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An empirical comparison among China's top three municipalities

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Dynamic Externalities and Manufacturing Productivity: An empirical comparison among China's top three municipalities

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Abstract

By reviewing and improving previous empirical works on this topic, the present paper investigates the dynamic externalities of agglomeration in China. Taking China's top three municipalities (i.e., Beijing, Shanghai, and Tianjin) as sample regions, it assesses empirically and compares how three types of dynamic externalities—namely MAR (Marshall–Arrow–Romer), Jacobs, and Porter externalities—affect manufacturing productivity. The main findings of this paper are threefold. First, all three types of dynamic externalities measured in labor productivity can be found in the three sample regions, but large differences in the degrees and directions of the effects exist among them. Second, the degree and sign of the effects of each type of externality vary with changes in time lags. Third, the positive effects of these externalities seem to be substitutable for one another. Specifically, if MAR externalities contribute more to productivity growth in one city, Jacobs or Porter externalities do so to a lesser degree and vice versa.

***Keywords*:** Agglomeration, Dynamic externalities, Productivity, Chinese municipalities.

JEL Classification: L11, O11, O18, O33, O53

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I. Introduction

Since the pioneering work of Glaeser et al. (1992), three types of dynamic externalities of agglomeration, namely MAR (Marshall–Arrow–Romer), Jacobs, and Porter externalities, have become one of major focus areas that have stimulated increasing empirical interest among urban and regional economics researchers. A number of influential empirical studies based on the multi-region cases of large or small economies have expanded or revised the view and/or methodology proposed by Glaeser et al. (1992).

As one of the largest emerging market economies with the quickest growth rates in the world over the past three and half decades, the Chinese economy has naturally attracted the academic attention of researchers with various objectives. Indeed, some research has already covered or connected the cases of China in this line. However, it is easy to find problems with such research. One issue relates to the choice of sample regions. Most studies adopt Chinese provincial region-level data without considering their compatibility in the sense of spatial size or the real spatial implications of the externalities of economic agglomeration. However, a normal Chinese province is much bigger than a similar administrative region overseas (e.g., a state in the US, a province in France, or a prefecture in Japan), both in terms of land coverage and in that of population size. It is thus clear that most non-China-based studies on this topic choose cities and towns as sample region-units, which is closely consistent with the externalities of industrial agglomeration in a limited area. By contrast, most of the studies that choose Chinese provincial regions as sample units are inconsistent. This causes an obvious problem, in the sense that the sizes of sample regions are too large to show the nature of agglomeration and its externalities. It is also unrealistic to expect provinces that have very large land coverage in China, say Xinjiang or Qinghai (with a land coverage of 1,660,000 and 720,000 square kilometers, respectively), to form similar degrees of agglomeration to those that have comparatively small land coverage, say Zhejiang or Jiangsu (approximately 100,000 square kilometers).

Another issue originates from the data collection method. Almost all studies of this issue use panel data instead of time-series data. However, panel data insufficiently demonstrate the externalities of agglomeration. Indeed, a number of researchers (e.g., Henderson, 1997, 2003; Bun & Makhloufi, 2007; Zheng, 2010) suggest that it is hard to capture dynamic externalities fully using only panel data, as the time lag in the real world cannot be fully considered and simulated.

In light of these issues, this paper revises the empirical methods used by earlier researchers and applies it to Chinese cases. Further, it aims to make better choices of sample regions by paying more attention to their compatibility with the issues under investigation. Specifically, in contrast to earlier research, we replace panel data with time-series data and choose the top three metropolitan areas instead of all provincial regions in China.

The main reasons for choosing the top three municipalities in China as sample regions are that they are more compatible with the aims of this research and show greater importance in the Chinese economy in terms of both GDP share and the agglomeration of R&D resources. The top three municipalities not only occupy important positions in the two giant cores of the Chinese economy, namely the Yangtze River Delta area and the area around the Bohai Sea, but also have the same administrative status as central direct-ruled municipalities. In addition, their regional sizes in terms of land coverage are much smaller than provincial regions, and besides, they have already existed as regional and even as national cores of economic activities. All these features make them good samples for identifying the effects among similar cities abroad.

Before going onto the core themes of the topic, it is necessary to clarify certain conceptual issues. Three types or patterns of dynamic externalities resulting from the geographic concentration of firms have already been identified and contextualized by researchers, namely MAR, Jacobs, and Porter externalities. The definitions and related classifications of these three typies of externalities are generally clear among regional economists. MAR externalities result when agglomeration occurs within an industry or sector. They facilitate spillovers of knowledge and innovation among firms that manufacture or supply closely substitutable goods and eventually result in an increase in the industry's productivity in the agglomerated area (e.g., Romer, 1986). Similarly, Jacobs externalities (Jacobs, 1969) commonly result when spillovers occur among firms in different industries of sectors that are located in close proximity. Finally, Porter externalities (Porter, 1990; Glaeser et al., 1992) exist when innovation mainly comes from firms' competition in specialized, geographically concentrated industries; these are commonly considered to complement MAR externalities. In addition, geographic proximity may also reduce the costs of transporting intermediate inputs, thereby representing a pecuniary spillover according to Krugman (1991).

It is also clear that important phenomena are defined by researchers using different concepts. As a result, a phenomenon can have several synonymous definitions or meanings. For example, a MAR externality is often taken to be synonymous with specialization or localization effects, while a Jacobs externality is synonymous with diversity or urbanization economies. Further, although a Porter externality stresses the importance of intra-industry competition (Porter, 1990) given that local competition is more growth-conducive than is a local monopoly, it also agrees with the view that intra-industry specialization is a source of growth. The differences and connections among these terms and concepts are summarized in Table 1.

Table1. Comparison of the resources of dynamic externalities in different conceptual situation

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">definition of market competition</td></tr>
<tr><td>Low competition</td><td colspan="2">High competition</td></tr>
<tr><td rowspan="3">Resource of externalities</td><td rowspan="2">intra-industry</td><td>MAR externalities</td><td>Porter's externalities</td><td></td></tr>
<tr><td>Specialization = localization</td><td></td><td></td></tr>
<tr><td>Inter-industry</td><td></td><td>Jacobs Externalities</td><td>Diversification =Urbanization</td></tr>
</table>

Note: Summarized by authors.

In addition, according to Glaeser et al. (1992), viewing the externalities of a specific type of agglomeration as static or dynamic rests on whether a researcher stresses its effects on growth. For example, if researchers stress the effects of agglomeration on city specialization rather than on growth, it is usually understood as an investigation into static localization externalities rather than dynamic ones. In other words, dynamic externalities of agglomeration concern the effects of firm agglomeration on regional growth. As productivity growth is a basic indicator of growth, the productive effects of agglomeration also fall into the category of dynamic externalities. Our main objective is thus to identify the productivity effects of agglomeration externalities based on data on the top three Chinese metropolitan areas.

The remainder of this paper is structured as follows. Section 2 summarizes previous research on this topic critically with the purpose of drawing a line between what is known and what is unknown. Section 3 discusses the choice of empirical models according to our subject and objective. Section 4 describes the empirical testing, while Section 5 concludes and compares these conclusions with those of other studies.

II. Dynamic externalities of agglomeration: a critical review of previous research

The paper by Glaeser et al. (1992), the pioneering empirical work on the dynamic externalities of agglomeration, is a natural starting point for this literature review. Using data sets on the growth of large industries in 170 US cities between 1956 and 1987, Glaeser et al. (1992) find that local competition and urban variety rather than regional specialization encourage employment growth. This research result supports the theoretical inference of Jacobs (1969). Further, Henderson et al. (1995) state that industrial characteristics might influence the local environment for industrial growth, while knowledge accumulation might influence spillovers and growth. Their empirical works (see Henderson et al., 1995; Henderson, 2003) re-examine the dynamic externalities of both MAR and Jacobs agglomerations by considering additional factors (e.g., introducing a time lag as a way of bringing knowledge accumulation into the context).

