW M_i are measured by linking the BRDIS (or SBO) with CMF. The data from the BRDIS and SBO allow me to identify the origin of technology for firms' production, and the data from the CMF provide information on the number of products.

The aggregate labor endowments for the U.S. and the ROW are measured by using total equipped labor data from Penn World Table (PWT), multiplied by the share of employment in manufacturing sector from the UNIDO. The equipped labor in each state is then constructed by multiplying the share of employment in each state by the total equipped labor measured from the PWT.

4.5.1 Calibrated Parameters and Targeted Moments

Table 5 summarizes the calibrated parameters and the targeted moments in the data. I take the multi-variable Pareto shape parameter $\theta = 4.5$, correlation parameter $\rho = 5.5$, and the elasticity of substitution from $\sigma = 4$ from Arkolakis et al. (2018). I set Frechet distribution parameter $\kappa = 3$ following Hsieh et al. (2013) and Lagakos and Waugh (2013).

The rest of the parameters are calibrated following Arkolakis et al. (2018). First, I implement an extended version of Head and Ries (2001) approach to estimate the bilateral trade and MP costs. Given the data on trade, MP shares and the total consumption X_n, the model determines all the trilateral trade flows X_{iln}.[21] Assume that both the trade costs and MP costs are symmetric, I compute the matrices $\hat{\tau}_{ln} = \left(\sqrt{\frac{X_{inn}X_{ill}}{X_{iln}X_{inl}}}\right)^{\frac{1-\rho}{\theta}}$ and $\hat{\gamma}_{il} = \left(\sqrt{\frac{X_{iin}X_{lln}}{X_{iln}X_{lin}}}\right)^{\frac{1-\rho}{\theta}}$.

Given the estimated matrices of trade and MP cost, I set parameters T_i^e, T_i^p and f_i to match MP deficit $\sum_l \lambda_{il}^{M} Y_l - Y_i$, the total output Y_i and the number of varieties respectively.

[21] See appendix for the proofs.

Table 5: Calibrated Parameters and Data Targets

Parameters	Value	Description	Target/Source
σ	4	elasticity of substitution	Arkolakis et al. (2018)
κ	3	Frechet shape parameter	Lagakos and Waugh (2013); Hsieh et al. (2013)
θ	4.5	MVP shape parameter	Arkolakis et al. (2018)
ρ	0.55	MVP correlation parameter	Arkolakis et al. (2018)
$\bar{f}$		innovation entry cost	number of varities
τ_{ln}		trade cost	bilateral trade shares
γ_{il}		MP cost	bilateral MP shares
T_i^P		productivity in production	gross output
T_i^e		productivity in innovation	MP deficit

Notes: This table summarizes the calibrated parameters and the targeted moments in the data.

4.5.2 Mapping Revenue Equation to the Empirical Revenue Function

The region's capability in fostering innovation $g(L_i^p)$ is estimated by mapping the revenue function from the theoretical model to the empirical model. Given the expected sales of firm i serving the market n through l in Equation (25), the log expected revenue of firms from i with innovation level $v = \left(f_i - \bar{f}_i\right)^{g(L_i^p)}$ choosing region l to serve all potential markets can be written as[22]

$$\ln\left(x_{il}\right) - \frac{1}{1-\rho}\ln\left(T_l^p w_l^{-\theta}\right) - \ln\left(D_{il}\right) - \ln T_i^e + \frac{\theta}{1-\rho}\ln\left(\gamma_{il}\right) = g\left(L_i^P\right)\ln\left(f_i - \bar{f}_i\right), \quad (34)$$

where $D_{il} = \sum_n \frac{\sum_l T_l^p\left(\gamma_{il} w_l^p \tau_{ln}\right)^{-\theta}}{\sum_k M_k \Phi_{kn}}\left(X_n \tau_{ln}\right)$ can be thought of as the aggregate demand for the production plants using technologies from region i to serve the markets, and $\tilde{f}_i - f_i = \frac{1}{1-g(L_i^p)} f_i$ is the R&D expenditure that firm i spends on process innovation.

