Industrial Policy and the Rise of China's Strategic Emerging Industries

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Abstract

China officially launched its policy prioritization of emerging industries in 2010, and within about a decade it has become one of the major players in a wide range of cutting-edge technologies such as green energy (including electric cars), 5G telecommunication, artificial intelligence, drones, and high-speed trains. We propose a theory to explain why industrial policy works in China for promoting the new industries. To test our theoretical predictions, we construct a time-varying measurement of China's industrial policy intensity in the emerging industries from China's state-level policy documents, and evaluate its causal effect on the productivity of China's listed firms in those industries in 2011-2020. The empirical validation survives a broad set of robustness checks.

JEL Classification: F15; F20; O19; O53

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1 Introduction

China officially launched its policy prioritization of strategic emerging industries in 2010, and within about a decade it has become one of the major players in a wide range of cutting-edge technologies such as green energy (including electric cars), 5G telecommunication, artificial intelligence, drones, and high-speed trains. In this paper, we follow Mao et al. (2021)[16] to propose a theoretical framework for understanding why industrial policy has been helpful for China to achieve the success in the strategic emerging industries, and corroborate our theoretical conjectures with extensive data analysis.

We first divide China's strategic emerging industries into two types according to their relative development stages versus the world's technological frontier: Domestically Emerging industries (industries where China is at the ferment stage, while the world frontier is at the take off stage), and Globally Emerging industries (industries where both China and the world frontier is the ferment stage). We then argue that China's industrial policy will have productivity boosting effect on the strategic emerging industries in general, and that there is significant divergence of effect magnitude between the two types of emerging industries. Namely, the average effect of industrial policy for the Globally Emerging industries will be markedly larger than for the Domestically Emerging ones.

Next, we construct an aggregate measure of China's industrial policy intensity at the second-level industry category from China's state-level policy documents and combine it with a dataset on China's listed companies in the strategic emerging industries from 2011-2020 to empirically evaluate our hypotheses. [1] In our benchmark econometric analysis with multi-way panel fixed effects regression and a wide range of alternative specifications, we obtain broad and consistent support of our hypotheses. Further analyses with newly developed causal inference methods also corroborate the major empirical findings.

Our study is most closely related to and builds on the recent literature on China's industrial policy. Aghion et al. (2015)[2], by focusing on trade policies such as tariffs, export subsidies, FDI policies, and tax holidays, reported that "industrial policies allocated

[1] According to the 2018 version of China's "Catalogue of Strategic Emerging Industries", the 9 Strategic Emerging Industries have 40 second-level sub-categories and 189 third-level sub-sub-categories. After experimented with keywords search, we find that quantifying industrial policy at the second-level is the best choice.

to competitive sectors or that foster competition in a sector increase productivity growth." Boeing (2016)[4] estimates the effect of government R&D subsidies with the method of propensity score matching and difference-in-differences on a panel of Chinese listed firms from 2001 to 2006 and finds that government R&D subsidies instantaneously crowd out firms' own R&D investment, and that the "crowding-out effect is not prevalent for repeated recipients of R&D subsidies, high-tech firms, and minority state-owned firms." Guo et al. (2016)[12] studies the effect of Innofund, a particular government support program targeted on small to medium Chinese firms, and finds that firms supported by the fund tend to produce more innovations than firms not supported. With panel data from China Annual Report of Industrial Enterprise 2001-2007, Howell (2017)[14] investigates the effect of public subsidies on innovations of Chinese firms, and discovers that public subsidies promote innovation in the higher technology industries. Kalouptsidi (2018)[15] estimates that China has injected between 1.5 to 4.5 billion US dollars to its shipbuilding industry between 2006 and 2012. Kalouptsidi concludes that these subsidies have helped China's shipbuilding industry grab significant market share from Japan and South Korea.

Mao et al. (2021)[16] classify China's industries into three categories: globally mature industries, domestically catching-up industries, and globally emerging industries according to their relative development stage to that of the world technology frontier. They evaluate the effect of China's industrial policies with a self-constructed measurement of policy intensity and a national database of firm surveys and find that China's industrial policy contribute to greater productivity growth in globally emerging high-tech industries than in domestically catching-up and domestically mature industries. By quantifying information on firms and public security procurement contracts in China's facial recognition AI industry, a special sub-category of China's strategic emerging industries, Beraja, Yang, and Yuchtman (2022)[17] find that data-rich contracts, compared to data-scarce ones, lead recipient firms to develop significantly and substantially more commercial AI software. They conclude that Chinese government's collection and provision of data, a special form of industrial policy implementation, contributes to the rise of China's facial recognition AI firms.

Our research is mostly related to Mao et al. (2021)[16] and Beraja, Yang, and Yuchtman

(2022)[17], who create quantitative measures from industrial policy documents to assess the effectiveness of China's industrial policy with a touch on the strategic emerging industries. Our work is distinct from Mao et al. (2021)[16] and Beraja, Yang, and Yuchtman (2022)[17] in the following ways. First, we focus particularly on the whole range of China's SEIs, while Mao et al. (2021)[16] cover a selective collection of all industries that encompass the SEIs, and Beraja, Yang, and Yuchtman (2022)[17] concentrate on a particular subgroup of strategic emerging industries. Second, we make a finer division of China's SEIs than Mao et al. (2021)[16], and find significant policy effect heterogeneity across the sub-divisions of the SEIs. Third, our study period is 2011-2020. This is the first decade following China officially announced its commitment to the SEIs. It is during this period that China launched the most comprehensive and aggressive industrial policy packages to boost its SEIs. In comparison, Mao et al. (2021)[16] cover 2005-2012, during which period China has placed moderate policy attention upon its fledgling SEIs. Our research thus enriches the existing literature that evaluates the effect of China's industrial policy on firms' innovation productivity, and provide a focusing view on the SEIs.

In what follows, we present a brief review of China's industrial policy towards strategic emerging industries in Section 2. Section 3 outlines our theoretical arguments and derives empirical hypotheses. Section 4 describes data and variables used in empirical analysis. Section 5 presents the econometric models and the main results. Section 6 concludes with a discussion of implications and direction of future work.