However, their research results seem to be contradictory. Their 1995 paper, based on data on eight typical manufacturing sectors in the US between 1970 and 1987, shows that many mature industries benefit only from MAR externalities, while emerging high-tech industries (e.g., computer manufacturing, medical equipment manufacturing, and electronic components manufacturing) harvest both MAR and Jacobs externalities. They believe that these results concur with the product lifecycle location theory suggested by Duranton and Puga (2001) that states that emerging industries tend to be concentrated in large industrially diverse cities, while mature capital goods industries tend to be located in cities or areas where industry specialization is comparatively higher. However, Henderson (2003), based on firm-level data on the US machinery manufacturing and high-tech industries from 1972 to 1992, finds that both industries benefit from MAR externalities, whereas there is no obvious evidence that they benefit from Jacobs ones.

Other empirical research finds different results. For example, based on data on non-farm industries (that is, manufacturing, wholesale and retail, financial and insurance, and service industries) in Japan from 1975 to 1995, and by replacing the TFP (total factor productivity) growth rate with output growth as the dependent variable, Dekle (2002) finds that these three dynamic externalities are dependent on the features of specific industries. Specifically, the TFP growth rate of the manufacturing industry benefits much more from MAR externalities compared with the other two externalities, whereas those of the service and financial industries benefit more from Jacobs externalities than the others. Finally, Porter externalities are more obvious in service industries, including general service, wholesale, and retailing, than they are in other industries in terms of TFP growth.

De Lucio et al. (2002) use panel data on 26 Spanish manufacturing sectors from 1978 to 1992 to investigate the effects of these three externalities on labor productivity changes and find that the effect of specialization seems to change according to its degree. Specifically, at an early stage of specialization, its effect is negative, but once it reaches a certain degree of specialization, its effect turns positive. The authors suggest that this is mainly because of knowledge sharing among firms. However, there is no clear evidence of the presence of diversity (Jacobs) and competition (Porter) externalities.

Combes (2000) uses data on 52 industrial sectors and 42 service sectors in France between 1984 and 1993 to assess the effects of these three externalities on employment growth and finds that both sector specialization and diversity negatively affect growth in the majority of sectors. In service sectors, for example, there is a negative specialization effect and a positive diversity effect. In addition, competition has a negative impact in most cases. Cingano and Schivardi (2004) test the three externalities on growth in manufacturing industries using both firm-level-based TFP indicators and employment-based proxies for 10 manufacturing sectors between 1986 and 1998 in Italy. They find that industrial specialization positively affects TFP growth at the city-industry level, but find no evidence that either the degree of local competition or productive variety influences subsequent productivity growth. Moreover, employment-based regressions yield nearly the opposite results. They also show that later regressions based on employment growth can suffer from serious identification problems when interpreted as evidence of dynamic externalities.

Bun and Makhloufi (2007) use sample data on 18 manufacturing sectors in Morocco from 1985 to 1995 and a dynamic panel data model to examine productivity changes in the three situations and find that both specialization and variety have incremental effects on manufacturing productivity but competition does not. Lee et al. (2010) use firm-level data on 70,000 Korean firms to find that the deeper the specialization and the greater the industrial diversification, the clearer are their positive effects on labor productivity in firms. However, these productivity effects differ among firms in terms of their changing characteristics, ages, sizes, and organizational forms. Specifically, they find that firms in traditional industries benefit mainly from specialization, while those in emerging industries do so mainly from diversification, which supports the findings of Henderson and colleagues. In addition, they show that firms with certain shared enterprise characteristics benefit more from specialization than they do from diversification.

Finally, some previous empirical works have studied the effects of dynamic externalities on industrial productivity in China. For instance, Batisse (2002) uses data on 30 industrial sectors across 29 provincial and municipal regions from 1988 to 1997 to show that both the outside diversification and the inside competition of an industry favor growth, while the effect of specialization is negative. The main above-presented studies and their results are summarized in Table 2.

Table 2. Summing up of the empirical studies on agglomeration externalities

Researchers (citation)	Sample country	Dependent variables	Pattern of externalities		
			MAR	Jacobs	Porter
Glaeser et al (1992)	US	Employment growth	-- (Negative)	+ (positive)	+ (Positive)
Henderson et al (1995)	US	Employment Growth	+	+(only for new high-tech industries)	n.a
Henderson (2003)	US	TFP	+	Not significant	n.a
Dekle (2002)	Japan	TFP	+（manuf.） Not significant (for non-manuf.)	+(for non-manuf.）	+(service, wholesale & retail
De Lucio et al（2002）	Spain	Labor productivity	Nonlinear	Ambiguous	ambiguous
Combes（2000）	France	Output	-	--（manuf.） +（service）	--（manuf.） --（service）
Cingano&Schivardi（2004）	Italy	TFP	+	Ambiguous	ambiguous
Bun & Makhloufi（2007）	US Morocco	Labor productivity	+	+	-
Lee et al(2010)	Korea	Labor productivity	+（tradition） +（group or multi-factor firms）	+（emerging） +（single factory firms）	n.a
Batisse（2002）	China	Output	--	+	+

Notes: +means positive effect while – means negative one.

As shown in Table 2, the previous literature is full of contradictions because of two main methodological issues. First, these studies overlook the use of time-series data. The one important nature of dynamic externalities is their changeability over time (Audretsch & Feldman, 2004). Thus, they cannot fully capture the effects of the dynamic externalities of a specific pattern of agglomeration on productivity changes without a time-series view. Second, the overwhelming reliance on cross-sectional or panel data ignores the effects of regional characteristics. Obviously, different regions have different industrial structures and business environments, while the manufacturing industry may benefit from different types of dynamic externalities. Unlike previous empirical studies, this paper thus takes account of the two elements neglected above. In addition, we take the top three Chinese municipalities instead of all regions as sample areas.

III. Econometric methodology

As is typical in empirical papers, the central work comprises two steps. One is finding an appropriate empirical method and designing a feasible route to launch it. The other is choosing and describing suitable data.

3.1. The model

Although the method used by Glaeser et al. (1992) is not fully available for use with Chinese cases, it is still a good starting point for us to choose an appropriate model. As stated earlier, their model pioneered the study of the dynamic externalities of agglomeration. Let us thus start with their model, which examines employment growth patterns between two time periods. The basic form of the model is as follows:

$$\log\left(\frac{l_{t+1}}{l_t}\right) = -\log\left(\frac{\omega_{t+1}}{\omega_t}\right) + \log\left(\frac{A_{national,t+1}}{A_{national,t}}\right) + g(specilization, compitition, diversity) + e_{t+1} \tag{1}$$

Where $A_t = \dfrac{\omega_t}{f'(l_t)}$, is the overall level of technology at time t, ω_t , wage , l_t, the labor input at time t, $f(l_t)$,production function.

Therefore, a change in *A* represents a change in technology and price simultaneously. Specialization, competition, and diversity (in brackets) represent MAR, Jacobs, and Porter externalities, respectively. One of the distinguishing features of this model is its implicit assumption about the mechanism of effects. As Henderson (1997) comments, Glaeser et al. (1992) assert the level of employment in an industry today being correlated with local-owned industry employment 15 or 30 years ago as evidence of dynamic externalities, which, of course, is an exaggeration.

As stated earlier, some limitations with this model need to be revised in three aspects. First, in order to avoid possible estimation bias caused by the use of employment growth, we apply labor productivity standing for industrial growth. Second, in order to show the temporal structures between dynamic externalities and industrial productivity growth and its various compositions we apply a vector autoregressive (VAR) model and further conduct impulse response functions, forecast error variance decomposition, and the Johansen–Juselius test (hereafter the J-J test) based on the VAR model. Finally, in order to avoid possible distortion caused by industrial characteristics, sample industries must cover a full range of sectors.

As we know, VAR is a statistical model used to capture linear interdependencies among multiple time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. All the variables in a VAR are treated symmetrically; each variable has an equation that explains its evolution based on both its own lags and the lags of all other variables in the model. VAR modeling does not require expert knowledge, which previously had been used in structural models with simultaneous equations. The VAR model has thus proven to be especially useful for describing the dynamic relationships between economic time series and for forecasting. Specifically, an unrestricted VAR model with p lags (hereinafter referred to as the VAR (p)) is as follows[①]:

$$y_t = c + A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t \qquad (2)$$

We adopt the dynamic properties of a VAR to implement three types of structural analyses in order to show the dynamic interaction between dynamic externalities and industrial productivity growth and its various compositions. Our empirical work is thus done in three steps: a) the impulse response functions test; b) forecast error variance decompositions; and c) the J-J test.