The log revenue in the empirical model is a function of the aggregate market con-

[22] Firms from region i will choose the optimal level of process innovation $v = \left(\frac{1}{1-g(L_i^p)}\bar{f}_i\right)^{g(L_i^p)} = \left(f_i - \bar{f}_i\right)^{g(L_i^p)}$.

ditions, the capital stock and the plant-specific performance, as in Equation (5). Plant-specific performance evolves over time, and depends on its own investment in R&D, as well as the transfer of technology from other R&D plants in the same firm. The performance evolution function is general enough to cover different organization structures of production and innovation within an R&D firm. For example, it allows more than one innovation plant within an R&D firm to provide technology for the production plants. The theoretical model is a simplification of what we can observe in the real data, assuming there is only one innovation plant within an R&D firm. To map the log revenue function to the empirical model, I simplify the performance evolution function by considering the case that there is only one innovation plant within an R&D firm, and I look at the long-run impact of innovation on plant performance.[23]

The log revenue function from the empirical model can then be written as

$$\tau_{jj'}^{-1}\left(\ln Rev_j - d_{j_k} - \frac{\sigma-1}{1-\alpha_1}\alpha_0\right) = \frac{\sigma-1}{1-\alpha_1}\left(\beta_1 \ln r_{j'} + \beta_2 \ln r_{j'} \ln\left(emp_{j'_{l'k}}\right)\right), \qquad (35)$$

where plant j is the technology-receiving plant and plant j' is the innovation plant.[24]

Comparing the revenue function from the theoretical model in Equation (34) with that from the empirical model in Equation (35), the left hand side of both equations gives the production plants' revenue after controlling for region-specific characteristics in production, the aggregate demand, the fundamental productivity and the loss of technology from the transferring. The region-specific productivity in production is captured by the term $\ln\left(T_l^p w_l^{-\theta}\right)$ in the theoretical model, and the empirical counterpart is d_{j_k}. The aggregate demand depends on D_{il}, which is captured by d_{j_k} in equation 35. Both equations relate revenue to the long-run predicted productivity. $\bar{T}_i^e$ determines the fundamental productivity in innovation in the model and $\frac{\sigma-1}{1-\alpha_1}\alpha_0$ captures the long-run effects of innovation on productivity. The friction of technology transfer is captured by γ_{il} theoretically and by $\tau_{jj'}$ empirically.

The right hand sides of both equations relate the production plant's revenue to the investment in R&D. In the theoretical model, the plant's revenue depends on the invest-

[23]The long run effect of R&D investment on plant performance is captured by α_1 and α_2. More than 90% of current period can be explained by its performance in the previous period. For simplification, I only consider the first-order effects of R&D investment on plant long-run performance.

[24]I surpress the constant term $\gamma_0 = log(\frac{\theta}{\theta-\sigma+1})$ in the equation.

ment in R&D at the innovation plant, as well as the regions' capacity in fostering innovation. The capacity is an increasing function of the local manufacturing employment, denoted as $g(L_i^p)$. Empirically, the plant's revenue depends on the investment in R&D $\frac{\sigma-1}{1-\alpha_1}(\beta_1 \ln r_j)$ and the spillovers from the local manufacturing $\frac{\sigma-1}{1-\alpha_1}\left(\beta_2 \ln r_{j'} \ln\left(emp_{j'_{l'k}}\right)\right)$. Given that the estimate of β_1 in Equation (7) is not significantly different from zero, I will mainly focus on the spillover effects from the local manufacturing. Assume innovation capacity $g(L_i^p) = \mu \ln L_i^p$, where μ captures the strength of the spillovers from the local manufacturing to innovation. The spillover strength parameter takes the value $\mu = \frac{\hat{\sigma}-1}{1-\hat{\alpha}_1}\hat{\beta}_2$, where the estimates are from Table 3 column (b). With $\hat{\alpha}_1 = 0.9125$, $\hat{\beta}_2 = 0.0002$ and $\hat{\sigma} = 2.9568$, the strength parameter is estimated to be $\mu = 0.005$.

