The effect of external demand shocks on local industrial evolution: a study about the US-China trade friction

Abstract: In recent years, evolutionary economic geography has made great progress. However, some scholars have pointed out that evolutionary economic geography has neglected the impact of demand-side elements and external factors on regional economic evolution. To respond to this situation, this paper explores the impact of external demand shocks on the local industrial evolution based on Chinese city-level data and the difference-in-difference model, using the US-China trade friction in 2018 as a research case. It is found that the external demand shock lead local industries into a path-dependent and technical-complexity-reducing evolutionary path. The decline in innovative capacity due to the narrowing of exports as a global channel plays a mediating role between the external demand shock and regional industrial evolution. In addition, there is regional heterogeneity in the impact of the external demand shock on regional industrial evolution. Regions with high levels of related diversification are more vulnerable to shocks.

Keywords: Evolutionary economic geography, US-China trade friction, external demand shocks, regional industrial evolution

1 Introduction

Around 2000, geographers, represented by Ron Boschma, combined ideas from evolutionary economics with economic geography topics to create the branch of *Evolutionary Economic Geography* (EEG) (Boschma and Lambooy, 1999; Boschma and Frenken, 2006). EEG reveals the intrinsic mechanism of the evolution of regional economic activities with its unique dynamic perspective. EEG believes that regional economic development is based on history, specifically, the path of the past determines the direction of future development (Boschma, 2005; Maskell, 2001; Simmie, 2012). In recent years, the study of EEG has made great progress, forming a wealth of research topics such as *evolution of industrial clusters*, *evolution of correlation, diversity and complexity*, *regional economic resilience*, and so on (Balland and Rigby, 2017; Boschma, 2015; Boschma, 2017; Boschma and Iammarino, 2009; Frenken et al., 2007; Martin and Sunley, 2015). Nevertheless, some scholars have pointed out the limitations of EEG. First, the research of EEG is almost exclusively conducted from the supply-side perspective, which regards the reorganization and diffusion of productive knowledge as the fundamental driving force for the evolution of regional economic activities and ignores the role played by demand-side factors (Martin et al., 2019). Second, EEG focuses more on the role of factors and capabilities within the region and pays less attention to the local effects of external factors (Boschma et al., 2017). To address the limitations of current EEG research, this paper will attempt to discuss the impact of external demand shocks on the local industrial evolution.

The US-China trade friction that opened in 2018 provides a good case for this paper to study the shock of reduced external demand on the local industry evolution. In an effort to close the trade deficit with China and stimulate the development of local manufacturing, the U.S. government announced an additional 10% tariff on $200 billion of products imported from China starting September 24, 2018, and this amount will be increased to 25% from January 1, 2019 onwards. This decision set off this round of US-China trade friction. The US is China's largest trading partner, with China's exports to the US increasing from 8.3% of total exports in 1990 to 17.5% in 2020 (Caliendo & Parro, 2023). This trade friction, initiated by the US, has caused China's external demand level to plummet. The data shows that in 2017, China's export growth rate was 10.76%, falling to 7.06% in 2018 and further down to 5.02% in 2019. The decrease in external demand has brought a serious shock to China's economic development (Shen et al., 2021). Studies have shown that US-China trade frictions have reduced China's overall welfare level by about 2% (Ding et al., 2022), and the level of market returns on sanctioned products has been thrown into fluctuation (Wen et al., 2023). Since China's accession to the World Trade Organization (WTO) in 2001, it has gradually integrated into the global market and established an export-oriented economic model that serves external demand. Exports have become an important driver of China's economic development as well as regional industrial evolution (Lin and Li, 2003). Therefore, the external demand shock brought to China by the trade friction between China and the US is bound to reshape China's industrial evolution path and pattern.

In this paper, based on the model constructed by Balland et al. (2019), we will characterize China's industrial evolution in terms of two dimensions, path dependence and technological complexity, and analyze the impacts of the external demand shock event of trade friction between China and the US by using a difference-in-difference model. Compared with the past literature, the work of this paper may have the following contributions: first, this paper observes the driving force of regional industrial evolution from the demand-side perspective, responding to the limitations of EEG that focuses on supply but not demand, as suggested by Martin et al. (2019); second, this paper observes the influence of external factors on regional industrial evolution, providing ideas to introduce an external perspective to EEG.

The organization of the main content of this paper is as follows. Section 2 will review the literature related to this paper and present the research hypotheses. Section 3 will introduce the research methods and data sources. Section 4 will provide a descriptive analysis of China's external demand characteristics and the evolution of industries at the city level. Section 5 will report the results of the empirical analysis. Section 6 will summarize and discuss the main conclusions of this paper.

2 Literature review and research hypothesis

2.1 Regional industrial evolution

Regional industrial evolution is a metabolic process in which new industries continuously replace old ones, and is influenced by the entry of new industries and the survival and decline of existing industries (Alcorta et al., 2021; He et al., 2018). EEG attempts to reveal the laws and mechanisms of regional industrial evolution and has made remarkable progress.

First, EEG has given a high priority to industrial entry. Industrial entry usually refers to the introduction or creation of new industries in a region that were not previously available (Liang, 2017). Newly entering industries largely influence the future direction and trajectory of the region. According to the EEG, in the absence of exogenous factors, industrial entry is constrained by a region's technology and knowledge base (Doloreux and Turkina, 2021; Gong et al., 2023; J. H. Chen and Y. Chen, 2015). In other words, the stronger the relatedness to the region's technology and knowledge base, the easier it is for new industries to enter the region (Boschma et al., 2013; Neffke et al., 2011). This pattern of industrial evolution, which has a strong correlation with the original regional industrial structure and foundation, is known as path dependence. Although the EEG views path dependence as a general phenomenon of industrial entry, the reality is that there is also a special phenomenon of new entrants that are weakly related to their local base. A number of scholars have theorized about this particular phenomenon (Hassink et al., 2019). The findings suggest that, first, some endogenous forces drive regional industries to create new paths. For example, research by Plummer et al. (2022) shows that new knowledge, industrial diversity, and industrial transformation are conducive to enabling the creation of new paths. Second, exogenous factors such as policies, organizational behavior, and external knowledge facilitate breaking the self-reinforcing cycle of the evolutionary path within the region, thus breaking the dependence on the original path (Apajalahti and Kungl, 2022). Third, EEG not only emphasizes the role of “history”, but also pays attention to “future” and “expectations”. Studies have shown that forward-looking entrepreneurship can be a way for regional industries to create new evolutionary paths (Baumgartinger-Seiringer et al., 2022).

In addition to new entry industries, existing industries have also received attention from scholars. The development and operation of existing industries will likewise influence the direction of the region's evolution. For the development and evolution of existing industries, the study of EEG proposes the concepts of path transformation and path upgrading. Path transformation or path upgrading is the enhancement of the productivity of existing paths through embedding in global value chains, technological transformation, organizational or business model innovation, asset restructuring, and niche creation to achieve higher returns (Baumgartinger-Seiringer et al., 2021; Grillitsch et al., 2018).

From the above review, it can be seen that both new entry industries and existing industries have important impacts on the trajectory and direction of regional industry evolution. Balland et al. (2019) constructed a framework as shown in Figure 1 in their discussion of smart specialization policies. This framework provides a good idea for us to examine both new entry industries and existing industries at the same time. In Figure 1, the horizontal axis indicates the degree of technological relatedness between the new entry industries and the regional base, which is used to identify the degree of path dependence of the regional industrial evolution; the vertical axis indicates the degree of technological complexity within the region, and the increase in technological complexity implies that the region realizes the industrial path upgrading. Based on this framework, this paper will look at regional industrial evolution in terms of two dimensions: technological relatedness and technological complexity. These two dimensions categorize regional industrial evolution into four paths: ①Path-dependent and technical-complexity-increasing, ②Path-dependent and technical-complexity-reducing, ③Path-breaking and technical-complexity-increasing and ④Path-breaking and technical-complexity-reducing.