3.1.1 Impulse response functions

Impulse response functions (IRF) are useful for studying the interactions between variables in a VAR model. They represent the reactions of the variables to shocks that hit the system. In matrix form, the triangular structural VAR (p) model is

$$BY_t = c + \Gamma_t Y_{t-1} + \Gamma_2 Y_{t-2} + \cdots \Gamma_p Y_{t-p} + \eta_t \qquad (4)$$

Where

$$B = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ -\beta_{21} & 1 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -\beta_{n1} & -\beta_{n2} & \cdots & 1 \end{pmatrix} \qquad (5)$$

The algebra of least squares will ensure that the estimated covariance matrix of the error vector η_t is diagonal. Once recursive ordering has been established, the world representation of Y_t based on orthogonal errors η_t is given by

① The lag length for the VAR(p) model can be determined using model selection criteria. The two most common information criteria are the Akaike (AIC), Schwarz(SC)

$$Y_t = \mu + \Theta_0 \eta_t + \Theta_1 \eta_{t-1} + \Theta_2 \eta_{t-2} + \cdots \tag{6}$$

Where $\Theta_0 = B^{-1}$ is a lower triangular matrix. The impulse responses to the orthogonal shocks

η_{jt} are

$$\frac{\partial y_{i,t+s}}{\partial \eta_{j,t}} = \frac{\partial y_{i,t}}{\partial \eta_{j,t-s}} = \theta_{ij}^{s}, i, j = 1, \cdots n; s \rangle 0 \tag{7}$$

3.1.2 Forecast error variance decomposition

Forecast error variance decomposition (FEVD) is used to determine what proportion of each of the variables can be explained by exogenous shocks to other variables. According to VAR (∞), the *i*-th variable can be expressed as

$$y_{it} = \sum_{j=1}^{k} (c_{ij}^{(0)} \varepsilon_{jt} + c_{ij}^{(1)} \varepsilon_{jt-1} + c_{ij}^{(2)} \varepsilon_{jt-2} + \cdots) \tag{8}$$

the variance of *i*'th variable is

$$E\left[\left(c_{ij}^{(0)} \varepsilon_{jt} + c_{ij}^{(1)} \varepsilon_{jt-1} + c_{ij}^{(2)} \varepsilon_{it-2} + \ldots\right)^2\right] = \sum_{q=0}^{\infty} (c_{ij}^{(q)})^2 \sigma_{jj} \qquad i, j = 1,2,\ldots,k \tag{9}$$

So the variance of y_i is k times (9), which is

$$\mathrm{var}(y_{it}) = \sum_{j=1}^{k} \left\{ \sum_{q=0}^{\infty} (c_{jj}^{(q)})^2 \sigma_{jj} \right\}, \qquad i = 1,2,\cdots k, \qquad t = 1,2,\cdots T \tag{10}$$

The effects of j on i , which is the relative variance contribution RVC may be expressed as follows

$$RVC_{j \to i}(s) = \frac{\sum_{q=0}^{\infty} (c_{ij}^{(q)})^2 \sigma_{jj}}{\mathrm{var}(y_{it})} = \frac{\sum_{q=0}^{\infty} (c_{ij}^{(q)})^2 \sigma_{jj}}{\sum_{j=1}^{k} \left\{ \sum_{q=0}^{\infty} (c_{ij}^{(q)})^2 \sigma_{jj} \right\}}, \qquad i, j = 1,2,\cdots k \tag{11}$$

$$RVC_{j \to i}(s) = \frac{\sum_{q=0}^{\infty} (c_{ij}^{(q)})^2 \sigma_{jj}}{\mathrm{var}(y_{it})} = \frac{\sum_{q=0}^{\infty} (c_{ij}^{(q)})^2 \sigma_{jj}}{\sum_{j=1}^{k} \left\{ \sum_{q=0}^{\infty} (c_{ij}^{(q)})^2 \sigma_{jj} \right\}}, \qquad i, j = 1,2,\cdots k \tag{12}$$

$0 \leq RVC_{j \to i}(s) \leq 1$,The bigger the RVC represents, the greater effects that j on i.

3.1.3 Cointegration test

Cointegration tests are carried out to ascertain whether a group of non-stationary series is cointegrated. Johansen first proposed the cointegration method in 1988 (see Johansen, 1995) and extended it with Juselius in 1990. The J-J test has since been a very popular tool in applied economic work. Johansen's methodology starts from the VAR (p) model (see equation(2)), where y_t is an n×1 vector of variables that are integrated of order one (commonly denoted I(1)) and ε_t is an n×1 vector of innovations. This VAR can be rewritten as

$$\Delta y_t = c + \prod y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \qquad (13)$$

Where

$$\prod = \sum_{i=1}^{p} A_i - I \qquad and \qquad \Gamma_i = -\sum_{j=i+1}^{p} A_j \qquad (14)$$

If the coefficient matrix π has a reduced rank r<n, then there exist n×r matrices α and β *e*ach with rank r such that $\prod = \alpha\beta'$ and $\beta' y_t$ are stationary and r is the number of cointegrating relationships. Further, the elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a cointegrating vector.

It has been proven that for a given r, the maximum likelihood estimator of β defines the combination of y_{t-1} that yields the r largest canonical correlations of Δy_t with y_{t-1} after correcting for lagged differences and deterministic variables when present. The Johansen cointegration approach produces two statistics (the trace and maximum eigenvalue statistics) to determine the number of cointegrating relations, shown in equations (15) and (16), respectively.

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_t) \qquad (15)$$

$$J_{\max} = -T \ln(1 - \hat{\lambda}_{r+1}) \qquad (16)$$

where T is the sample size and $\hat{\lambda}_t$ is the *i*-th largest canonical correlation. The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors. The maximum eigenvalue test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r +1 cointegrating vectors.

3.2. Data description

We choose as sample regions the largest three metropolitan areas in coastal China, namely Beijing, Shanghai, and Tianjin. These municipalities are directly ruled by the central government, and systematic data series are available from official statistics agencies both at a national level and at a municipal level. The data we select include value added, total output value, and employment according to the two-digit industry codes of these three metropolitan areas. The time range is from 1993 to 2009. Because the validity of the empirical results is significantly determined by the length of the observation period, a long-term data set of 15 years or more is preferable (Dornbusch et al., 2000). In our analysis, the data cover 17 years. Detailed descriptions of the variables and information on data measurement are summarized in Table 3.1.

Table 3.1 Variables for our calculation and data measurement

Variable	Measurement
Labor Productivity	LP_{it}=value added of manufacturing in city i/employment of manufacturing in same city
MAR Externalities	MAR_{it} = $(y_{it}/y_i)/(y_{jt}/y_j)$,specifically, variable y_{it} denote the total output value of 20 manufacturing industries in city i in year t; y_i denotes gross industrial output value for city i in the same year; y_{jt} denotes national output value of 20 manufacturing industries in year t; while y_j denotes gross national industrial output value in the same year.
Jacobs Externalities	$JACOBS_{it} = HHI_{it} = \sum_{i=1}^{9} s_i^2$,s_i indicates the share of the ith one-digit industry's output in all other output in the city at time t. (There are 9 one digit industries in a city, which is shown in Appendix A2).It is well known that the lower the region's HHI, the greater the region's industrial diversity will be.
Porter Externalities	$PORTER_{it} = (y_{it}/f_{it}) / (y_{ij}/f_{ij})$, where y_{it} and fit are the output and the number of firms of industry i in the region at time t, respectively. And, y_{jt} and f_{jt} are, respectively.

All variables are extracted from the statistical yearbooks of the three metropolitan areas and converted into real data using 1993 price indices. The empirical analysis is carried out by using up to 20 industries for each city.