2 A brief review of China's industrial policy towards strategic emerging industries

China has a long history of catching-up with the developed world in key technologies using industrial policy. In 1986, China initiated the "863 Program" (i.e., the "National High-tech R&D Program"). In 1997, China launched the "973 Program" (i.e., the "National Key Basic Research Program"). In 2003, China launched the "Medium and Long-term Plan for Science and Technology (2006-2020)". All these can be viewed as the precursors for its official inauguration of the comprehensive industrial policy support for strategic emerging industries in 2010: the "Decision to Accelerate the Fostering and Development of the Strategic Emerging Industries by the State Council". It was in this document that China officially defined its first version of the "strategic emerging industries", which closely followed those identified by OECD countries (Chen & Naughton, 2016; Zhi & Pearson, 2017)[8;27] as the key industries in the future. The 2010 State Council Decision identified seven industries as SEIs: Energy Conservation and Environmental Protection, New Generation of Information Technology, Biologicals, High-end Equipment Manufacturing, New Energy, New Materials, and New Energy Automobiles.

The ensuing decade witnessed escalating policy enactments to advance China's strategic emerging industries. In 2012 China's National Bureau of Statistics compiled its first version of the "Catalogue of Strategic Emerging Industries". In the same year, China's state council issued the "The 12th Five-Year Plan for the Development of National Strategic Emerging Industries". In December 2016, China's state council issued the "The 13th Five-Year Plan for the Development of National Strategic Emerging Industries". One month later, China's National Reform and Development Commission (NDRC), a key state agency for drafting and implementing China's industrial policy, issued the "Directional Catalogue of the Key Products and Services of the Strategic Emerging Industries". In 2018, China's National Bureau of Statistics compiled its revised version of the "Catalogue of Strategic Emerging Industries". The 2018 edition included two additional industries into China's list of SEIs: Digital Creatives, and Related Services. [2]

We can see that the development of SEIs are hailed as the key part of the two of the "Five Year Plan", the most important policy documents in China, as the policy for the SEIs were issued as separate documents along with the five-year plans.

Besides those major policy documents, other government agencies, from the state level to the local provincial level, also issued a wide variety of policies to clarify, strengthen, complement and implement the guidelines in the major documents (For a detailed account on the organizational structure of China's industrial policy related agencies, see Mao et al., 2021)[16]. In Section 4 we'll explain in detail what agencies are related to the drafting and

[2]For a finer decomposition of those nine industries, see Table 11.

implementing the SEIs related policies, the content of the documents, and how to generate appropriate numerical measures of industrial policy intensity for a properly defined sub-category of SEIs.

What kinds of tools are used to implement those policies? Frankly speaking, there are many. Over the years China has employed a dynamic and comprehensive package of instruments to implement its industrial policy. Various forms of subsidies (especially R&D related subsidies and sales rebates) are popular tools for encouraging firms' innovation investment, which is crucial for productivity upgrading. China also adopted a variety of measures to attract foreign investment and facilitate technology transfer in key sectors. Technical standard is another widely used policy tool for selective entry and exit in a number of industries. Quotas on the usage of final products in the competing industries is also a very important policy tool to promoting target industries. Public procurement is another widely used policy instrument in the emerging industries where market demand is limited. China also enacted laws in environmental protection and safety to force out firms with obsolete technologies.

We can hardly exhaust all instruments that China employs to achieve its industrial policy target. For a particular targeted industry, there are typical quite a few distinct policy tools at work simultaneously even within a short period of time. Moreover, a large chunk of the policy instruments are elusive to accurate quantitative measurement. It is therefore a painful task to isolate the marginal effect of any particular type of policy instrument. One fortunate fact is though, most of the policy interventions, and the resources behind them, are coordinated and implemented by only few key state institutions such as the NDRC. Thus by quantifying the policy intensities originated from these institutions, we can come close to a reasonable measure of aggregate policy intensity encompassing all involved instruments (for more discussions, see Mao et al., 2021)[16].

3 Theory and Hypotheses

Productivity comes from innovation by the firms themselves, or is acquired from outside innovation with a cost. Let's focus on the former case, which is most typical. Innovation is a highly risky endeavor, especially for firms in a less developed country, such as China.

Obstacles for innovation can be divided into two types: those from the supply side (i.e., production), and those from the demand side (i.e., sales). Supply side obstacles can be financial, such as lack of fund or resources to conduct and expand sustained R&D; or non-financial, such as restricted by physical law (when the technology has reached the top of the S-curve) or technical restrictions set up by powerful players (i.e., lead firms in the developed world) in the production network. Demand side obstacles can also be financial, such as being unable to sale the products at a profitable price; or nonfinancial, such as the lack of demand.

Imagine that there is a well-intended, well-funded and well-informed government that is willing to provide help for the new comer firm's innovation efforts. For the financial supply side obstacles, the government can provide financial aid to assist the firm's innovation through such as R&D subsidy, rent and utility cost reduction, etc. For the nonfinancial supply side obstacles, the government is perhaps unable to help the firm to solve the physical restriction of technology upgrading, but it might be able to negotiate with the lead firms for better terms for the new comer firm, say, through technology in exchange for market. For the financial demand side obstacles, the government can lift the actual price received by the firm through policies such sales rebate. For the nonfinancial demand side obstacles, such as the lack of demand due to the novelty of the products, the government can pump up the sales of the firm through policies such public procurement, or quotas for competing products.

In the real world there is no such government. Even if the government is well-intended, it is usually not well-funded and not well-informed. Its purpose of helping firms to overcome the obstacles is hence usually not fruitful.

Moreover, even if the government manages to basically satisfy the requirements, it is not guaranteed to succeed with its industrial policy. For China, Mao et. al (2021)[16] propose a theoretical framework for explaining why and when its industrial policies may succeed or fail. They argue that the effect of industrial policy on an industry's productivity growth depends on three factors: (1) the timing of a policy, (2) the attributes of a policy; and (3) the attributes of the industry. Mao et. al (2021)[16] evoke the technological S-curve theory to classify China's industries into three types according to their development stage relative to that of the industrial world frontier: (1) domestically mature, for which the industry of China and that of the world frontier are both at mature stage; (2) domestically catching-up, for which the industry of China is either at the ferment or the take off stage, whereas the corresponding industry of the world frontier has reached the mature stage ; and (3) globally emerging, for which the industry of China is at the ferment stage, while the industry of the world frontier is also at the ferment or take off stage. [3]

Regarding the effect of industrial policy for China in in the first decade of the new millennium, Mao et. al (2021)[16] propose the following hypotheses. First, industrial policy on the domestically mature industries will often do more harm than good to firms' productivity, as there is little room for technology upgrading in those industries and subsidiary policy can promote over capacity and generate zombie firms. Second, industrial policy on the domestically catching-up industries will have a diminishing boosting effect to firms' productivity, as lead international firms in those industries will keep their key technology as secret and build firewalls to protect them from been imitated or reverse-engineered after sharing some technology know-hows in the beginning period of cooperation. Third, industrial policy on the globally emerging industries will have highest potential to boost firms' productivity, provided that the policy addresses firms' problems from both the supply side and the demand side. Mao et. al (2021)[16] empirically validate the three hypotheses using Chinese firm level data from 2005-2012.