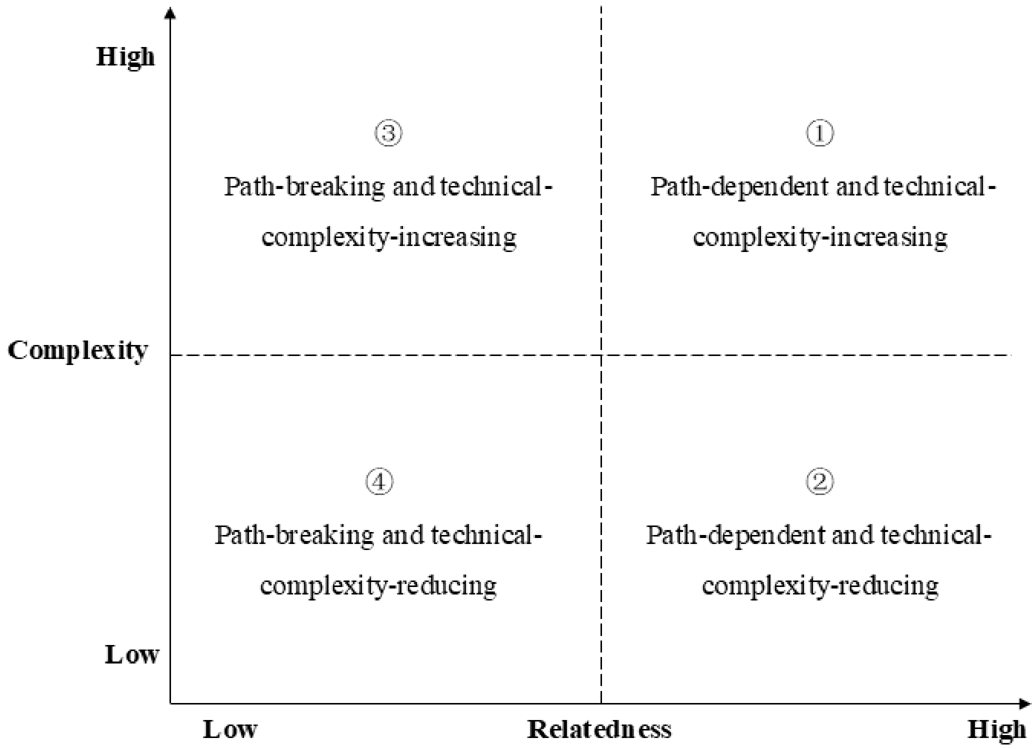

Figure 1 Regional industrial evolution framework

2.2 External demand shocks

External demand shocks refer to the turbulence and decline in the scale of demand for local products in overseas markets, which may have a negative impact on local economic and social development (Branstetter & Kwon, 2018; Wu et al., 2023). After the 2008 financial crisis, the impact of external demand shocks on regional economic development began to receive widespread attention. The existing literature has focused on analyzing the specific manifestations of the socio-economic effects of external demand shocks.

First, external demand shocks can affect local macroeconomic performance. Specifically, external demand shocks can reduce total local exports, raise regional unemployment rates, affect industrial and business output, and increase economic development gaps between regions (Cashin and Sosa, 2013; Chen et al., 2021; Horvath and Zhong, 2019; Justiniano and Preston , 2010; Nguyen et al., 2020). Second, there is regional heterogeneity in the impact of external demand shocks. Studies have shown that the higher the degree of related diversification of local industries, the larger the shock to local economic resilience from external demand is likely to be, as inter-industry relatedness allows shocks in one industry to be transmitted to other industries in the region (He et al., 2021). There is also empirical evidence that regions with greater factor mobility are more resistant and resilient in the face of external demand shocks (Di Pietro et al., 2021). Third, while most of the literature focuses on the negative effects of external demand shocks, some studies have empirically analyzed the beneficial effects of external demand shocks on innovative activities based on Schumpeter's “creative destruction” hypothesis (Barrot et al., 2018; Erixon, 2007; Erixon, 2016). For example, Aarstad and Kvitastein (2021) demonstrate that when the scale of external demand decreases, competition among local industries increases, thus forcing firms to invest more in innovative R&D.

Currently, attention to external demand shocks is mainly focused on the field of economics, and the study of EEG has not yet paid enough attention to this issue. In recent years, the intensification of political, military and economic conflicts worldwide has greatly impacted the balance of the international supply and demand system and trade patterns, and the frequency and intensity of external demand shocks can be elevated as a result. In this context, the evolutionary trajectory of regional economic activity is bound to be affected by external demand shocks. Exploring the impact of external demand shocks in the context of EEG not only enriches its content system, but also provides theoretical references for different subjects to cope with external demand shocks.

2.3 External demand shocks and industrial evolution

In the era of globalization, regional industrial evolution paths are not only the product of endogenous drives, but also influenced by external factors (Martin and Sunley, 2006). Changes in external demand are very likely to disrupt the process of knowledge accumulation in the region and thus reshape the path of regional industrial evolution. This paper argues that the decline in external demand may have two implications for regional industrial evolution. First, external demand shocks may raise the share of related industries in newly entered industries, reinforcing the path-dependent tendency of regional industrial evolution. The reason for this is that a decline in external demand will negatively affect the region's ability to cope with risk (Marin & Modica, 2021; Dutt & Ros, 2007). Balland et al. (2019) point out that the emergence of a large number of new technologies that are not related to the local base can impose greater costs and risks on local development. Compared to related industries, unrelated industries will inevitably lead to more unrelated new technologies, exposing the region to greater risk. In order to avoid the risk, under the situation of insufficient external demand, the government, production enterprises, financial institutions and other main agents are more inclined to introduce new industrial activities with strong relatedness to the existing technological base, thus reinforcing the trend of path dependence in the evolution of regional industries. Second, external demand shocks may hinder the process of regional industrial path upgrading, which is manifested in a decline in technological complexity. This is because lower external demand makes local agents less profitable and less able to afford the costs required to develop complex technology (Rafferty & Funk, 2004). In summary, external demand shocks may reinforce the tendency of the ② evolutionary path in Figure 1. Accordingly, research hypothesis 1 is proposed.

Hypothesis 1: External demand shocks cause regional industries to evolve in a path-dependent and technical-complexity-reducing direction.

Changes in innovation capacity brought about by the narrowing of the export pipeline may play an important role in the above effects of external demand shocks on the regional industrial evolution. Exporting is an important “global pipeline” through which local connections to the globe are established, allowing external knowledge to enter the local area, and thus laying the knowledge base for new local industry creation (Bathelt et al., 2004). The clogged global pipeline affects the ability to innovate, making both industrial path breaking as well as upgrading technological complexity more difficult (Coenen et al., 2015; Salomon & Shaver, 2005), which in turn shapes the regional industrial evolution paths described above. Accordingly, this paper proposes research hypothesis 2.

Hypothesis 2: The decline in innovation capacity due to the narrowing of the export pipeline plays a mediating role between external demand shocks and regional industrial evolution.

In addition, there may be regional heterogeneity in the impact of external demand shocks on regional industrial evolution. Specifically, regions with higher levels of related diversification are likely to be hit harder. Regions with higher related diversity imply a higher degree of inter-industry relatedness. Inter-industry relatedness can allow shocks in one industry to be transmitted to other industries in the region, which could lead to greater negative impacts on the region as a whole (He et al., 2021). This leads to the research hypothesis 3 in this paper.

Hypothesis 3: Regions with high levels of related diversification are likely to be more affected by external demand shocks.

3 Data sources and research methods

3.1 Data sources

The data used in this paper to measure industry relatedness, technological complexity, and related diversity come from the *China Business Enterprise Registration Database* (2000-2022). The database divides industry categories by China's National Economic Industry Classification (NEC) codes, including 481 three-digit industries, with a data range covering 337 cities. Other data, such as control variables, come from the city statistical yearbooks of each prefecture-level city for the years 2000-2022 and the *Patsnap* patent database (2000-2022). Data on provincial-level exports to the US are from the *China Customs Database* (2000-2022).