IV. Empirical findings

By using labor productivity as the dependent variable and labor productivity as well as MAR, Jacobs, and Porter externalities as endogenous variables, we can establish an unrestricted two-lag-order VAR model (unrestricted VAR (2)) as follows:

$$\begin{aligned}\ln LP_{it} &= a_0 + a_{11}\ln LP_{it-1} + a_{12}\ln LP_{it-2} + a_{13}\ln MAR_{it-1} + a_{14}\ln MAR_{it-2} + a_{15}\ln JACOBS_{it-1} \\ &\quad + a_{16}\ln JACOBS_{it-2} + a_{17}\ln PORTER_{it-1} + a_{18}\ln PORTER_{it-2} + \varepsilon_{it}\end{aligned} \tag{13}$$

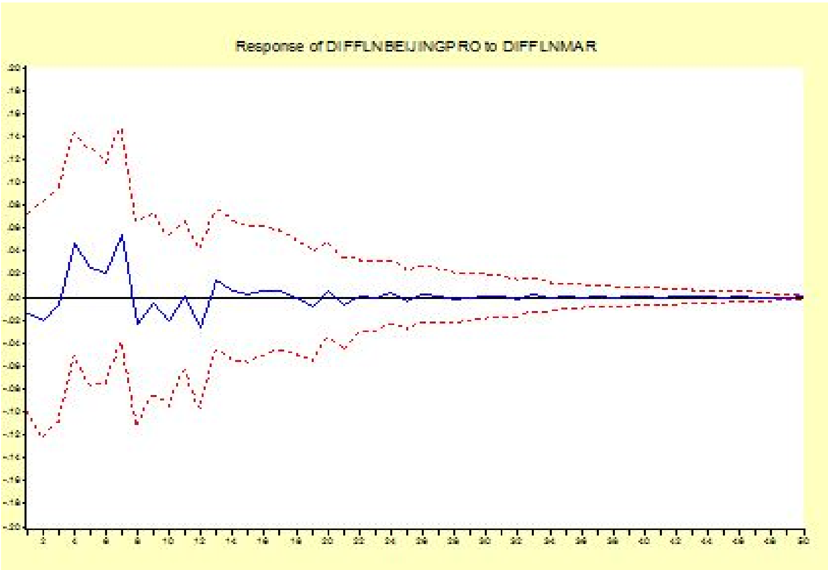
Before turning attention to regression modeling and the related regression analysis of equation (13), we must assess the stationarity of the series using the augmented Dickey–Fuller (ADF) approach. The test results suggest that all the variables are stationary in first-order differences (see Appendix B).

4.1 Test results for Beijing

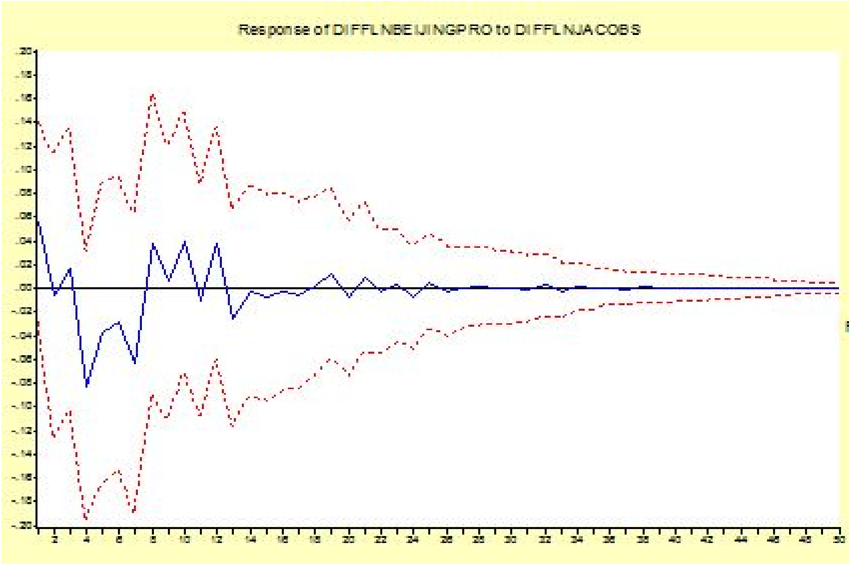
"We now proceed to conduct the three tests outlined in the previous section and analyze their results."

4.1.1 Impulse response functions for Beijing

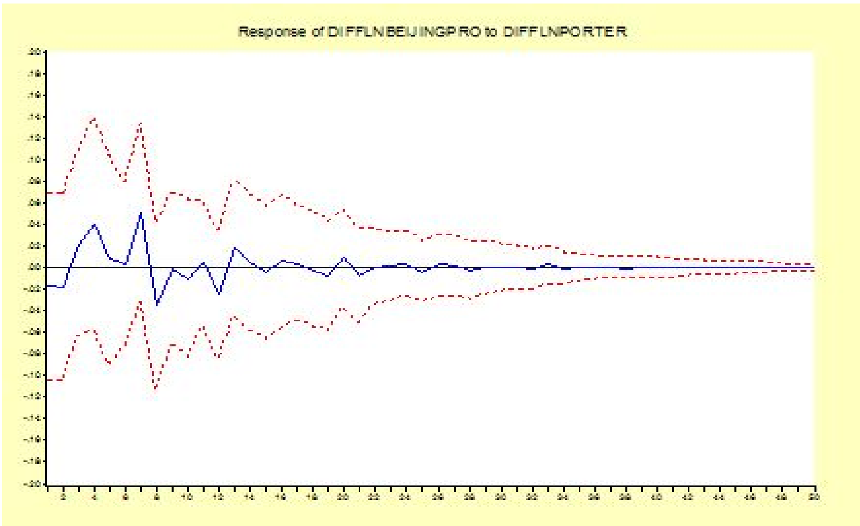
The impulse response functions for the MAR, Jacobs, and Porter externalities for the Beijing manufacturing industries are presented in Graphs 4.1(a)–(c), respectively. As suggested by these graphs, these externalities affect the labor productivity of the manufacturing sectors in Beijing in different ways over time. Specifically, the impact of the MAR externality on manufacturing labor productivity changes from negative to positive after four lags and rises to its maximum value by seven lags before stabilizing after 20 lags. The impacts of the Jacobs externality in the first seven stages are negative, but they turn positive after eight lags and stabilize after 25 lags. The Porter externality's impact on the manufacturing industry is negative in the first two lags but turns positive after three lags. Moreover, it achieves its maximum value after eight lags and eventually becomes stable after 25 lags. It is thus clear that the MAR and Porter externalities positively affect the productivity of the manufacturing industry in Beijing.



Graph4.1(a) Impulse response function of MAR externality for Beijing



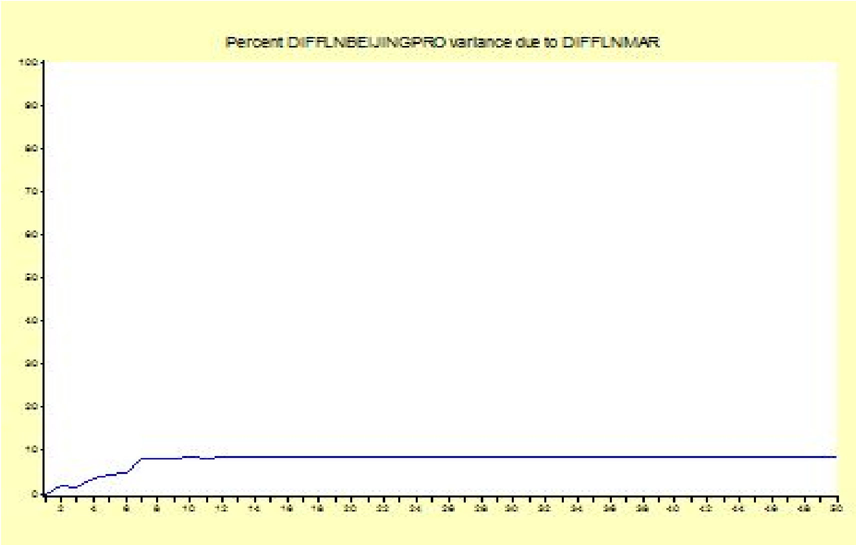
Graph4.1(b) Impulse response function of JACOBS externality for Beijing