Noteworthily, China's strategic emerging industries were only at their sprouting stage in the first decade of the new millennium. It was during the second decade of the new millennium that China's emerging industries had gained remarkable growth and worldwide attention. In fact, it was until 2012 that China issued its first experimental classification of strategic emerging industries, which means that by that time China viewed its emerging industries had grown into noticeable size for statistical classification. Has China's industrial policy been helpful to achieve this new success?

Before answering this question theoretically and empirically, let's first take a closer

[3]Mao et. al (2021) define globally emerging industries as those that are at the ferment stage for China while at the ferment or take off stage for the world frontier. Such definition is designed to be consistent with China's own phrase of "strategic emerging industries".

look at China's definition of "strategic emerging industries", as there is substantial heterogeneity within China's "strategic emerging industries". In fact, China's definition of "strategic emerging industries", from its 2012 version to the later revisions, is very broad. For example, software and information services, manufacturing of computer and related products, biomedicine and biomedical equipment, aviation equipment, and so on, were all well-developed industries in the West in the 2000s and 2010s. But because those industries were lagged behind in China, they were still classified as strategic emerging industries by China's Bureau of Statistics.

Let's divide China's definition of "strategic emerging industries" further into two subcategories: Domestically Emerging Industries (DEI): the industries that are at the ferment stage for China but at the take-off stage for the world frontier, and Globally Emerging Industries (GEI): the industries that are at the ferment stage for both China and the world frontier. [4]

Why does industrial policy work for China's Domestically Emerging Industries in the past decade? The reason is similar to that for China's domestically catching-up industries given by Mao et al. (2021)[16]. Technologies in this type of industries are still undergoing considerable changes worldwide. So theoretically Chinese firms in the domestically emerging industries stand high potential for productivity growth. However, such potential is restricted by international lead firms' self-protection practices. Remember that China's firms are at the lower end of the global value chains in these industries. By the time of 2010s, they probably have coming close to the technological limits of their segmented tasks assigned by the lead firms. For example, China has many accessories suppliers for Apple. Those suppliers belong to the broad classification of strategic emerging industries. However, it's hard to imagine that they can break through the dominance of Apple over the whole design, production and sales network. So we would expect that firms in the domestically emerging industries would benefit from governmental industrial policy support yet the effect is limited.

Why does industrial policy work for China's Globally Emerging Industries in the past

[4]Note that we borrow Mao et al. (2021)'s term of globally emerging industries and make it more stick to its original meaning.

decade? First, firms in globally emerging industries have great potential for productivity growth, as they are competing at today's technological frontier, which is featured with rapid technological changes. Second, there is no major international competitor that can dominate the market and preside the international task segmentation which might be non-favorable for the domestic firms. Firms in both China and the developed countries face similar uncertainty in future directions: no one knows for sure the future of technology. Hence, if Chinese firms are lucky in innovation investment whereas firms in developed countries are unlucky, Chinese firms can not only catch up with but also leapfrog over firms in developed countries. Third, as there are no successful lead firms to follow, or even if there is, the rapid pace of development in globally emerging industries makes it imperative for domestic firms to invest heavily on innovative R&D just as their foreign rivals do. With ample growth space and congruous innovation incentive, Chinese firms in globally emerging industries stand a better chance of making a breakthrough.

Nevertheless, the likelihood of innovation success for firms in China's strategic emerging industries (both GEIs and DEIs) relies critically on market demand (Canepa and Stoneman, 2008; Gao and Rai, 2019)[7;10]. Lack of demand is an important non-financial obstacle to firm innovation (Pellegrino and Savona, 2017; Boon and Edler, 2018)[5;19]. This is especially severe for globally emerging industries, as the innovators in such industries may be well ahead of the time hence face tremendous difficulty in marketing their products. In this case, supply side industrial policy (such as subsidies) per se does not solve the problem, while a number of demand side policy instruments such as demand subsidies and tax allowances which stimulate consumers to buy the innovative products, and direct public procurement of innovation, have the potential of resolving the demand side market failure. Basically, the demand side industrial policy aims to facilitate the generation and diffusion of the innovation, which could be vital to the sustainable development of the challenge oriented innovation of the strategic emerging industries.

In short, for globally emerging industries at the frontier of technological progress, both OECD firms and Chinese firms face great uncertainties in the future directions of technology and product. As a result, by allocating financial support (i.e., the supply side) and creating the market demand via incentives to consumers or governmental procurement (i.e., the demand side) to globally emerging industries, the Chinese state might have provided critical initial support to firms in those industries. Consequently, Chinese firms in these industries may indeed end up with some competitive advantages over their OECD counterparts. And if these industries happen to be within a "window of opportunity" (Perez and Soete, 1988)[21], such double-whamming policies (i.e., both supply and demand) might have been decisive.

To summarize, regarding to the effect of China's industrial policy on its strategic emerging industries, we propose the following two hypotheses:

- **H1**: China's industrial policy has positive effect on firms' productivity for its strategic emerging industries.
- **H2**: China's industrial policy has positive effect on firms' productivity for both its domestically emerging industries and globally emerging industries, and the effect for the later is larger than the former.

Surely, the efficacy of China's industrial policy on the emerging industries is contingent on the fact that by the beginning of our study period China has already experienced decades of catching up and accumulated significant capacity for venturing into the emerging industries. After about three decades of investment in infrastructure, higher education, R&D, and learning from the developed economies, by the early 2010s, China has acquired substantial innovation capacity which empowered it to venture into the new industries. Moreover, by the early 2010s, China has well exploited its comparative advantage and made a very successful integration into the world's manufacturing network for the domestically catching-up industries for more than two decades. These earlier achievements have not only provided China with adequate financial capital for accessing more advanced technologies in the emerging industries, but also equipped its emerging industries with solid downstream industry support.