3.2 Relatedness and path-dependent industry identification

Most of the EEG literature analyzes the region's industrial dynamics and evolutionary trends by measuring the relatedness between new entry industries and existing industries. The most widely used measures of industry relatedness in the current literature include Hierarchical Relatedness, Co-occurrence Relatedness, and Resource-based Relatedness (Boschma et al., 2012; Frenken et al., 2007; Hidalgo et al., 2007; Neffke and Henning, 2013; Whittle and Kogler, 2020). The limitation of these methods is that they can only analyze macro trends in the region and cannot identify individual industry types. Coniglio et al. (2018) proposed a *dartboard approach* for identifying path-dependent industries based on the degree of relatedness, which solves the difficulty of identifying individual industry types. This approach will be used in this paper to calculate the number and share of path-dependent industries among new entrants. The specific measurement process of this approach is as follows:

In the first step, the revealed comparative advantage (RCA) of an industry in a city is measured and new entry industries are identified. The RCA is calculated as shown in Eq.1. $RCA_{c,i,t}$ denotes the revealed comparative advantage of industry i of city c in year t. $Amount_{c,i,t}$ denotes the number of firms in industry i of city c in year t. The idea of identifying a new entry industry is to consider an industry as a new entry industry if its RCA is less than 0.5 in year t and greater than 1 in year $t+n$. In this paper, we set n to 1.

$$RCA_{c,i,t} = \frac{(Amount_{c,i,t}/\sum_i Amount_{c,i,t})}{\left(\sum_c Amount_{c,i,t}/\sum_{c,i} Amount_{c,i,t}\right)} \quad \text{Eq.1}$$

In the second step, the inter-industry relatedness is calculated. The calculation is shown in Eq. 2. $\varphi_{i,j,t}$ is the relatedness between industry i and j in year t. The idea is to calculate the conditional probability that the RCA of industry i and industry j in the same city is greater than 1 at the same time and take the minimum value.

$$\varphi_{i,j,t} = \min\left[P\left(RCA_{c,i,t} > 1 | RCA_{c,j,t} > 1\right), P(RCA_{c,j,t} > 1 | RCA_{c,i.t} > 1)\right] \quad \text{Eq.2}$$

The third step is to calculate the relatedness of the new entry industry to the industrial base of its city. Coniglio et al. (2018) propose three indicators to represent this relatedness. The first indicator is expressed as the maximum value of the relatedness between new entry industries and all other industries. The second indicator is expressed as the mean value of the relatedness between new entry industries and all other industries. The third indicator is expressed as the weighted mean value of the relatedness between new entry industries and all other industries (weighted by the share of the number of firms). In this paper, the first indicator is adopted, i.e., it is measured by the maximum value, and the equation is shown in 3. $D_{c,i,t}$ denotes the maximum value of the relatedness between industry i and all the existing industries j in city c. Where j belongs to city c.

$$D_{c,i,t} = \max(\varphi_{i,j,t}) \qquad \text{Eq.3}$$

In the fourth step, the counterfactual distribution of relatedness between new entry industries and existing industries is established through Monte Carlo sampling random sampling method, and path-dependent industries are identified through the counterfactual distribution. This is done by randomly selecting r industries from the city's non-existing industries (those with RCA less than 1 in year t) if city c has r new entry industries in year $t+n$. The maximum value of the relatedness between the randomly selected industry and other existing industries is calculated according to Equation 2 and Equation 3, and then the mean value is calculated. Repeat the above process 1500 times to establish the counterfactual distribution. An industry is considered path-dependent if the maximum value of the relatedness of a particular new entry industry to other industries in the city is within a confidence interval of 95% or more of the counterfactual distribution.

On the basis of identifying path-dependent industries, this paper measures the industrial evolution characteristics of a city in terms of the ratio of path-dependent industries in the new entry industries. The larger the ratio is, the more path-dependent the city's industrial evolution path is.

3.3 Urban technological complexity indicator measurement

The existing literature usually measures the complexity of regional economic activity through export or product production data. Regions with a high level of economic complexity imply the mastery of complex technologies. There are four main approaches. One is the *EXPY* method proposed by Hausmann et al. (2007). This approach assumes that only high-income countries can export complex products. If a product is frequently exported by high-income countries, it is more technically complex. Regional complexity is then measured on the basis of product complexity; the more high-complexity products are exported from a region, the higher the complexity of that region. The second approach is the *Economic Complexity Indicator* (ECI) proposed by Hidalgo and Hausmann (2009), which solves the problem of circularity between product and regional complexity in the *EXPY* approach by measuring regional technological complexity in terms of "ubiquity" and "uniqueness". The third approach is the *Fitness* indicator proposed by Tacchella et al. (2012). This approach measures regional technological complexity through the adaptation of knowledge and capabilities held by the region to the demand for new products, overcoming the problem that the ECI approach ignores industry diversity. The fourth approach is the *ECI*+ proposed by Albeaik et al. (2017). This approach measures regional technological complexity by defining "export difficulty" as a correction for "export size". In this paper, the basic idea of ECI+ approach is adopted to measure the technological complexity of Chinese cities, and the main steps are as follows.

The matrix Xci is first constructed to represent the number of firms of industry i in city c. On this basis, the difficulty of developing a certain industry i in city c ($Diff_{ci}^{0}$) is measured. The smaller the size of an industry in a city, the higher the complexity of the technology contained in the industry, and the more difficult it is to develop. Therefore, “difficulty” and “size” are inversely proportional to each other. The measurement method is shown in Eq. 4.

$$Diff_{ci}^{0} = 1/\sum_{c} \frac{X_{ci}}{X_{c}^{0}} \qquad \text{Eq.4}$$

$$X_{c}^{0} = \sum_{i} X_{ci}$$

In Eq.4, the superscripted numbers indicate the number of corrections. On the basis of measuring the difficulty of industrial development, it is necessary to use the difficulty of industrial development to fix the size of the regional industry and get the corrected industrial size. The more the number of corrections, the closer the result is to the real industrial size in reality. The revised equation is shown in 5.

$$X_{c}^{N} = \sum_{p} X_{cp} Diff_{cp}^{N-1} \qquad \text{Eq.5}$$

The *ECI*+ approach determines whether industry size has been sufficiently corrected through a standardized coefficient of industry size. If the size of the industry remains stable after the standardized treatment, the number of corrections is sufficient. Based on the measurement, the number of corrections in this paper is set at 50, i.e., N = 50. The standardized treatment equation is shown in 6.

$$X_{c}^{N} = \frac{X_{c}^{N}}{\left(\prod_{c'} X_{c'}^{N}\right)^{\frac{1}{\{c\}}}} \qquad \text{Eq.6}$$

Finally, the equation for the regional technological complexity is shown in 7.

$$TCI_{c} = log(X_{c}^{50}) - log\left(\sum_{i} \frac{X_{ci}}{X_{i}}\right) \qquad \text{Eq.7}$$

3.4 Difference-in-difference model design

The basic idea of the difference-in-difference (DID) model is to divide the study sample into experimental and control groups, and then to divide the study period into experimental and control periods. The exogenous effects of the system are accurately measured by performing two differencing between the experimental and control groups and between the experimental and control periods. In this case, the experimental group is the study samples that were exogenously influenced, while the control group is the unaffected samples. The experimental period was the stage that was exogenously influenced and the control period was the stage that was unaffected. This paper constructs a DID model to analyze the impact of US-China trade friction on the regional industrial evolution, and the basic setting of the model is shown in Eq. 8.

$$Y_{c,t+1} = \alpha_{0} + \alpha_{1} did_{c,t} + \alpha_{2} control_{c,t} + \mu_{c} + \delta_{t} + \varepsilon_{c,t} \qquad \text{Eq.8}$$

In the above equation, subscripts c and t denote city and time, respectively. $Y_{c,t+1}$ denotes the dependent variable. The dependent variables include two indicators, the proportion of path-dependent industries in new entry industries (*Dependence*) and the city's technological complexity (*TCI*), which are used to assess the impact of the US-China trade friction on path dependence and path upgrading, respectively. Due to the existence of a certain time lag in the change of the industrial evolution path, this paper lags the dependent variable by one year.

$did_{c,t}$ denotes the difference-in-difference variable, i.e., the interaction term between the staged dummy variable and the grouped dummy variable. Since the US-China trade friction occurs in 2018, this paper sets 2000-2017 as the control period and assigns a value of 0, and sets 2018-2021 as the experimental period and assigns a value of 1. Regarding the setting of the experimental group and the control group, we believe that the cities that are more affected by the trade friction between China and the US should have two characteristics: a higher dependence on exports for economic development and closer economic ties with the US. Based on this judgment, we divided the experimental and control groups by the following steps. The first step is to calculate the degree of dependence of the city's economic development on exports, which is calculated as the ratio of the total value of exports to GDP; the larger the ratio, the more dependent the city is on exports. The second step is to calculate the degree of the city's economic ties to the US. This is done by calculating the ratio of exports to the US from the province to which the city belongs to its total exports. The larger the share of exports to the US from the provincial district in which the city is located, the stronger the city's economic ties to the US. The reason for adopting provincial- level data to judge the economic links between cities and the US is that we lack data that directly reflect the cities' exports to the US. However, cities belonging to the same province are relatively similar in terms of geography and economic structure, so this idea can also reflect the export characteristics of cities to some extent. In the third step, the cities whose dependence on exports and dependence on the US are both greater than the mean value are categorized as the experimental group (assigned a value of 1), while the other cities are categorized as the control group (assigned a value of 0). The experimental group was measured to contain a sample of 49 cities and the control group contained a sample of 243 cities.