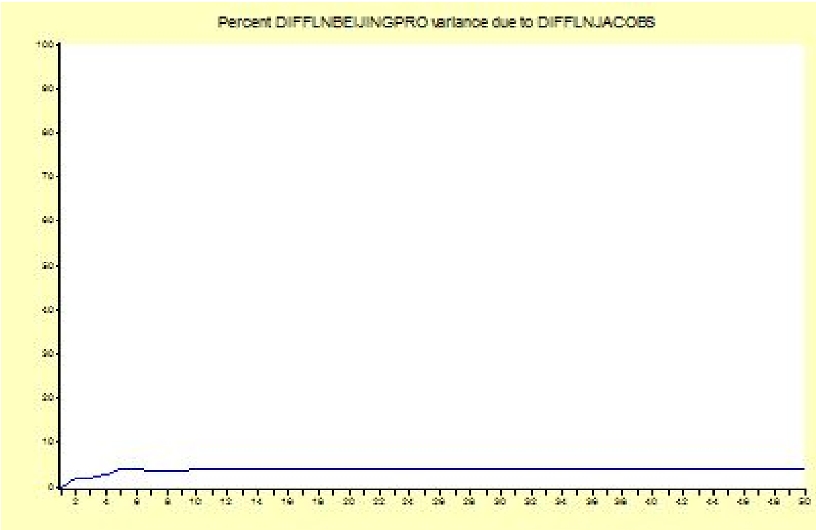
Graph4.1(c) Impulse response function of PORTER externality for Beijing

4.1.2 Forecast error variance decomposition for Beijing

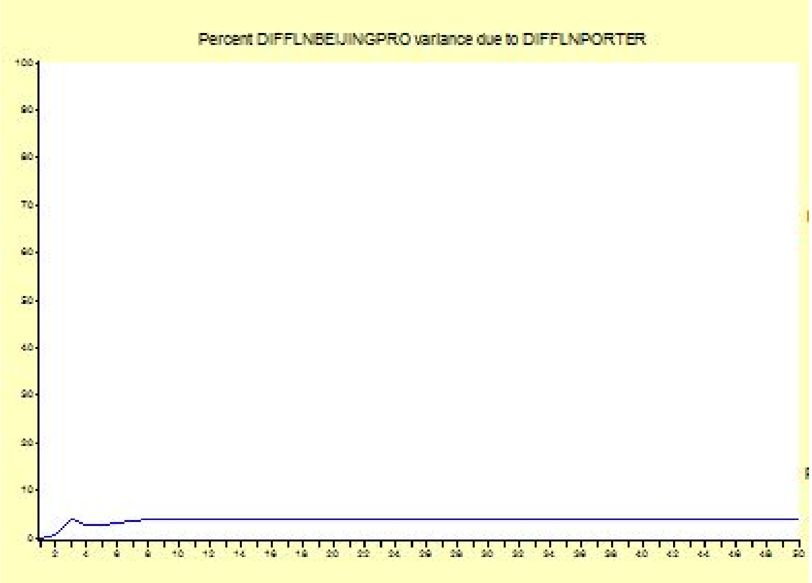
Graphs 4.2(a)–(c) show how these three types of externalities affect labor productivity in the manufacturing industry. Graph 4.2(a) demonstrates that the contribution rates of MAR to productivity in the manufacturing industry peak at 10% and remain stable after seven lags. Graphs 4.2(b) and (c) show that Jacobs and Porter externalities' contributions to productivity in the manufacturing industry in Beijing are not significant, reaching approximately 5% over the period studied, which is far less than the contribution rates of MAR.



Graph 4.2(a) Contribution of the MAR externality on manufacturing' productivity change in Beijing



Graph 4.2(b) Contribution of the JACOBS externality on manufacturing productivity in Beijing



Graph 4.2(c) Contribution of the PORTER externality on manufacturing productivity in Beijing

4.1.3 Cointegration test for Beijing

The results of the J-J test are reported in Table 4.1. Both the trace and max-eigenvalue test statistics indicate three cointegrating equations at the 16% significance level.

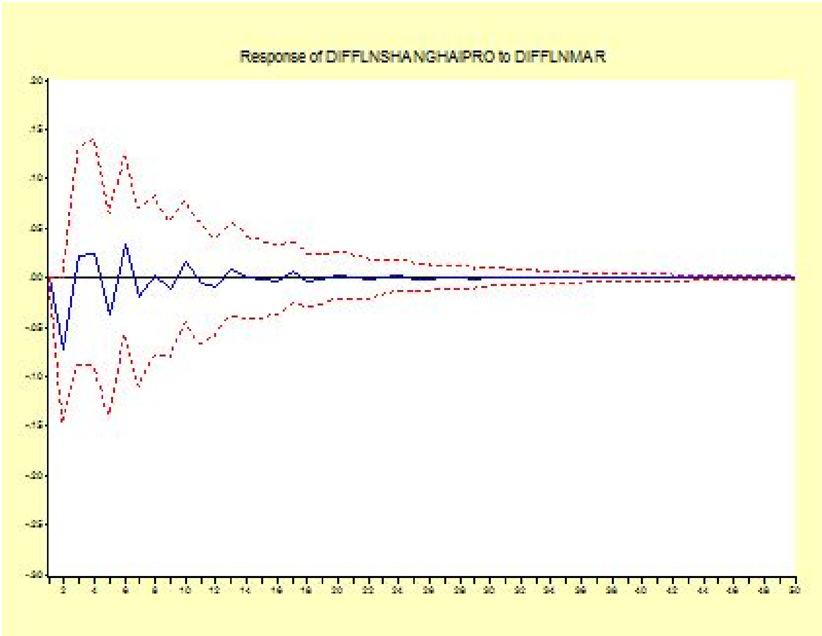
Table 4.1 Johansen and Juselius cointegration test for LP, MAR, JACOBS and PORTER externalities of Beijing's manufacturing industry

Null	Eigenvalue	Trace statistics	λ-max statistics	P value
r = 0	0.949844	102.1108	47.85613	0.0000
r <= 1	0.918593	57.22153	29.79707	0.0000
r <= 2	0.657454	19.59703	15.49471	0.0114
r <= 3	0.209525	3.526816	3.841466	0.1604