4 Data and Variables

4.1 Sample Selection

The selection of firm samples refers to the SEI Composite Index (000891) released by China Securities Index Corporation and Shanghai Stock Exchange on January 25, 2017. The index is compiled to reflect the overall development trend of China SEIs. We select its constituent firms covering all nine SEIs after trading closed on October 29, 2021 as our samples, and exclude those whose information cannot be effectively obtained through public market during the modeling period. There are 1,766 valid samples, including 899 firms listed on the Shenzhen Stock Exchange, 448 firms listed on the Shanghai Stock Exchange, 41 firms listed on the Beijing Stock Exchange, and 378 firms listed on the National Equities Exchange and Quotations platform. After referring to Shenyin Wanguo Security's latest Individual Stock Industry Classification (July 2021 Edition) and manually identifying their main business scope as stated in public reports, we classify the samples into the first-, second-, and third-level categories of SEIs, in accordance with the Strategic Emerging Industry Classification (2018 Edition) issued by the State Council.

4.2 Explained Variables

The explained variable is the total factor productivity (TFP) of a firm. Labor productivity and capital productivity are the best-known single factor productivity that measures output produced by a unit of labor or capital input. Compared with the simplicity of single factor productivity, Tinbergen (1942)[24] first proposed an indicator to measure the production efficiency of combined factor inputs, namely total factor productivity (also known as system productivity), which comprehensively reflects the productivity performance of a firm. The "Solow Residuals" proposed by Robert Solow (1957)[22] represents the contribution of technological progress to output growth other than the increase in factor inputs, which is TFP in a broad sense. At present, the commonly used methods for estimating firm TFP include, the instrumental variable method, the fixed effect method and the control function method. We use the control function method in this paper. Cobb-Douglas production

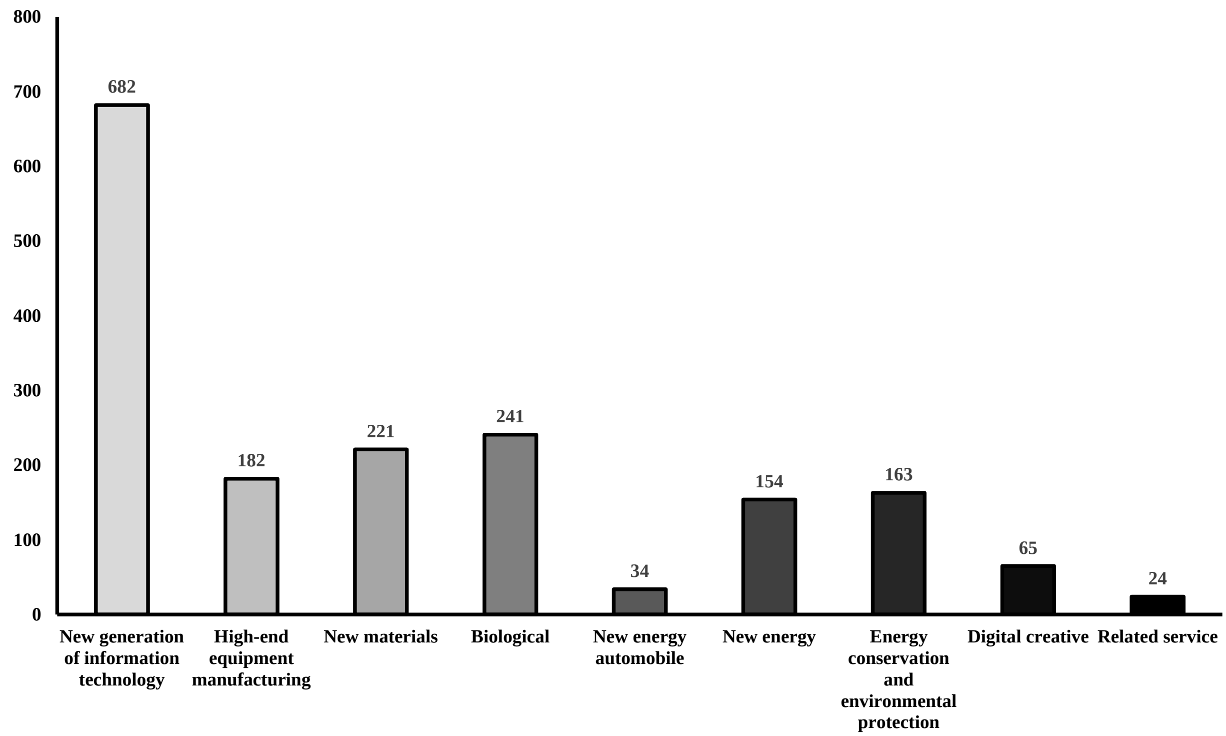

Figure 1: Number of sample enterprises in strategic emerging industries

function is the most common form of production function:

$$Y_{i,t} = A_{i,t} \cdot L_{i,t}^{\alpha} \cdot K_{i,t}^{\beta} \tag{1}$$

In Eq. (1), $Y_{i,t}$ is output, $L_{i,t}$ is labor input, $K_{i,t}$ is capital input, and $A_{i,t}$ thus is total factor productivity in a broad sense. The improvement of its level can simultaneously increase the marginal output of all factors. Taking the logarithm of both sides of Eq. (1), we can get:

$$y_{i,t} = \alpha l_{i,t} + \beta k_{i,t} + u_{i,t} \tag{2}$$

$y_{i,t}, l_{i,t}, k_{i,t}$ represent the logarithmic form of output, labor input, and capital input, respectively. The residual item $u_{i,t}$ is the logarithmic form of TFP, which needs to be estimated. However, if OLS is used for estimation, the problem of simultaneity bias arises, that is, the choice of current factor input combination that a firm makes under the principle of profit maximization is based on current observed productivity level. Now that the residual term represents TFP, there is a correlation between the residual term and the regression term. To solve this problem, the residual term of Eq. (2), $u_{i,t}$, can be split into the current productivity level that can be observed by the firm $\omega_{i,t}$ and the real residual term $\epsilon_{i,t}$ which comes from unobservable productivity shocks and measurement errors. This leads to Eq. (3):

$$y_{i,t} = \alpha l_{i,t} + \beta k_{i,t} + \omega_{i,t} + \epsilon_{i,t} \tag{3}$$