The benchmark estimation in the empirical section also considers the case of no spillovers from the local manufacturing to innovation. In this case, the plant's revenue only depends on the innovation plant's investment in R&D. To shut down the spillovers from the local manufacturing in the model, I assume the local innovation capacity is a constant and it equals $g(\cdot) = \frac{\hat{\sigma}-1}{1-\hat{\alpha}_1}\hat{\beta}_1$, where the estimates are taken from Table 3 column (a). With $\hat{\alpha}_1 = 0.9088$, $\hat{\beta}_2 = 0.0014$ and $\hat{\sigma} = 2.9568$, the constant local innovation capacity is estimated to be $g(\cdot) = 0.03$. In the counterfactural exercises, I will compare the changes of innovation efficiency in cases where there are spillovers to these cases where there are no spillovers.

4.6 Counterfactural Exercises

The increase in U.S. imports from China has asymmetric impacts across regions. Autor et al. (2013) shows that labor markets with greater exposure to the increase in import competition from China experienced a larger decrease in manufacturing employment. In this section, I will use the China import competition to quantify the effects of production reallocation on the local innovation efficiency.

4.6.1 Identifying the Trade Shocks

Given that not all the observed changes in U.S. imports from China are the results of a change in Chinese productivity, I replicate the procedure in Autor et al. (2013) to identify the supply-driven components of Chinese imports. I compute the predicted changes in the U.S. imports from China *a la* Bartik. The predicted changes are the inner product of the initial U.S. imports in each sector and the sectoral growth of Chinese imports in eight other developed countries,[25]

$$\Delta IMP_{China \to US} = \sum_k IMP^k_{1997} \times g^k_{China \to OTH}, \tag{36}$$

where IMP^k_{1997} is the U.S. imports from China in 1997, $g^k_{China \to OTH}$ is the growth of Chinese imports in eight other developed countries in sector k, and $\Delta IMP_{China \to US}$ is the changes in imports during the period 1997-2012.

I model the rise of China as the productivity shocks to the ROW ΔT^p_{ROW}, and use the predicted changes in the U.S. imports from China to quantify the size of the productivity shocks. I calibrate these shocks such that the simulated changes in aggregate expenditure shares on goods from the ROW match the change in these expenditure shares that is driven by the rise of China during 1997-2012.

4.6.2 The Impact of production reallocation on innovation

In this section, I will remove the China shock to see how that will affect the innovation and production across all states.

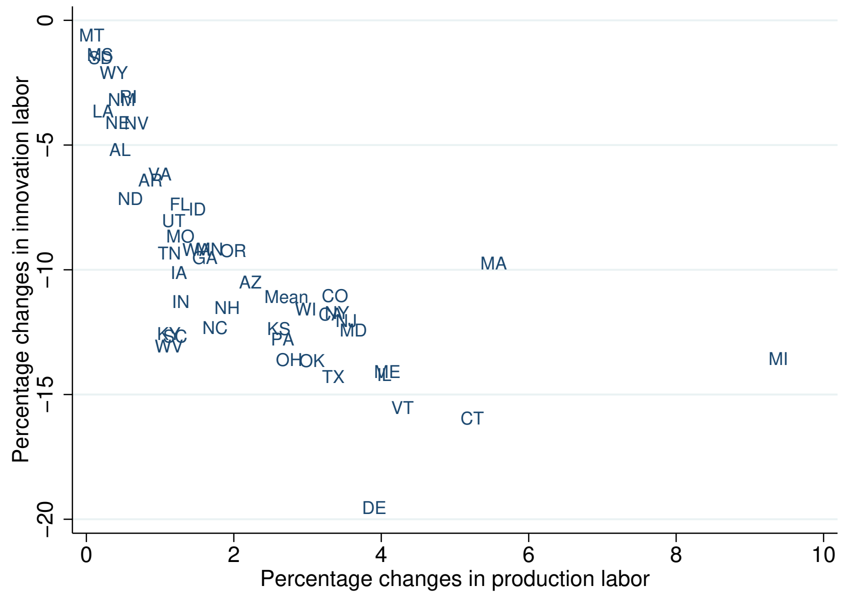
Figure 3 plots the percentage changes in innovation and production labor for each state when removing the import competition from China. In this case, each state will have a larger employment in production but less employment in innovation. That is to say, most states will be less specialized in innovation when comparing with the current equilibrium. In another words, the rise of China leads to the decrease in production cost in the ROW, which makes it possible for each state in U.S. to be more concentrated in innovation and reallocate some of its productions to the ROW. Michigan experiences the largest decline in manufacturing, followed by Massachusetts, Connecticut, and Texas due to the rise of China.[26]