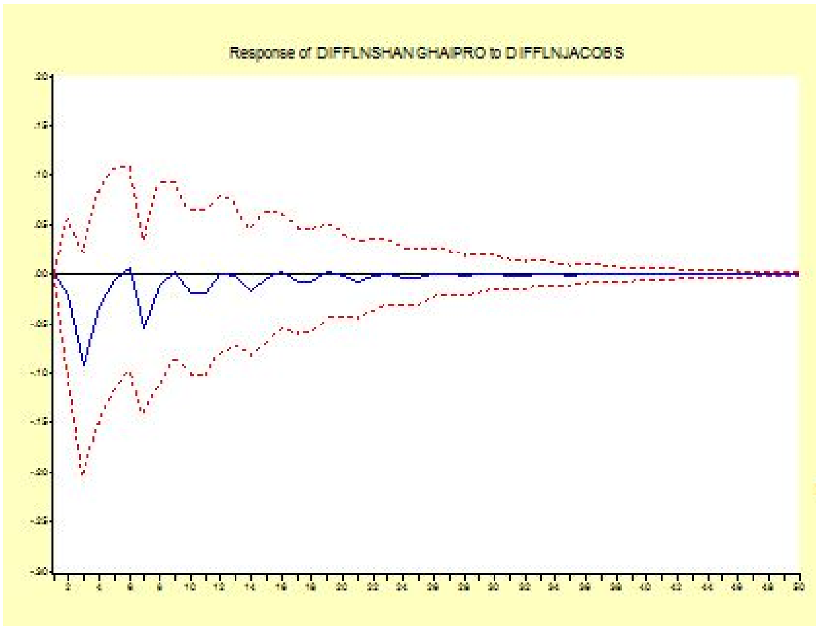
4.2 Test results for Shanghai

4.2.1 Impulse response functions for Shanghai

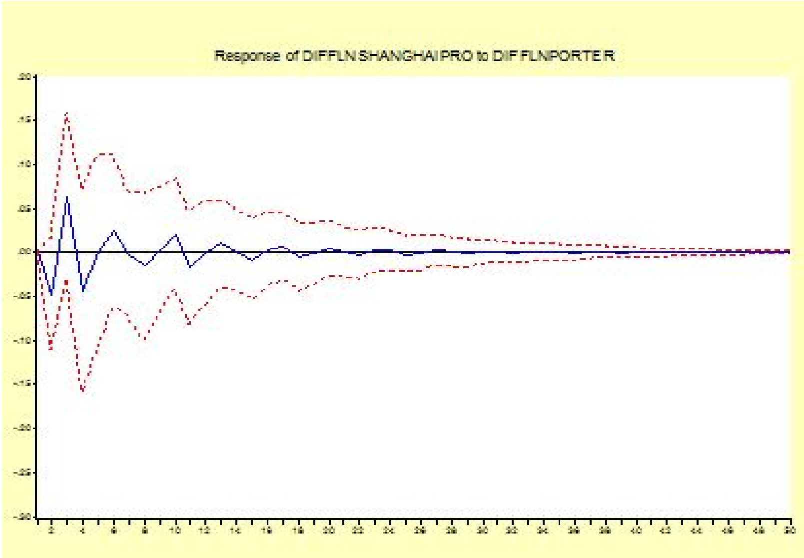
As before, Graphs 4.2(a)–(c) present the impulse response functions for the MAR, Jacobs, and Porter externalities for the manufacturing industry in Shanghai, respectively. As suggested by these graphs, these externalities affect the labor productivity of the manufacturing industry very differently. In particular, the impact of the MAR externality on manufacturing's labor productivity is uncertain even after 20 lags. Further, the impacts of the Jacobs externality are all negative, while that of the Porter externality peak after three lags and decrease dramatically thereafter.



Graph4.2(a) Impulse response function of MAR externality for Shanghai



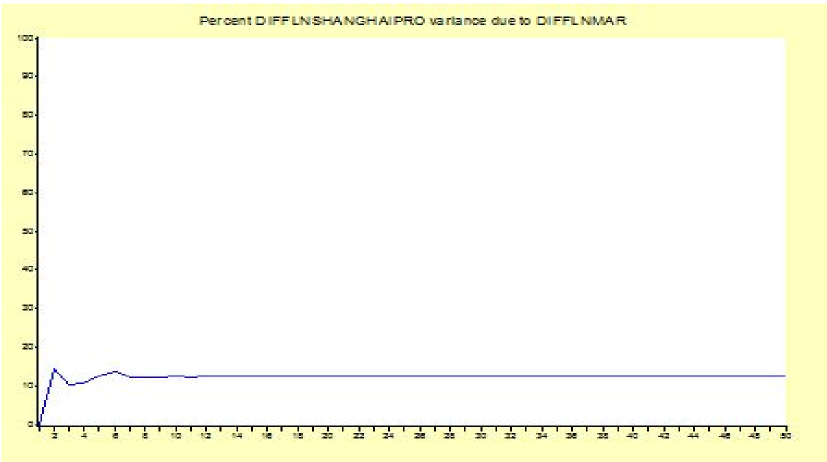
Graph4.2 (b) Impulse response function of JACOBS externality for Shanghai



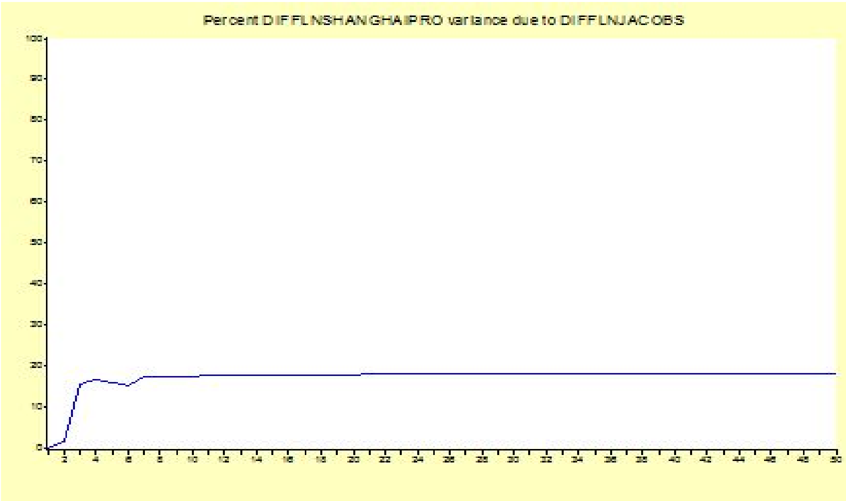
Graph4.2(c) Impulse response function of PORTER externality for Shanghai

4.2.2 Forecast error variance decomposition for Shanghai

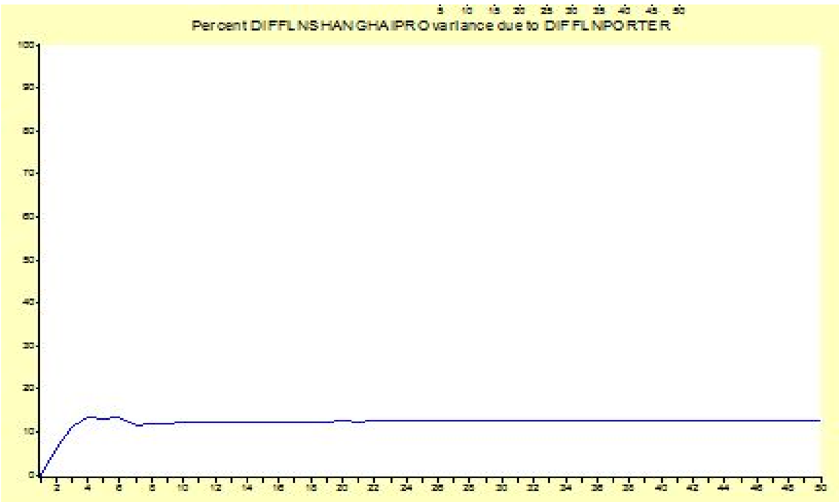
Graph 4.3(a) demonstrates that the contribution rates of the MAR, Jacobs, and Porter externalities are similar. In particular, the contribution rates of MAR to productivity in the manufacturing industry peaks and stabilizes at 13% after seven lags. The contribution of the Jacobs externality is even higher, reaching approximately 15%, while that of the Porter externality remains at approximately the 10% level over the study period.



Graph 4.3(a) Contribution of the MAR externality on manufacturing productivity in Shanghai



Graph 4.3(b) Contribution of the JACOBS externality on manufacturing productivity in Shanghai



Graph 4.3(c) Contribution of the PORTER externality on manufacturing productivity in Shanghai

4.2.3 Cointegration test for Shanghai

The results of the J-J test are reported in Table 4.2. Both the trace and max-eigenvalue test statistics indicate two cointegrating equation at the 15% significance level.

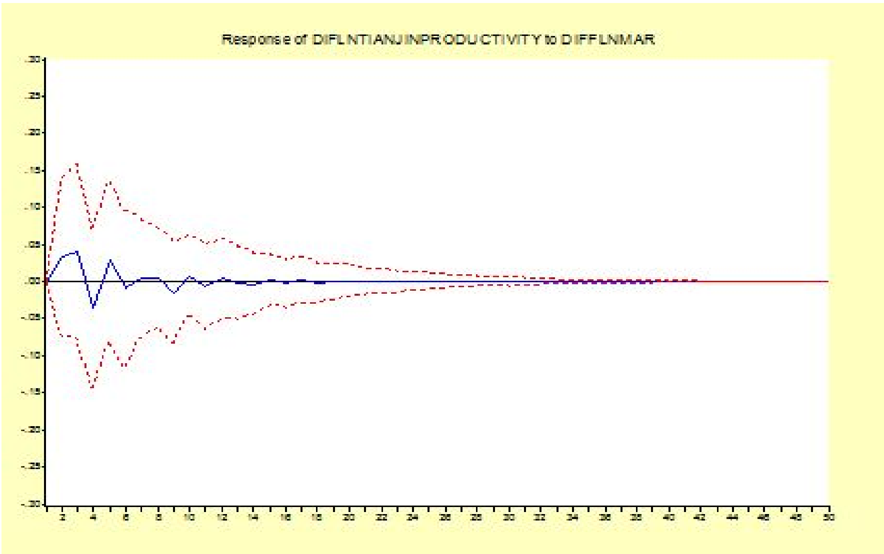
Table 4.2 Johansen and Juselius cointegration test for LP, MAR, JACOBS and PORTER externalities of Shanghai's manufacturing industry