α_0, μ_c, δ_t and $\varepsilon_{c,t}$ denote the constant term, city fixed effect, year fixed effect, and error term, respectively. $control_{c,t}$ represents the control variables. α_1 and α_2 represent the regression coefficients of the independent variable and the control variables. The following control variables are selected for this paper: ①Innovative capacity, measured by the number of patents granted. Regional innovative capacity is an important force in shaping the evolutionary path of regional industries (Tödtling and Trippl, 2018). ②Consumption level, expressed as total retail sales of consumer goods. Local demand, represented by consumption, has a causal effect on production and innovation activities and is one of the forces that shape the evolution of regional industries (Martin, R. and Martin, H., 2023). ③The influence of the government is measured by the level of government public expenditure. The government's investment in and emphasis on specific industries will greatly influence the future direction of industrial development in the region (He et al., 2018; Zhu et al., 2019). ④COVID-19, which started in 2020, brought global production and trade activities to a standstill, significantly hitting China's export trade (Liu et al., 2022). In this paper, a dummy variable is created to reflect the exclusion of the disturbance of COVID-19, which is set to 1 in 2020-2022 and 0 in the rest of the years. ⑤Industrial structure which is measured by the share of added value of tertiary industry in GDP. The characteristics of industrial structure reflect the economic base of the region, which has an important impact on innovation capacity, investment activities, etc. (Greunz, 2004; Jin, 2012), and will most likely have an impact on the evolution of regional industries as well.

4 External demand and industrial evolution of China

4.1 External demand characteristics of China

The scale of imports from overseas markets can directly reflect the scale of external demand, so this paper utilizes data on overseas imports to conduct a descriptive analysis of China's external demand pattern, with data from the CEPII-BACI database.

Figure 2 reflects changes in the scale of imports of Chinese products into the global market (black line) and the US market (blue line) over the period 2000-2020. Overall, both the global market and the US market have seen a significant increase in the scale of demand for Chinese products, and the trends in both are essentially the same. Between 2000-2020, there were three notable declines in demand in the global market and the US market, occurring in 2008, 2014, and after 2018. The financial crisis of the US in 2008 caused a decline in market demand globally, leading to a contraction of China's external demand market (Bricongne et al., 2012; Jing, 2012). The decline in the scale of demand after 2014 could be attributed to the sluggish demand for commodities due to the fall in international crude oil prices (Grigoli et al., 2019). The decline in the scale of demand after 2018 is a result of the negative impact of trade frictions between the US and China (Zhu et al., 2022).

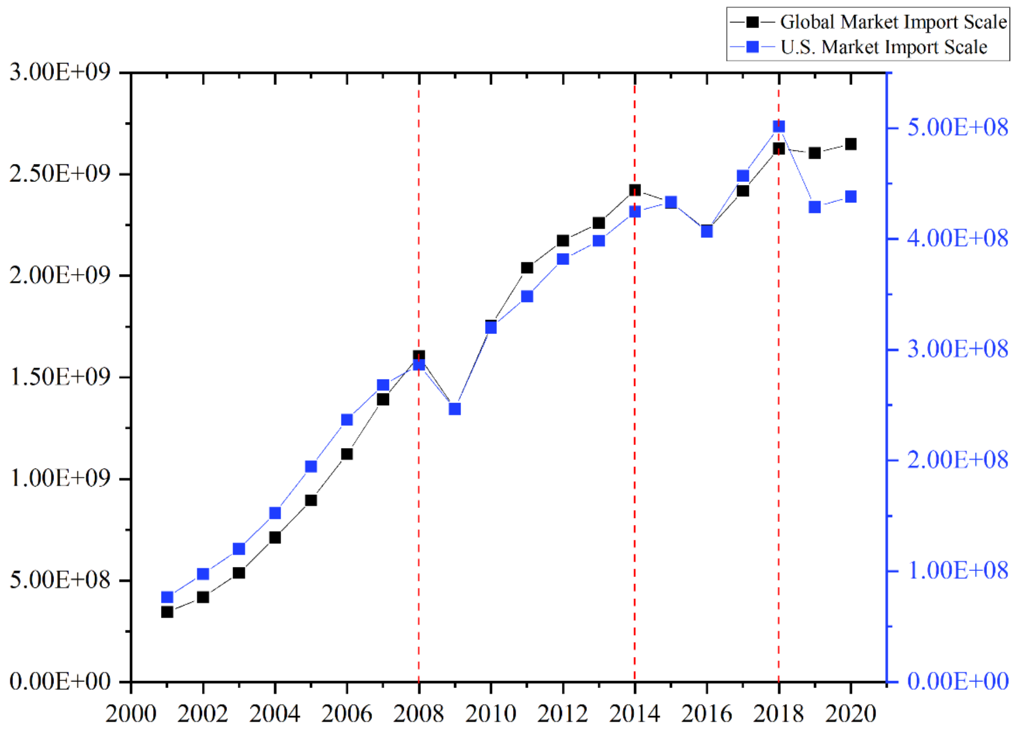

Figure 2 Import scale of Chinese products in the global market and the US market during 2000-2020

Note: Data in tens of thousands of dollars

In terms of the spatial pattern of external demand, China has actively opened up many new overseas markets. Figure 3 reflects the spatial pattern of China's overseas markets in 2000 and 2021, where the ratio of the import size of the countries in red to the global market size exceeds 1%, and we refer to the countries with a ratio of more than 1% as core overseas markets. China's core overseas markets in 2000 were mainly North America (including the United States and Canada), East Asia (including Japan and South Korea), Western Europe (including the United Kingdom, France, Germany, Spain, Italy, etc.) and Australia. By 2021, China is aggressively expanding its core markets into Central and South America (including Mexico and Brazil), Eastern Europe (including Poland and Russia), and South & Southeast Asia (including India, Vietnam, the Philippines, Indonesia, and others). Of all the core markets, the US has always been the market with the largest share. During the period 2000-2021, the ratio of US imports of Chinese products to total Chinese exports was above 10%. However, the US share shows a significant decline (Figure 4). Especially after the trade friction between China and the US in 2018, the share of the US rapidly declined from 19.09% to 16.47%. China's overseas market diversification strategy and the decrease in the US market share reflect the trend of gradual decoupling of the US and Chinese economies.