Olley and Pakes (1996)[18] first proposed consistent semi-parameter estimation in the control function method to overcome the simultaneity bias, assuming that a firm makes investment decisions based on its current productivity level, and using the firm's current investments to represent unobservable productivity shocks. OP method first describes the relationship between current firm capital stock and current investments as Eq. (4), which demonstrates that current capital stock is orthogonal to current investments:

$$K_{i,t+1} = (1-\delta)K_{i,t} + I_{i,t} \tag{4}$$

Here K is firm capital stock, and I is current investments. In addition, it also assumes that current investment amount is positively correlated with the firm's current observable productivity level. Because if the firm's productivity level is developing, it will increase its investment to expand. Based on this, the optimal investment function can be written as Eq. (5):

$$i_{i,t} = i_t(\omega, k_{i,t}) \tag{5}$$

Assuming $h(\cdot) = i^{-1}(\cdot)$, the inverse function of the optimal investment function is:

$$\omega_{i,t} = h_t(i_{i,t}, k_{i,t}) \tag{6}$$

Substituting Eq. (6) into Eq. (3), we can get:

$$y_{i,t} = \alpha l_{i,t} + \beta k_{i,t} + h_t(i_{i,t}, k_{i,t}) + \epsilon_{i,t} \tag{7}$$

Let $\phi_{i,t} = \beta k_{i,t} + h_t(i_{i,t}, k_{i,t})$, a polynomial composed of the current investments and the logarithm of the capital stock, and then the first step can be done by estimating the consistent unbiased coefficient of labor input, $\hat{\alpha}$ of Eq. (8):

$$y_{i,t} = \alpha l_{i,t} + \phi_{i,t} + \epsilon_{i,t} \tag{8}$$

Next, the second step uses the estimated $\hat{\alpha}$ to fit $\phi_{i,t}$ to get the estimated coefficient of capital input. Let $V_{i,t} = y_{i,t} - \hat{\alpha} l_{i,t}$, and then estimate Eq. (9):

$$V_{i,t} = \beta k_{i,t} + g(\phi_{t-1} - \beta k_{i,t-1}) + \mu_{i,t} + \epsilon_{i,t} \tag{9}$$

Here $g(\cdot)$is the function of the lagged term of ϕ and capital stock, which can be estimated by high-order polynomials of ϕ_{t-1} and k_{t-1}. The estimation process of the second step is much more complicated than that of the first step, because Eq. (9) contains both contemporary and lagged terms of capital stock, which needs to be estimated by nonlinear least square method. After the estimation of Eq. (9), all the coefficients in the production function have been estimated. Substitute them into Eq. (2) and we can get the logarithm of the residual, that is, the log value of TFP. Ackerberg, Caves, and Frazer (2015) [1] make some modifications to the OP method's assumption that firms can adjust instantly and frictionlessly when facing productivity shocks, which is the ACF correction.

This paper uses firm TFP estimated by OP method and OP method with ACF correction as the explained variable of benchmark model and robustness test, respectively. Input values required to calculate the TFP of a firm include: (1) Operating Revenue, (2) Net Value of Fixed Assets, (3) Total Number of Employees, (4) Cash Paid to and for Employees, and (5) Cash Paid for Purchase and Construction of Fixed Assets, Intangible Assets and Other Long-term Assets, where (2) is used as a state variable, (3) and (4) are used as free variables, and (5) representing the current firm's investment level is used as a proxy variable for productivity shocks. We collect these data of our samples from 2011 to 2020 on the Wind database. In addition, this paper also uses an alternative indicator that can reflect the level of productivity in replace of TFP, output per capita (operation revenue/number of employees), to conduct the robustness tests.

4.3 Key Explanatory Variables

The key explanatory variable is the industrial policy intensity on the SEIs. Most of microscopic researches on SEI policies use dummy variables to define the scope and intensity of policy implementation. For example, Zhang Yuwang (2020)[25] distinguishes whether an industry is intensively focused by the usage of positively addressing modifiers, such as "prioritize the development of ..." and "strongly support ...", in the policy contents. The disadvantage is that Chinese semantics are usually vague and unclear in such contexts, and dummy variables are not precise enough to describe the intensity. Based on this, this paper creatively measures the intensity of industrial policies by the number of relevant policies issued by the central government (the State Council and its ministries). Section 3 above demonstrates the likelihood of innovation success for firms in China's strategic emerging industries relies critically on double-whamming policies (i.e., both supply and demand). However, government subsidies or other forms of financial support, such as tax relief and interest concessions, commonly used by scholars in current research are only applied to the supply side in a package of policies. Those alone cannot cover tools applied to the demand side, such as public procurement, price subsidies, etc. In addition, there are also some policy forms that cannot be easily quantified in the unit of a single firm, such as the government's investment in the infrastructure of SEI industrial parks and talent cultivation projects. In consideration of these factors, it is reasonable to use the number of policies as a proxy for the intensity of SEI policy's systematic effect on the firms.

According to the "Opinions of the State Council on Implementing the Division of Labor in Key Work Departments of the 'Government Work Report' " issued in 2010, the Ministries that are mainly leading and responsible in accelerating the cultivation and development of SEIs include, National Development and Reform Commission, Ministry of Industry and Information Technology, Ministry of Science and Technology, Ministry of Finance, Ministry of Commerce, etc. According to this, we collect 378 policy documents related to SEIs released from 2011 to 2020 by the central government from official websites, including 146 documents from the General Office of the State Council, 77 documents from National Development and Reform Commission, 61 documents from Ministry of Industry and Information Technology, 28 documents from Ministry of Science and Technology, 22 documents from Ministry of Education, 13 documents from Ministry of Commerce, 11 documents from Ministry of Agriculture, 10 documents from Ministry of Finance, 4 documents from Ministry of Culture, 3 documents from People's Bank of China, 2 documents from Ministry of Communications, and 1 document from Ministry of Health.