Figure 4 plots the percentage changes in innovation productivity against the changes in production workers. When there are no trade shocks, states with a larger increase in

[25] The eight other developed countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[26] Autor et al. (2016) also find that these states face highest exposure to trade shocks.

Figure 3: Reallocation of Innovation and Production Labor



Notes: This figure plots the percentage changes in innovation and production labor for each state when removing the import competition from China.

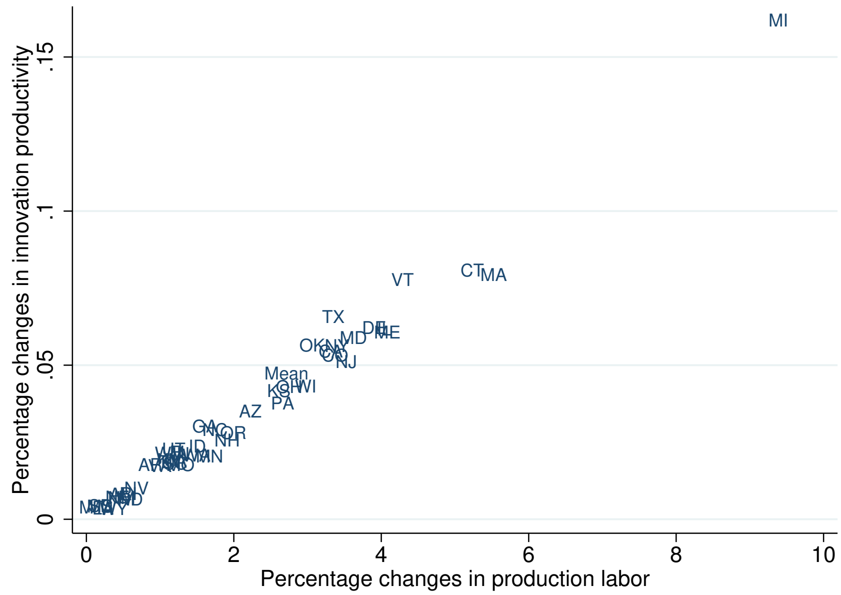
production workers will also experience a more substantial growth in innovation efficiency.

4.6.3 Spillovers versus no spillovers

I consider another counterfactual exercise by shutting down the spillovers from the local manufacturing to innovation. For cases with and without spillovers from the local manufacturing to innovation, I compute the changes in welfare, innovation productivity, and the number of varieties due to the exogenous trade shocks.