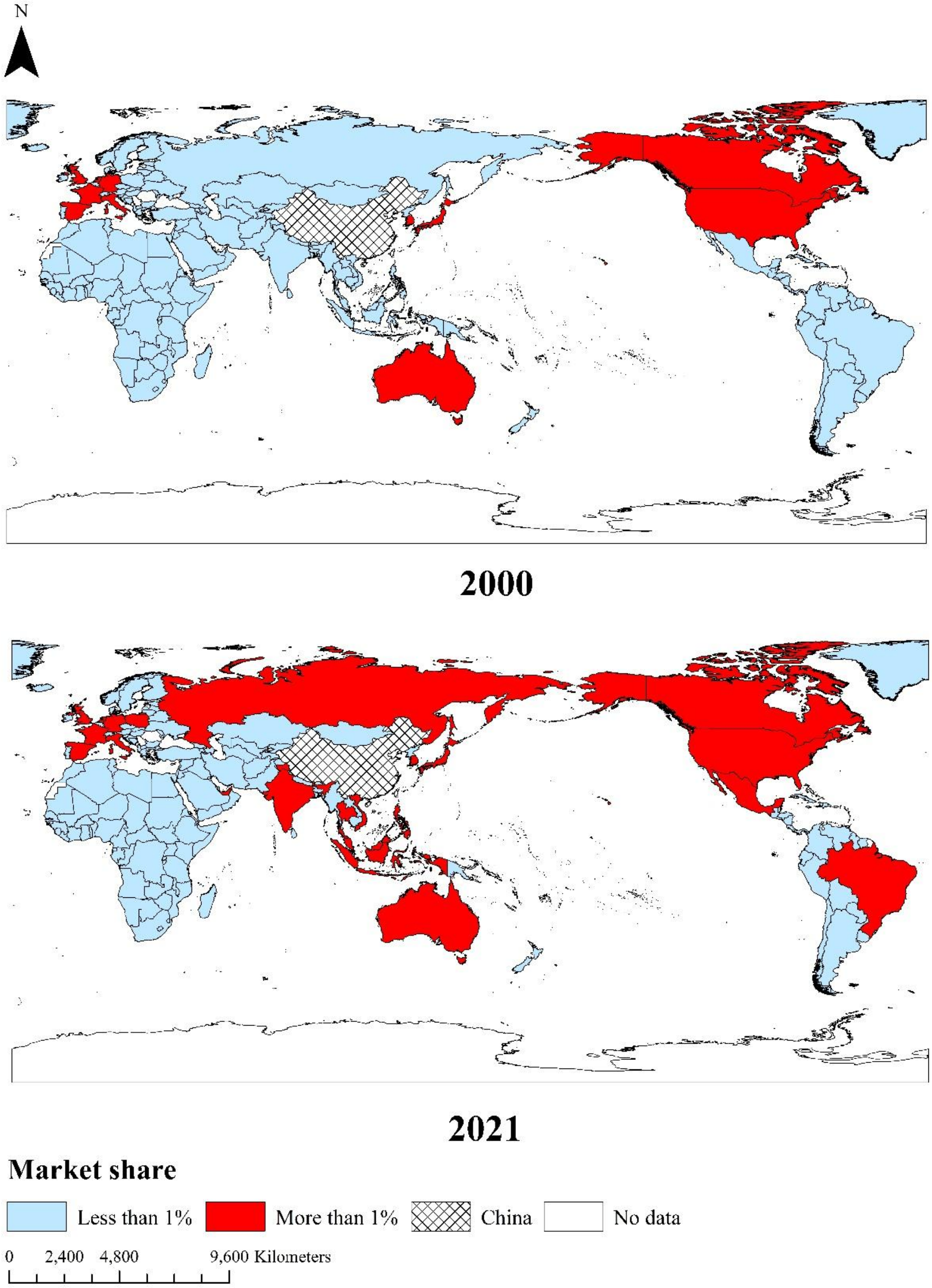

Figure 3 China's Overseas Market Pattern

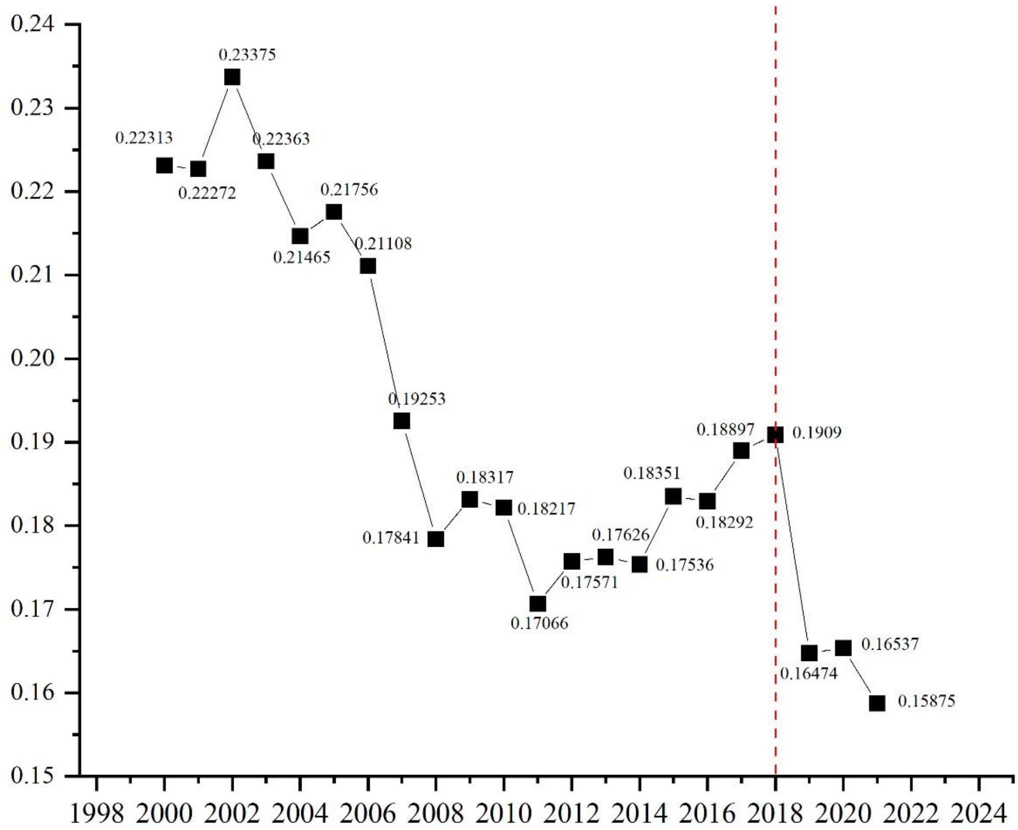

Figure 4 Share of the US market

4.2 Industrial Evolution paths of Chinese Cities

Calculate the share of path-dependent new industries and the technological complexity of Chinese cities based on the categorization of paths in Section 2 and the methodology described in Section 3. Path dependence and path breaking are classified by whether the share of path-dependent new industries is greater than the mean of all cities, with cities that are greater than the mean defined as path-dependent and those that are less than the mean defined as path breaking. The criterion for an increase or decrease in technological complexity is whether the difference between the current year's technological complexity and the previous year's is greater than 0. Cities that are greater than 0 are defined as having an increase in technological complexity, and cities that are less than 0 are defined as having a decrease in technological complexity. The sample of 292 cities was categorized into the four evolutionary paths described in Figure 1 based on the above criteria.

Figure 5 illustrates the spatial pattern of industrial evolution paths of Chinese cities in 2001 and 2022, which shows that the industrial evolution paths of Chinese cities have changed dramatically over time. In 2001, 239 cities, representing 81.85 % of the total, experienced an increase in technological complexity. 147 cities continued their dependence on the original path, while 92 cities achieved a path breaking. The spatial distribution of urban industrial evolution paths does not show obvious agglomeration characteristics. And by 2022, at which point most of China's cities seem to have reached a bottleneck in technological progress, only four cities have upgraded their complexity. In addition, unlike in 2001, in 2022 the industrial evolution of the city reveals agglomeration characteristics. Most of the cities that have achieved path breaking are located in the East, and those that are path dependent are located in the West and Northeast. The basic spatial characteristic of

China's economy is that regions along the eastern coast have a higher level of economic development. This suggests that the more economically developed the region, the easier it is to break out of the original evolutionary path. The features reflected in Figure 5 suggest that economically less developed cities appear to be locked into a low-end evolutionary path, with gradually increasing spatial differences in industrial development across the country.

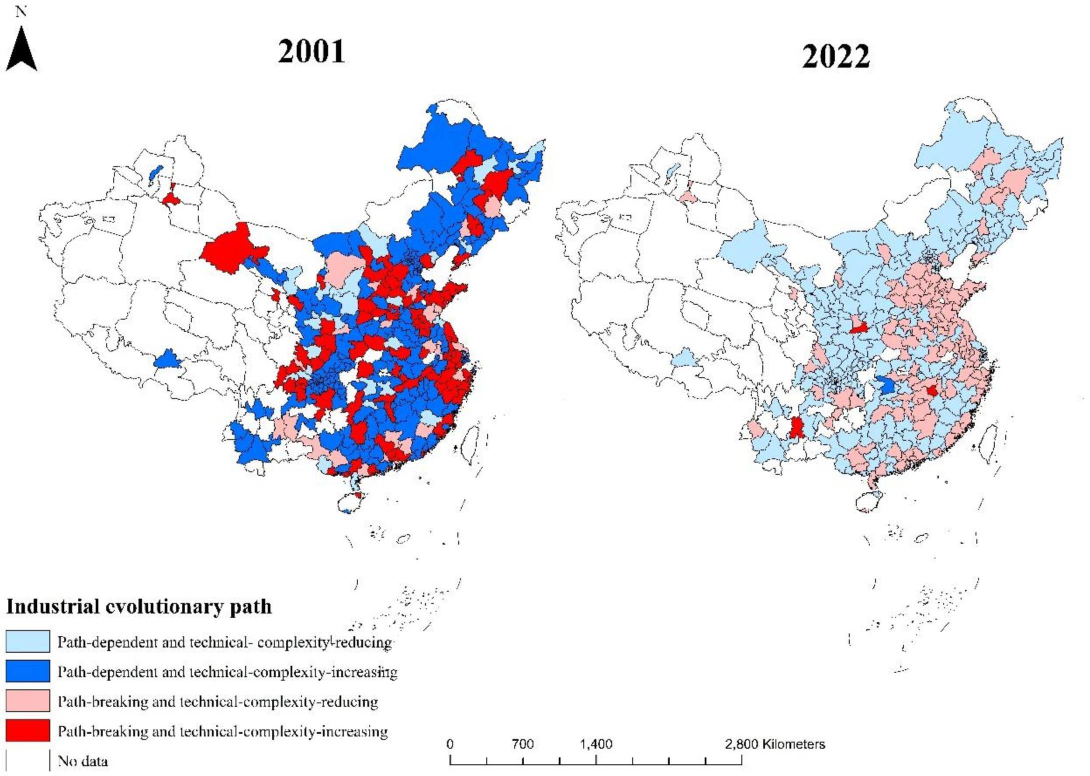

Figure 5 Evolution Path of Urban Industries in China

5 Empirical analysis

5.1 Baseline regression

The empirical analysis was conducted based on the indicator measures described in Section 3 and the model design ideas, and the results of the baseline regression are shown in Table 1. In Table 1, models (1) and (2) use the proportion of path-dependent industries in new entry industries (*Dependence*) as the dependent variable, reflecting the impact of the US-China trade friction on the path dependence or breakthrough of regional industries. Model (2) incorporates control variables. Models (3) and (4), on the other hand, use regional technological complexity (*TCI*) as the dependent variable. Model (4) incorporates control variables.