Null	Eigenvalue	Trace statistics	λ-max statistics	P value
r = 0	0.946252	81.10605	55.24578	0.0001
r <= 1	0.777948	37.25445	35.01090	0.0283
r <= 2	0.446965	14.68180	18.39771	0.1534
r <= 3	0.320538	5.796802	3.841466	0.0160

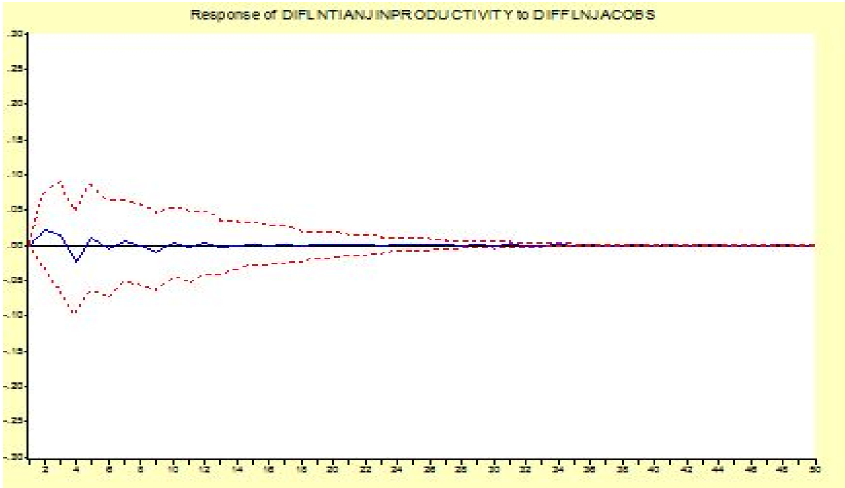
4.3. Test results for Tianjin

4.3.1 Impulse response functions for Tianjin

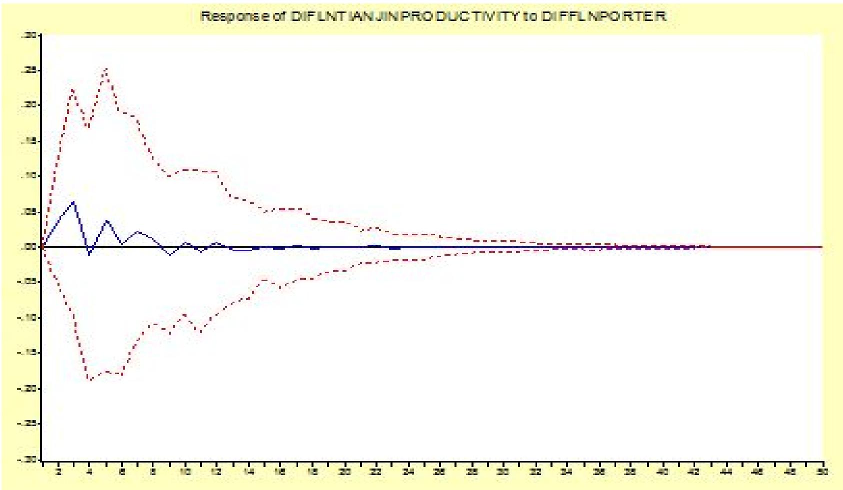
Here, the impact of the MAR externality on manufacturing labor productivity in Tianjin peaks after three lags and decreases sharply thereafter. Although the impacts of the Jacobs externality are not significant, that of the Porter externality peaks at 5% after three lags and decreases gradually thereafter. Thus, the Porter externality accelerates the productivity of Tianjin's manufacturing industry most of these three dynamic externalities.



Graph4.4 (a) Impulse response function of MAR externality for Tianjin



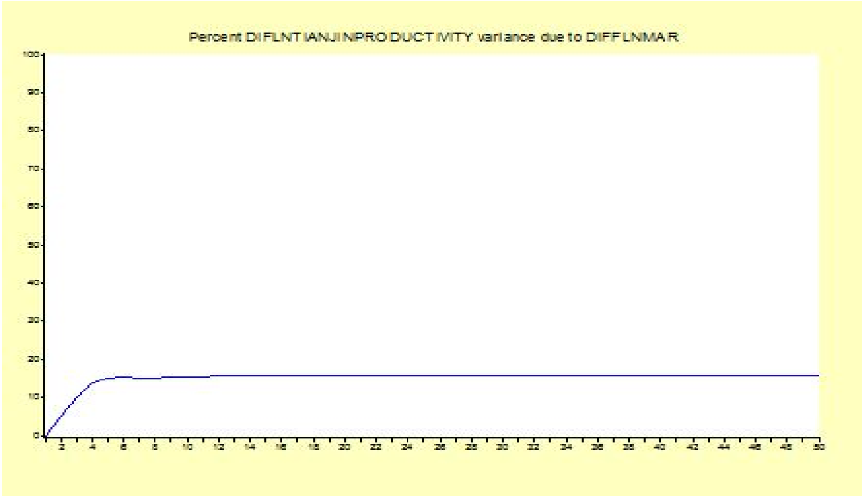
Graph4.4 (b) Impulse response function of JACOBS externality for Tianjin



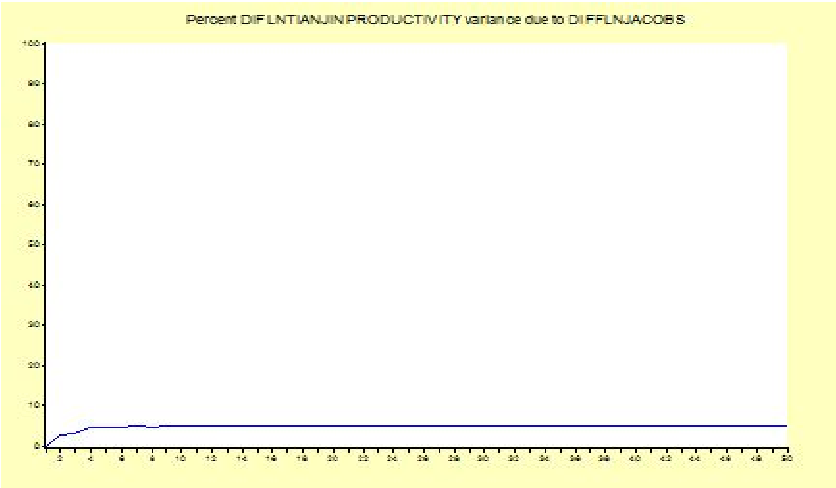
Graph4.4 (c) Impulse response function of PORTER externality for Tianjin

4.3.2 Forecast error variance decomposition for Tianjin

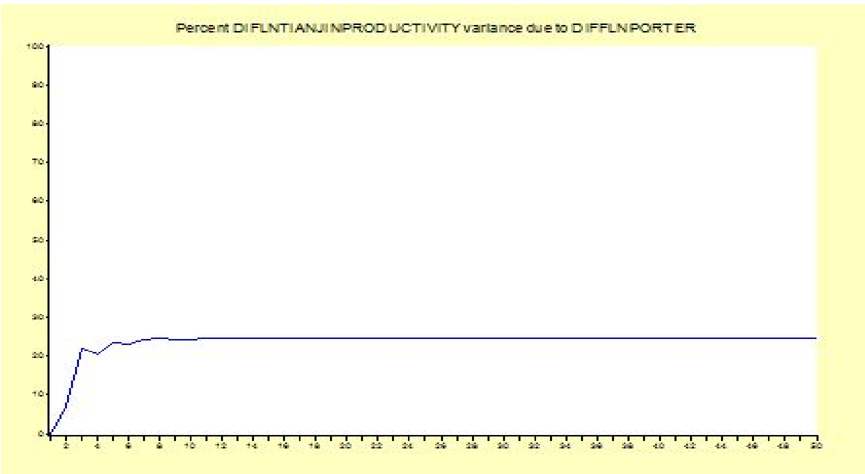
Graph 4.5(a) demonstrates that the contribution rates of the MAR externality peaks and stabilizes at 15% after four lags. The contribution of the Jacobs externality is much smaller, reaching approximately 5%, while that of the Porter externality remains at approximately 25%, which is the highest of the three externalities.