In the following, I will compare the difference in changes across the two scenarios. In Figure 5, the y-axis in both subfigures plots the difference in welfare changes. The x-axis in the left panel reports the difference in the innovation productivity. When there are positive spillovers from the local manufacturing to innovation, the increase in the production employment leads to an increase in innovation efficiency. With a higher productivity in innovation, it obtains a higher welfare compared with the case of no

Figure 4: The Impact of Production Labor Reallocation on Innovation Efficiency



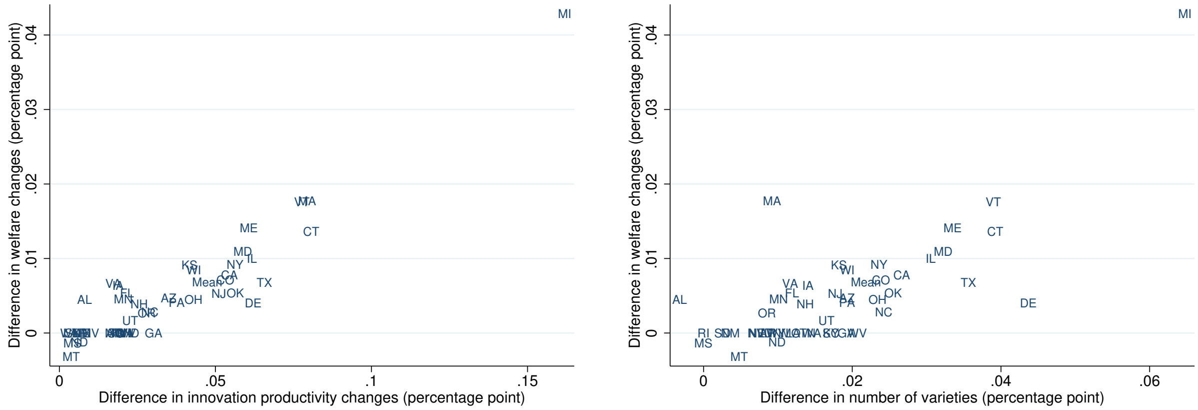
Notes: This figure plots the percentage changes in innovation productivity against the changes in production workers when removing the import competition from China.

spillovers. The scatterplot of the left panel indicates that the increase in innovation productivity due to the positive spillovers from the local manufacturing results in a higher welfare. More than that, a higher productivity in innovation also leads to a larger investment in R&D. As a result, more workers will be allocated to innovation activities. The increase in innovation labor further results in the increase in the number of varieties being created, as plotted on the x-axis in the right panel of the Figure 5.

5 Conclusion

This paper finds evidence that production proximity is crucial for innovation efficiency. I document two novel patterns on the spatial distribution of innovation and production: (i) innovation activities are more agglomerated than production ones, and (ii) innovation and production activities are geographically concentrated. Motivated by the stylized facts, I propose that local manufacturing can enhance innovation and develop an empirical model to allow for the spillovers from the local manufacturing to innova-

Figure 5: Difference in Welfare Changes



(a) Productivity in innovation

(b) Number of varieties

Notes: This figure compares the difference in welfare changes, innovation productivity, and the number of varieties for cases with and without spillovers from local manufacturing to innovation. The y-axis in both subfigures plots the difference in welfare changes. The x-axis in the left panel reports the difference in the innovation productivity and in the right panel displays the difference in the number of varieties.

tion. In my empirical model, the increment in plant performance depends both on its investment in R&D, and the interaction between R&D and local manufacturing workers. I estimate the model by using a unique confidential plant-level panel data on innovation and production from the U.S. Census Bureau. My estimates show that with more manufacturing workers in the local area, the returns to R&D are higher. My empirical finding is consistent with the idea that geographic proximity facilitates the transmission of knowledge (Audretsch and Feldman, 2004). I extend Arkolakis et al. (2018) to incorporate the positive spillovers from production to innovation that I find in the empirical study, calibrating it to 48 states in the U.S. and the ROW. I then evaluate the impact of China trade shock on innovation efficiency through the new channel of local spillovers. I find that states with a more significant decline in the manufacturing sector due to the China shock experience a more substantial loss in innovation efficiency.

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