The regression coefficients of *did* on *Dependence* in models (1) and (2) are 7.392 and 8.073, respectively, and the results are significant at the 1% level. This suggests that the US-China trade friction has significantly increased the share of path-dependent new industries, reinforcing the path-dependent trend of regional industrial evolution. The regression coefficients of *did* on *TCI* in models (3) and (4) are -0.547 and -0.317, respectively, and again both are significant at the 1% level. This suggests that the US-China trade friction reduces regional technological complexity. The above results validate research hypothesis 1, that external demand shocks cause regional industries to evolve in the direction of path dependence and reduced technological complexity.

Table 1 Baseline regression

	(1)	(2)	(3)	(4)
	Dependence	*Dependence*	*TCI*	*TCI*
did	7.392***	8.073***	-0.547***	-0.317***
	(4.11)	(4.96)	(4.81)	(2.86)
Constant	74.264***	89.362***	14.041***	13.446***
	(245.69)	(92.19)	(640.51)	(192.65)
City fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes
N	6274	5943	6274	5943
R^2	0.26	0.38	0.23	0.31

*Note: *** p<0.01; ** p<0.05; * p<0.1. Absolute values of t-tests are in parentheses.*

5.2 Robustness test

5.2.1 Parallel trend test

The difference-in-difference method requires that the trends in the experimental and control samples are parallel before the exogenous shock occurs, otherwise the validity of the results cannot be demonstrated. In this paper, the model shown in Eq. 9 is utilized to test for parallel trends, where $year_t$ is a year dummy variable and $treat_c$ is a group dummy variable. This paper constructs year dummy variables for the period 2014-2020. If the interaction term between the grouped dummy variables and the year dummy variables prior to 2018 (i.e., *year2014*, *year2015*, *year2016*, and *yer2017*) is not significant, this proves that the experimental group is not significantly different from the control group prior to the occurrence of the exogenous shocks, and confirms the parallel trend between the two.

$$Y_{c,t+1} = \beta_0 + \beta_t \sum_{2014}^{2020} year_t \times treat_c + \beta_1 control_{c,t} + \mu_c + \delta_t + \varepsilon_{c,t} \qquad \text{Eq.9}$$

The regression results of the model are shown in Figures 6 and 7. In particular, Figure 6 shows the parallel trend test plot for the model with *Dependence* as the dependent variable and Figure 7 shows the parallel trend test plot for the model with *TCI* as the dependent variable. The horizontal axes are the year dummy variables and the vertical axes are the regression coefficients. According to the information shown in Figures 6 and 7, none of the interaction terms between the dummy variables and the grouped variables are significant in the years prior to the occurrence of the external demand shock, proving that the model is consistent with the parallel trend assumption.

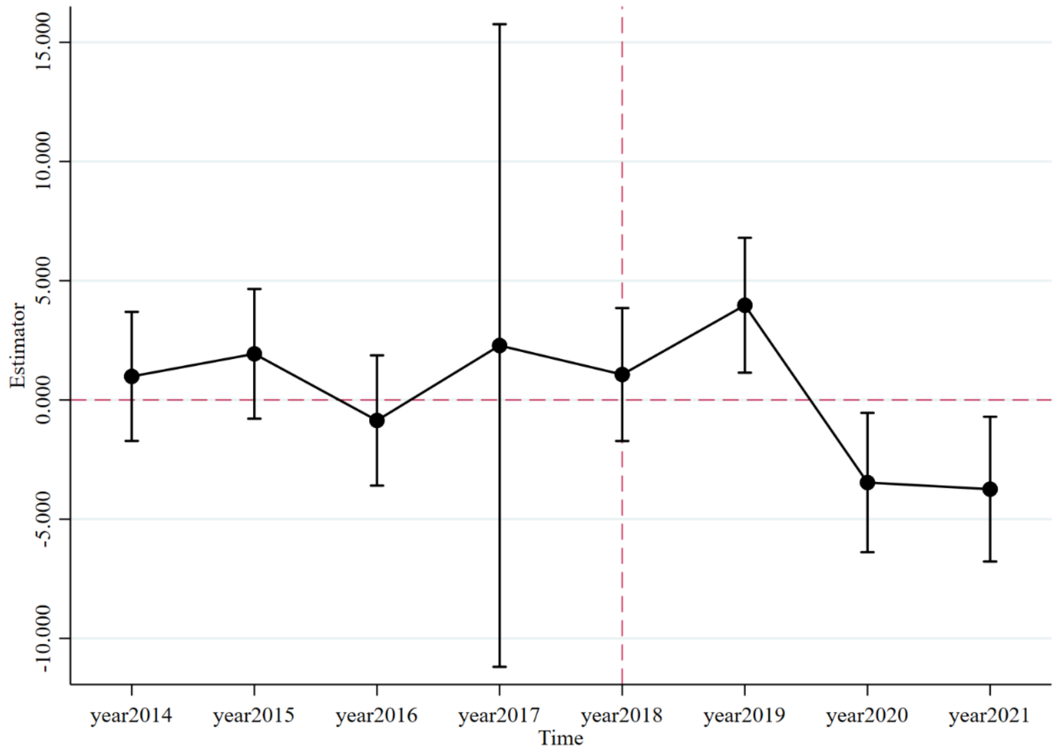

Figure 6 Parallel trend test for the *Dependence* model

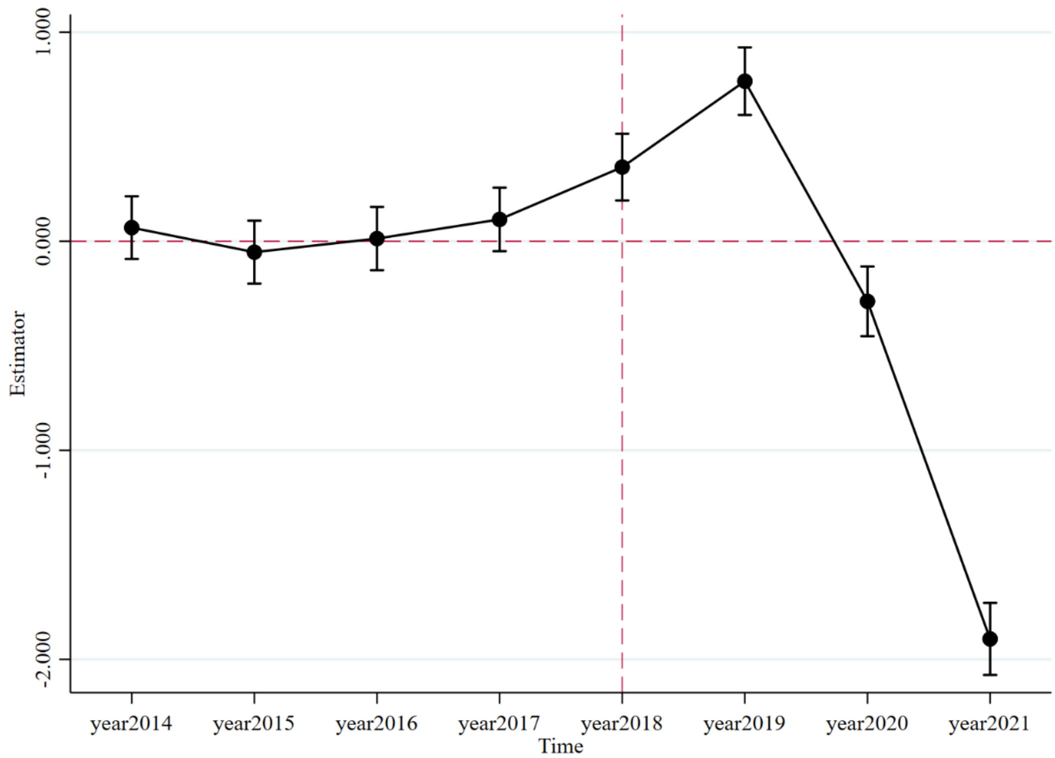

Figure 7 Parallel trend test for TCI model

5.2.2 Placebo test

To demonstrate that the model is not heavily influenced by omitted variables and random factors, this paper takes two ideas for a placebo test. The first idea is to construct a spurious timing of the external demand shock. In this paper, we bring forward the timing of the external demand shock by one year (i.e., 2017) and run the regression. If the regression results are still significant, it means that the results of the model are disturbed by other factors. The regression results are shown in Table 2. The structure of Table 2 is the same as Table 1. In Table 2, the regression results of the *did* variable on either *Dependence* or *TCI* are not significant, which to some extent proves the robustness of the findings.