After obtaining a series of policy documents, we file an SEI category keyword codebook to determine the target industry (or industries) of each policy. When a keyword appears in the policy content, the corresponding category is marked as target industry, and the number of policies for each SEI category is aggregated by year finally. We think it is most appropriate to classify target industries by the second-level category, which is more detailed than the first-level category, and more general than the third-level category. In order to show the keyword codebook and the classification process more intuitively, two secondary categories of the "New Generation of Information Technology Industry" are taken as examples below in Table 1. When second- and third-level category keywords, such as "information network", "network equipment" and "computer", etc. appear in the content of a policy document, it is considered that the "New Generation of Information Technology Industry" is one of its target industries; when "electronic core", "new electronic components", "new electronic equipment", etc. appear, the "Electronic Core Industry" is considered to be targeted. Taking part of the "Special Action Plan for the Deep Integration of Informatization and Industrialization (2013-2018)" issued by Ministry of Industry and Information Technology in 2013 as an example, as shown in Figure 2, the keyword "electronic component" appeared in the content. Then the number of policies targeted to the "Electronic Core Industry" in 2013 is counted plus one. In addition, this paper also records the frequency of industrial keywords in the policy contents as the explanatory variable for robustness test.

After counting all the policy documents, the number of policies for SEIs from 2011 to 2020 totaled 2,053. The industry distribution and year distribution are shown in Figures 3 and 4 below. Among them, the "New Generation of Information Technology Industry" is targeted most, accounting for 23% of policies. From the perspective of time trends, the number of policies related to SEIs in recent years has decreased overall compared with previous years.

Table 1: Example of Industry Category Keywords

First-level category	Second-level category	Second-level category keyword	Third-level category	Third-level category keyword
New Generation of Information Technology Industry	New Generation Information Network Industry	information network	Network Equipment Manufacturing	network equipment
			Manufacture of New Type of Computer and Information Terminal Equipment	computer, information terminal
			Information Security Equipment Manufacturing, New Generation of Mobile Communication Network Services	information security equipment communication network, mobile communication, network service
			Other Network Operation Services	network operation
			Computer and Auxiliary Equipment Repairment Service	computer and auxiliary equipment repairment, computer equipment repairment,computer auxiliary equipment repairment
	Electronic Core Industry	electronic core	New Electronic Components and Equipment Manufacturing	electronic component, electronic equipment
			Electronic Special Equipment and Instrument Manufacturing	electronic equipment, electronic special equipment
			High Energy Storage and Core Electronic Material Manufacturing	high energy storage material, core electronic material
			Integrated Circuit Manufacturing	integrated circuit

2. 行动内容

——增强电子信息产业支撑服务能力。加快集成电路、关键电子元器件、基础软件、新型显示、云计算、物联网等核心技术创新，突破专项行动急需的应用电子、工业控制系统、工业软件、三维图形等关键技术。围绕工业重点行业应用形成重大信息系统产业链配套能力，开展国产 CPU 与操作系统等关键软硬件适配技术联合攻关，提升产业链整体竞争力和安全可控发展能力。支持面向云计算、移动互联网、工业控制系统等关键领域安全技术研发与产业化，加快安全可靠通信设备、网络设备等终端产品研发与应用。

2. Action content

—To enhance the electronic information industry support services capacity. Accelerate integrated circuits, key electronic components. Basic software, new display, cloud computing, Internet of things and other core technology innovation, breakthroughs in special action urgently needed to apply electronic, industrial control systems, industrial software, three-dimensional graphics and other key technologies. Around the industrial key industry applications to form a major information system industry chain supporting capabilities, to carry out joint research and development of domestic CPU and operating systems and other key software and hardware adaptation technology, to enhance the overall competitiveness of the industry chain and the ability to develop a safe and controlled. Support for cloud computing, mobile Internet, industrial control systems and other key areas of security technology research and development and industrialization, and accelerate the development and application of safe and reliable communications equipment, network equipment and other terminal products.

Figure 2: The Section of Special Action Plan for the Deep Integration of Informatization and Industrialization (2013-2018)" issued by Ministry of Industry and Information Technology

4.4 Control Variables

The control variables of our model include three levels: firm level, industry level and province-industry level.

First, for control variables at firm level, we collect our sample firms' basic characteristics, including firm age, total asset size, ROA, asset-liability ratio, and the ratio of total R&D expenses to total revenue from 2011 to 2020. We also get firm ownership type and use dummy variables to describe the six types: state-owned firm, foreign-funded firm, public firm, incorporated firm, private firm, and other domestic firm. State-owned firm is used as