Graph 4.5(a) Contribution of the MAR externality on manufacturing productivity in Tianjin



Graph 4.6(b) Contribution of the JACOBS externality on manufacturing productivity in Tianjin



Graph 4.6(c) Contribution of the PORTER externality on manufacturing productivity in Tianjin

4.3.3 Cointegration test for Tianjin

The results of the J-J test are reported in Table 4.3. Both the trace and max-eigenvalue test statistics indicate one cointegrating equation and two equations at the 66% significance level, and two at the 88% significance level.

Table 4.3 Johansen and Juselius cointegration test for LP, MAR, Jacobs and Porter externalities of manufacturing industry in Tianjin

Null	Eigenvalue	Trace statistics	λ-max statistics	P value
r = 0	0.914770	51.12297	47.85613	0.0239
r <= 1	0.587633	16.64942	29.79707	0.6658
r <= 2	0.208302	4.247645	15.49471	0.8826
r <= 3	0.067445	0.977584	43.841466	0.0258

V. Conclusion and discussion

The core objective of this paper was to examine three types of dynamic externalities in China: MAR (effects of specialization), Jacobs (effects of industrial diversity), and Porter (effects of competition rather than monopoly). Using time-series data on the three largest metropolitan areas, namely Beijing, Tianjin, and Shanghai, from 1993 to 2009, we found interesting evidence on how dynamic externalities affect local industrial growth. The main findings of the empirical work are discussed next.

a) All the three types of dynamic externalities, measured by labor productivity response, can be found in all three metropolitan areas, but there are large differences in both the degrees and the directions of the effects. Specifically, the growth in manufacturing industries benefits more from the MAR externality than it does from the other two types in two out of the three municipalities(Beijing and Shanghai). Tianjin is the exception, it seems benefits most from the Porter externality. Generally, the positive effects of the dynamic externalities brought about by intra-industry agglomeration are clearer compared with inter-industry agglomeration in all three metropolitan areas. Specifically, both the MAR and the Porter externalities have the highest contribution rates to the increment in manufacturing productivity, although all three have an average contribution of 13.3%. By contrast, the contributions of the Jacobs externality are small for Beijing and Tianjin (5%). Only Shanghai receives a high contribution (15%). These contributions to the increment in manufacturing productivity in the three metropolitan areas are summarized in Table 5.1.

Table 5.1：The Comparison of contribution of three types of externalities to the increment of the manufacturing productivity of the three metropolitan areas

		Cities		
		Beijing	Shanghai	Tianjin
Types of Externalities	MAR	10%	15%	15%
	Jacobs	5%	15%	5%
	Porter	5%	10%	25%

b) The effects vary substantially over time. As the test results show, the externalities for each of the sample cities are different over time. For example, in Beijing, the MAR externality affects the productivity of manufacturing industries negatively in the first period, positively in the second and third periods, and eventually disappears after the 12th period. The effects of the Jacobs externality are positive in the first period, but turn negative sharply from the second through fourth periods and turn positive again in the eighth period. For manufacturing in Shanghai, the effects of the MAR and Porter externalities are not stable until the 20th period, while the effects of the Jacobs externality are negative all the time. For manufacturing in Tianjin, the effects of all the three types of externalities are positive.

c) The effects of these three types of externalities seem to be substitutable. Specifically, if the MAR externality contributes most to productivity growth in one city, the Jacobs and Porter externalities do so less and vice versa. In Beijing, for example, the MAR externality has a general contribution of approximately 10% to the increment in productivity, while those of the Jacobs and Porter externalities are much smaller. In Shanghai, the MAR externality reaches a contribution of 15%, while the Porter externality is only 10%. In Tianjin, the Porter externality gives a contribution of 25%, while those of the MAR and Jacobs externalities are 15% and 5%, respectively.

In addition, we find that the MAR (specialization) and Porter (competition) externalities exert dominant effects on the increment in productivity in all three metropolitan areas, while the effect of the Jacobs (diversity) externality is much weaker. This finding contrasts with that presented by Glaeser et al. (1992), who conclude that local competition and urban variety rather than regional specialization encourage industry growth. Our finding is also different from that presented by Batisse (2002). His econometric and empirical work with panel data on Chinese industries at a provincial level suggests that both diversity and competition have positive effects on local growth, while specialization has a negative one. Our findings provide evidence to support the tests carried out by Henderson (1997) with US data. This study finds strong evidence of the MAR externality (specialization) but weak Jacobs externality (urbanization) effects.

A possible explanation for these differences is the institution-related differences and changing environment in China. As an economy in the process of market-oriented institutional transition, market system in China is not fully established and competition is not only different to that in the US and other mature market economies, but also, from time to time, to that in China itself. Although China's market-oriented economic reform started in the late 1970s and early 1980s, breakthrough progress towards building a market-oriented system for resource distribution only occurred in the early 1990s. The decade-long waves of market-oriented progress since 1992 have undoubtedly created both an increasing atmosphere and space for market competition. Firms now enjoy more market freedom than ever before. Related data in this analysis show that market competition has strengthened on average by 270% since 1993 (255% in Beijing, 112% in Shanghai, and 443% in Tianjin). On the contrary, during the same period, the diversity trend has been either overshadowed or weakened by this increasing market competition as well as competition among local governments. Our findings more or less reflect these changes.

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Appendices

TABLE A2: Nine one-digit industries

Industry name		
Mining	Construction	Financial Intermediation
Manufacturing	Transport, Storage and Post	Real Estate
Production and Supply of Electric Power ,Gas and Water	Wholesale and Retail Trades	Social Services

Appendix B: Unit root test for all variables

Variable name	Beijing	Shanghai	Tianjin
$lnlaborpro_{it}$	-4.239467 (0.0054)	-4.771980 (0.0020)	-2.848070 (0.0752)
$lnmar_{it}$	-5.508095 (0.0005)	-4.567889 (0.0029)	-7.462261 (0.0000)
$lnjacobs_{it}$	-5.663515 (0.0004)	-3.296268 (0.0327)	-3.923017 (0.0107)
$lnporter_{it}$	-3.656458 (0.0166)	-3.731096 (0.0144)	-3.533845 (0.0220)

Note :(1) The unit root test is then carried out under the null hypothesis of unit root is present.(2)The unit root tests are conducted with augmented Dickey–Fuller test (ADF), which is for first-order autoregressive process.(3) The values in the brackets show the level of significance at which ADF tests reject the null hypothesis.

Appendix C: Different Externalities of Three Metropolitans

TABLE C1: Externalities of Beijing

	1993	1995	1997	1999	2001	2003	2005	2007	2009
MAR	1.2875	1.8251	1.7718	1.1079	1.1692	1.1767	1.0858	1.021	0.978
Jacobs	0.6448	0.5779	0.4950	0.4570	0.3659	0.3242	0.3191	0.309	0.284
Porter	0.3151	0.3958	0.2489	0.3730	1.8476	1.9621	1.6791	1.662	1.166

TABLE C2: Externalities of Shanghai

	1993	1995	1997	1999	2001	2003	2005	2007	2009
MAR	0.9954	1.4038	1.6065	1.1355	1.1348	1.1013	1.1341	1.1241	1.0992
Jacobs	1.1691	0.8943	0.6220	0.5448	0.3803	0.3223	0.2815	0.3158	0.2641
Porter	0.5910	0.6569	0.8511	0.9400	1.8761	1.8794	1.7627	1.8466	1.1389

TABLE C3: Externalities of Tianjin

	1993	1995	1997	1999	2001	2003	2005	2007	2009
MAR	3.3864	2.8422	2.3181	2.0054	2.6006	2.7168	2.6490	2.5087	2.2924
Jacobs	1.0817	0.9689	0.8621	1.0639	0.7732	0.6719	0.6279	0.5069	0.4662
Porter	0.2168	0.3095	0.3856	1.3234	1.2964	1.4068	1.6133	1.7820	1.1766

Note: All data in Appendix are listed by selected years.