Table 2 Regression results based on the timing of spurious external demand shock

	(5) *Dependence*	(6) *Dependence*	(7) *TCI*	(8) *TCI*
did	0.104	-0.685	-0.127	-0.076
	(0.07)	(0.42)	(1.49)	(0.81)
Constant	73.082***	76.108***	14.026***	13.098***
	(312.22)	(243.36)	(725.39)	(190.22)
City fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes
N	6274	5943	6274	5943
R^2	0.16	0.23	0.25	0.22

*Note: *** p<0.01; ** p<0.05; * p<0.1. Absolute values of t-tests are in parentheses.*

The second idea is to construct spurious experimental and control groups to verify the robustness of the model. This is done by randomly selecting 49 cities out of a sample of all cities to constitute a spurious experimental group, repeating the sampling process 1,500 times and running the regression. Plot the density distribution of the spurious estimated coefficients. If the spurious estimated coefficients are distributed around 0, it implies that the model does not omit important influences, in other words, the baseline regression results are brought about by the external demand shock (Ferrara et al., 2012). The density distribution of the spurious estimated coefficients is plotted in Figures 8 and 9. Among them, Figure 8 shows the coefficient density plot with *Dependence* as the dependent variable and Figure 9 shows the coefficient density plot with *TCI* as the dependent variable. As shown in Figures 8 and 9, the spurious regression coefficients are all centrally distributed around 0, further validating the robustness of the model.

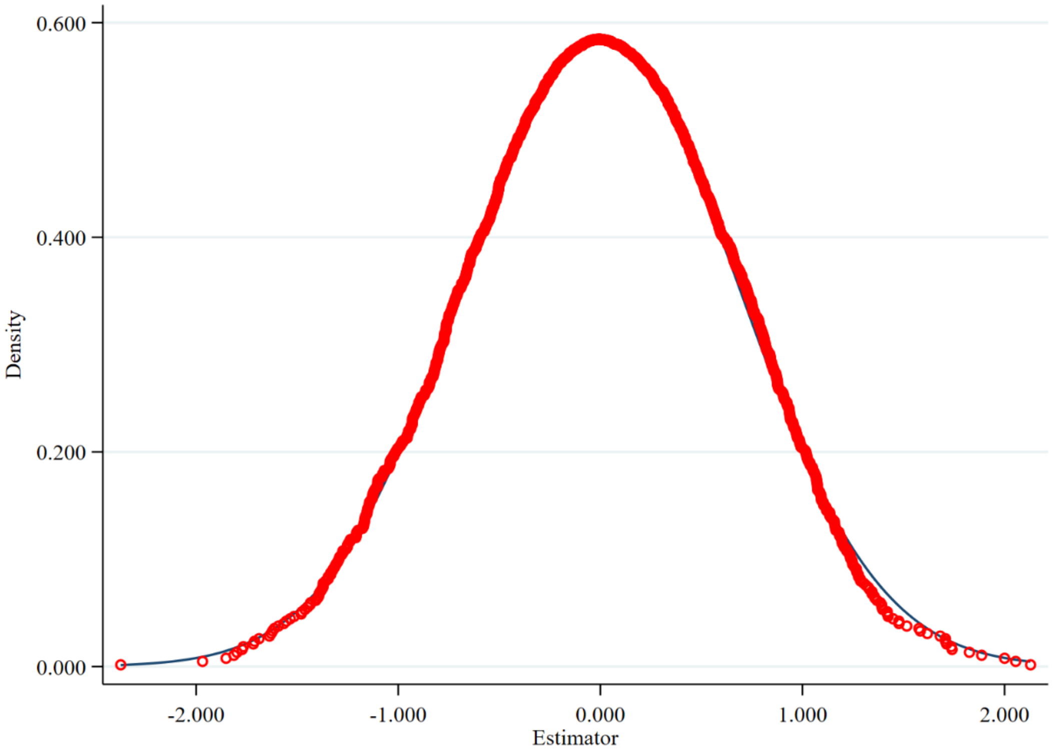

Figure 8 Spurious grouping regression results for the *Dependence* model

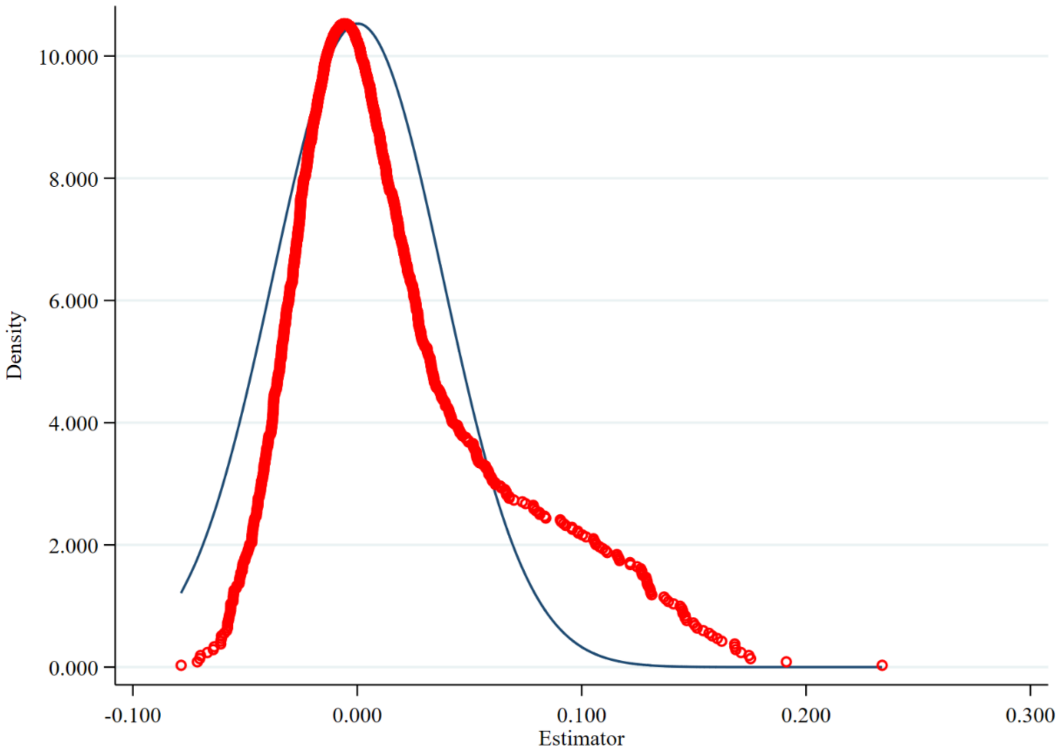

Figure 9 Spurious grouping regression results for the *TCI* model

5.3 Mechanism test

According to the literature review, external demand shocks lead to a narrowing of exports as a global pipeline, and the decline in exports affects regional innovation capacity, which in turn reinforces the evolutionary trend of regional industrial path dependence and reduced technological complexity. Validating this mechanism requires answering three questions: first, has the US-China trade friction negatively affected exports? Second, is there a positive correlation between exports and local innovative capacity? Third, can innovative capacity help industries to break out of path dependence and upgrade? In this paper, the number of patents granted (*Patent*) is chosen as an indicator of the city's innovative capacity. The three questions are verified through the model shown in Eq. 10-13 below. Eq. 10 is used to verify the effect of external demand shocks on exports, and *Export* denotes the total amount of exports of the city. Eq. 11 is used to verify the impact of exports on the city's innovative capacity. Eq. 12 and 13 are then used to verify the impact of innovative capacity on the evolutionary path of industries. As in the baseline regression, the dependent variables of the following models are lagged by one year.