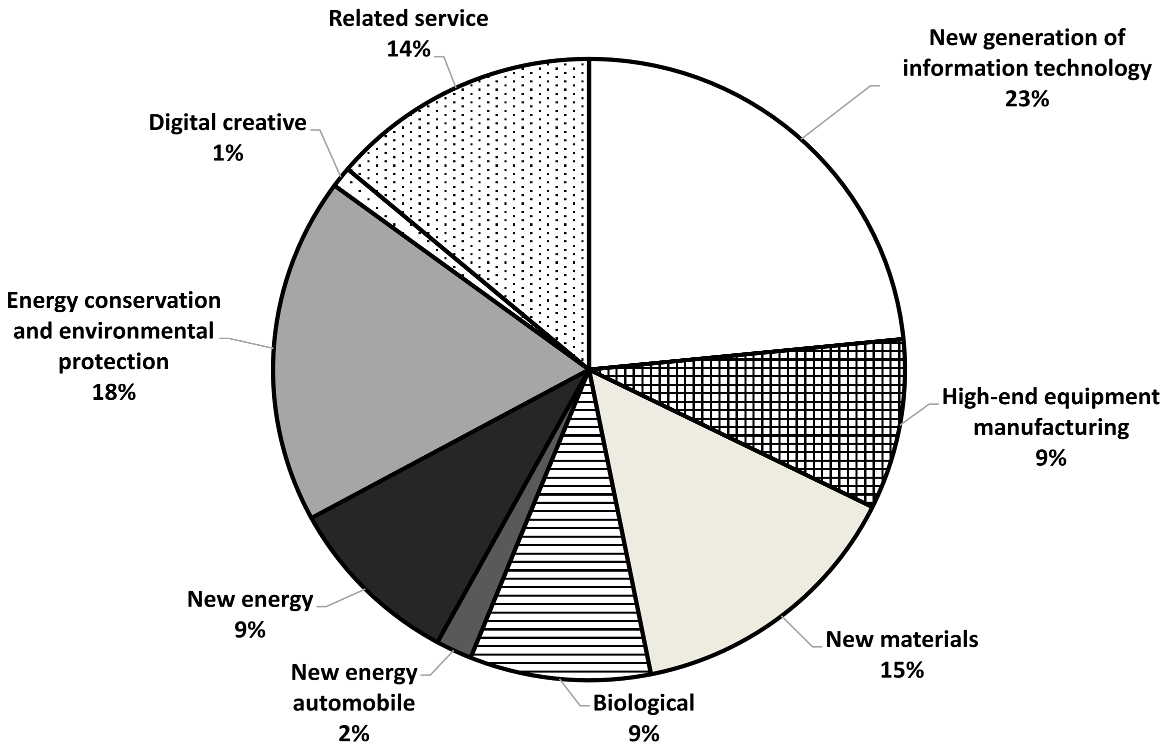

Figure 3: Number of strategic emerging industry policies based on industry from 2011 to 2020

benchmark variable in the model.

Second, we construct industry-level control variables to reflect industry agglomeration. We divide Mainland China 's 31 provinces into four regions (eastern, central, western, and northeastern region, respectively, referring to the official definition), and then for each industry, calculate the ratio of regional sales to the industry 's total sales annually. The ratio is used as the industry agglomeration indicator. We use eastern region as the benchmark group, that is, only the ratios of central, western, and northeastern regions appear in the model as control variables at the industry level.

Finally, province-industry level control variables include the average size of firms (measured by total firm assets), average profitability (measured by ROA), average asset-liability ratio, average ratio of R&D expenditure to total revenue, and average TFP, within each province-industry group. These variables reflect "born advantages" to a firm of certain industry in certain province. In particular, the calculation of the average excludes each firm itself. For example, assuming that in year t, province p has N firms of industry j, we

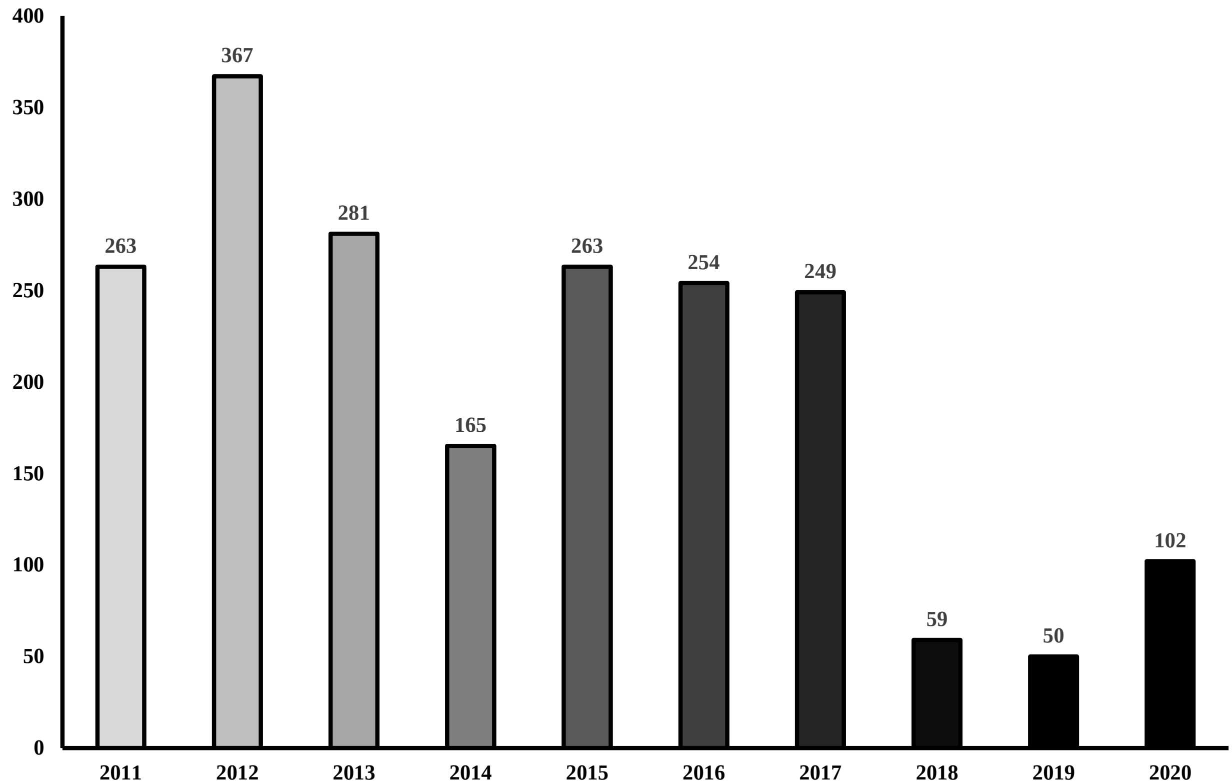

Figure 4: Number of strategic emerging industry policies based on year from 2011 to 2020

calculate the average of a series of indicators above of other N-1 firms, excluding firm i itself.

4.5 Descriptive Statistics

After dropping observations with missing and invalid values, our sample consists of 10,728 observations of 1,766 firms from 2011 to 2020. The descriptive statistics of the explained variables, key explanatory variables and control variables are reported in Table 2 below.