$$Export_{c,t+1} = \rho_0 + \rho_1 did_{c,t} + \rho_2 control_{c,t} + \mu_c + \delta_t + \varepsilon_{c,t} \quad \text{Eq.10}$$

$$Patent_{c,t+1} = \gamma_0 + \gamma_1 Export_{c,t} + \gamma_2 control_{c,t} + \mu_c + \delta_t + \varepsilon_{c,t} \quad \text{Eq.11}$$

$$Dependence_{c,t+1} = \theta_0 + \theta_1 Patent_{c,t} + \theta_2 control_{c,t} + \mu_c + \delta_t + \varepsilon_{c,t} \quad \text{Eq.12}$$

$$TCI_{c,t+1} = \sigma_0 + \sigma_1 Patent_{c,t} + \sigma_2 control_{c,t} + \mu_c + \delta_t + \varepsilon_{c,t} \quad \text{Eq.13}$$

The regression results are shown in Table 3. In Table 3, model (9) demonstrates the impact of US-China trade friction on exports, and the regression coefficient of the *did* variable on *Export* is -1.481, and the regression result is significant at 1% level, which indicates that US-China trade friction negatively affects the scale of exports. Model (10) demonstrates the relationship between exports and innovative capacity, and the regression coefficient of *Export* on *Patent* is a significant 0.365 at the 1% level, indicating that the growth of exports promotes regional innovative capacity. Model (11) demonstrates the effect of innovative capacity on the share of path-dependent new industries. The regression result is significantly negative at the 1% level (coefficient of -0.774), indicating that innovative capacity promotes path breaking in regional industries. Model (12), on the other hand, demonstrates the effect of innovation level on technological complexity. The regression results are significantly positive at the 1% level (coefficient of 0.874), indicating that innovative capacity has a positive impact on enhancing technological complexity. The above results validate the mechanism proposed in hypothesis 2.

Table 3 Mechanism test

	(9)	(10)	(11)	(12)
	Export	*Patent*	*Dependence*	*TCI*
did	-1.481***			
	(12.51)			
Export		0.365***		
		(4.77)		
Patent			-0.774***	0.874***
			(2.87)	(79.53)
Constant	4.255***	-993.185	107.890***	2.895***
	(38.69)	(0.16)	(22.73)	(14.05)
City fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
N	4588	4588	5942	5942
R^2	0.56	0.85	0.76	0.72

*Note: *** p<0.01; ** p<0.05; * p<0.1. Absolute values of t-tests are in parentheses*

5.4 Heterogeneity analysis

The literature review suggests that the higher the degree of industrial related diversification in a region, the greater the impact of external demand shocks is likely to be. This paper utilizes the *RV* indicator constructed by Frenken et al. (2007) to measure the level of regional related diversification. The equations for calculating the *RV* indicator are shown in 14 and 15. H_c is the process indicator for calculating the *RV* indicator. *k* denotes the three-digit industry and *j* denotes the two-digit industry. P_k denotes the number of firms under the three-digit industries as a share of the total number of firms in the city, and P_j denotes the number of firms under the two-digit industries as a share of the total number of firms in the city. *n* and *m* denote the number of two-digit and three-digit industries, respectively.

$$H_c = \sum_{k=1}^{n} \frac{P_k}{P_j} log_2\left(\frac{1}{P_k/P_j}\right) \qquad \text{Eq.14}$$

$$RV_c = \sum_{j=1}^{m} P_j H_c \qquad \text{Eq.15}$$

$$Y_{c,t+1} = \alpha_0 + \alpha_1 did_{c,t} + \alpha_2 RV_{c,t} + \alpha_3 did_{c,t} \times RV_{c,t} + \alpha_4 control_{c,t} + \mu_c + \delta_t + \varepsilon_{c,t} \qquad \text{Eq.16}$$

The regression results are shown in Table 4. Model (14) shows that the regression result of *RV* on *Dependence* is significantly negative, with a coefficient of -0.09. This indicates that the higher the degree of industrial related diversification, the more the city tends to introduce path-breaking new industries. The reason for this phenomenon may be the increased frequency of knowledge spillovers and interactions as a result of increased inter-industry relatedness. Frequent knowledge spillovers and interactions increase the innovative capacity of cities, giving them the ability to break out of their original evolutionary paths. In model (15), the regression result of the interaction term between *did* and *RV* on *Dependence* is significantly positive at the 1% level, with a coefficient of

0.051, suggesting that the related diversification reinforces the positive effect of US-China trade friction on path dependence. In model (17), the regression coefficient of *RV* on *TCI* is positive 0.008, indicating that industrial related diversification favors technological complexity. This phenomenon can likewise be explained by the impact of industrial related diversification on innovative capacity. The regression of the interaction term between *did* and *RV* on *TCI* in model (18) is significantly negative at the 10% level with a coefficient of -0.002. It indicates that the related diversification reinforces the negative impact of US-China trade friction on technological complexity. The results of models (15) and (18) validate research hypothesis 3.

Table 4 Heterogeneity analysis

	(13) Dependence	(14) Dependence	(15) Dependence	(16) TCI	(17) TCI	(18) TCI
did	8.073***		-15.546**	-0.317***		1.065***
	(4.96)		(2.45)	(2.86)		(2.71)
RV		-0.090***	-0.094***		0.008***	0.008***
		(52.71)	(56.48)		(65.53)	(59.85)
did×RV			0.051***			-0.002*
			(2.79)			(2.22)
Constant	89.362***	100.227***	103.14***	13.446***	11.955***	12.334***
	(92.19)	(136.53)	(113.15)	(192.65)	(209.51)	(202.84)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	5943	5943	5943	5943	5943	5943
R^2	0.38	0.60	0.62	0.31	0.54	0.56

*Note: *** p<0.01; ** p<0.05; * p<0.1. Absolute values of t-tests are in parentheses*

6 Conclusion and discussion

In recent years, geopolitical factors and the rise of local protectionism have continued to challenge the global economic order, and more and more external shocks are set to become important forces in reshaping local economic patterns and landscapes. This paper discusses the impact of external demand shocks on the local industry evolution using US-China trade friction as an external shock event. The study responds to the shortcoming of the current EEG literature, which ignores the influence of demand-side factors and external forces. Based on Chinese city-scale industrial data and *DID* models, this paper finds the following core conclusions:

First, the US-China trade friction, an external demand shock event, has had a significant impact on China's industrial evolution. Specifically, the US-China trade friction has led to a stronger path-dependent trend in the industrial evolution of Chinese cities and reduced technological complexity. The main reason for this phenomenon is the shrinking of exports as a global pipeline due to external demand shocks, which hinders the entry of external knowledge. The resulting decline in local innovative capacity hinders industrial path breaking and technological complexity. Second, there may be regional heterogeneity in the impact of external demand shocks on the local industrial evolution. This is reflected in the fact that regions with a higher degree of industrial related diversification are more exposed to external demand shocks. This is because inter-industry relatedness provides a channel for external demand shocks from a particular industry to spread to other industries, which in turn has a greater impact on the industrial evolution of the region as a whole.

What does it mean for regional development that external demand shocks can set local industries on a path of dependence and reduced technological complexity? We believe that, for developing countries, such a path would have a negative impact on regional development. First, developing countries are lacking the technology and capital to produce high-end products and services, and the reinforcement of the trend of path dependence will lock their industrial development into a low-end path. Second, the reduction in technological complexity has further weakened the ability of developing countries to develop high value-added industries. In addition, there are also usually large differences in levels of development between regions within developing countries, and the impact of external demand shocks may make it more difficult for lagging regions to catch up, thus increasing interregional disparities. How should developing countries reduce the negative impact of external demand shocks? In our view, developing countries should, on the one hand, actively explore new overseas markets to hedge against shocks from specific markets by diversifying overseas markets; and, on the other hand, they should actively explore and build up their domestic markets in order to replace external demand with internal demand.

Limitations to the findings of this paper remain, as evidenced by the fact that the choice of data and study cases prevents this paper from analyzing the long-term effects of external demand shocks. Some studies have found that there may be differences between the short-term and long-term effects of external demand shocks. In the short run, external demand shocks have predominantly negative effects. However, in the long run, external demand shocks may lead to “destructive creation” (Erixon, 2007; Erixon, 2016). The long-term effects of the US-China trade friction that occurred in 2018 cannot be shown as the data we obtained ends in 2022. After 2024, the macro data of the Chinese economy and technological breakthroughs in the high-tech sector seem to corroborate the positive impact of US-China trade friction, but this issue needs to be further examined.

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