Table 2: Descriptive Statistics of Main Variables

Variable name	Variable definition	Obs.	Mean	SD	Min	Max
Explained variables						
lntfpop	Natural log of TFP calculated by the OP method	10728	2.020	0.089	1.346	2.516
lntfpopacf	Natural log of TFP calculated by OP method with ACF correction	10728	1.366	0.150	-0.478	2.207
lnrevpw	Natural log of total sales per worker (in 1000 CNY)	10728	6.680	0.711	2.937	11.693
Key explanatory variables						
policy	Number of policies	10728	7.244	6.677	0	40
word_cnt	Frequency of industry keywords in policy contents	10728	48.413	89.892	0	714
Other control variables						
a. Firm level						
lnage	Natural log of firm age	10728	2.736	0.387	0.693	4.174
lnasset	Natural log of firm total assets (in million CNY)	10728	7.618	1.458	2.541	13.331
ROA	Return on assets	10728	6.511	8.536	-77.651	85.410
rndratio	The ratio of total R&D expenses to total revenue	10728	0.074	0.099	0	4.554
debt	Asset-liability ratio	10728	0.361	0.185	0.001	2.394
foreign	Dummy for foreign-funded firm	10728	0.027	0.161	0	1
incorporated	Dummy for collective firm	10728	0.002	0.043	0	1
other	Dummy for other domestic firm	10728	0.008	0.089	0	1
private	Dummy for private firm	10728	0.664	0.472	0	1
public	Dummy for public firm	10728	0.078	0.268	0	1
stateowned	Dummy for state-owned firm	10728	0.222	0.416	0	1
b. Industry level						
reg_east	Industrial concentration in the eastern region of China	10728	0.790	0.135	0.161	1
reg_central	Industrial concentration in the central region of China	10728	0.104	0.089	0	0.579
reg_northeast	Industrial concentration in northeastern region of China	10728	0.020	0.022	0	0.152
reg_west	Industrial concentration in the western region of China	10728	0.086	0.098	0	0.604
c. Province level						
bornadv_rnd	The ratio of R&D expenses to sales revenue on average for industrial enterprises in the province	10728	0.074	0.05	0	1.016
bornadv_roa	Average net asset margin of industrial enterprises in the province	10728	7.566	0.410	5.595	10.015
bornadv_debt	Average asset liability ratio of industrial enterprises in the province	10728	6.511	4.647	-69.947	57.207
bornadv_lnasset	Logarithmic value of the average total assets of industrial enterprises in the province	10728	8.214	1.049	3.514	11.843
bornadv_lntfpop	Logarithmic values of the average total factor productivity of industrial enterprises in the province	10728	2.022	0.054	1.722	2.304

5 Empirical Analysis

5.1 Econometric Models

Our purpose is to study whether China's SEI industrial policies can significantly improve the productivity performance of firms in related fields. This is a typical causal inference problem based on observational data. As pointed out by de Chaisemartin and D' Haultfoeuille (2020)[9], panel data regression models based on Two-way Fixed Effects (TWFE) are preferred method by academia to identify causal effects in such problems. We also adopt this classic model as the benchmark model. Specifically, the basic form of a difference-in-differences (DiD) model is as follows:

$$y_{it} = \alpha_0 + \theta_i + \delta_t + \beta D_{it} + \epsilon_{it}. \tag{10}$$

Here θ_i is individual fixed effects, δ_t is time fixed effects, D_{it} is the treatment indicator, being 1 if individual i receives treatment at time t and 0 otherwise, and ϵ_{it} is random error. It is easy to prove that in the standard 2×2 DiD design, i.e., when (1) The treatment is a binary variable; (2) There are only two observation periods; (3) There is a control group, i.e., subjects in this group are never intervened; (4) The treatment group only receives the disposal in the second period, β is equal to the difference of the difference between average out of the treatment group before and after the disposal and the difference between average treatment effect of the control group before and after the disposal. So the TWFE method is also called the DiD method, or the Regression-Difference-in-Differences (RDID) method. Also, if the parallel trends assumption is met, then β is equal to the average treatment effect (namely, average causal effect) defined based on the potential outcomes. It is worth noting that current academic research on the use of TWFE to identify causal effects mainly focuses on the situation where the treatment variable is a binary. Recent research in DiD, such as de Chaisemartin and D'Haultfoeuille (2020)[9], Goodman-Bacon (2021)[11], Callaway and SantAnna (2021)[6] and Sun and Abraham (2021)[23], point out that when there is treatment effects heterogeneity in multiple period panel data, then the TWFE estimator, i.e., the OLS estimator of β based on (10), does not deliver correct causal effect estimate, even if the treatment is binary.

In our scenario, the situation is even more complicated. We have a multiple period panel data where firms were treated by industrial policy in each period. The treatment variable, i.e., industrial policy intensity, is continuously valued, and can either increase or decrease from one period to the next. The remedies provided by the above research are not applicable to our case. In a recent working paper, Xiao (2022)[26] points out if the treatment effect is assumed to be homogeneous, i.e.,

$$\frac{\partial E[y_{it}]}{\partial D_{it}} = \beta, \forall i, t \tag{11}$$

then under the parallel trend assumption, β of Eq. (10) can still represent the average treatment effect, so it can be estimated based on TWFE as well, which is the consistent estimate of average causal effect.

Model (10) is an extremely simplified scenario: There is no other control variable. In fact, in real scenarios, many levels of control variables X_{it} are usually added to solve the problem of estimation bias caused by omitted variables, as Eq. (12):

$$y_{it} = \alpha_0 + \theta_i + \delta_t + \beta D_{it} + X_{it}'\gamma + \epsilon_{it} \tag{12}$$

In this paper, the benchmark RDID model takes firm TFP as the explained variable, and industrial policy intensity as the key explanatory variable, also including three levels of control variables as described in Section 4.4, and the fixed effects of industry, province, and year. The benchmark model is built as Eq. (13):

$$\ln(\text{tfpop})_{ijpt} = \alpha + \beta policy_{jt} + X_{it}'\eta + Z_{jt}'\theta + W_{jpt}'\phi + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt} \tag{13}$$

Here $\ln(\text{tfpop})_{ijpt}$ is the explained variable, $policy_{jt}$ is the number of policies targeted to industry j in year t, X_{it}, Z_{jt}, W_{jpt} are firm-level , industry-level and province-industry-level control variables, μ_j, λ_p, ν_t are the fixed effects of industry, province, and year, respectively, and ϵ_{ijpt} is the random interference term; α is the intercept term; β is the coefficient of the effect of industrial policy intensity on firm TFP; η, θ, ϕ are the coefficients of a series of control variables. Considering that it may take some time from policy release to implementation and finally to taking effect, we further explore the dynamic effect of industrial policy intensity on firm TFP. We add lagged terms of the key explanatory variable from 1-year to 3-year in our model. Another purpose of doing this is that if the model results show that lagged policy effect and contemporary policy effect on the explained variable are much identical, we can infer that reverse causality is not consequential in the model. The dynamic effect model is built as Eq. (14):

$$\ln(\text{tfpop})_{ijpt} = \alpha + \beta policy_{j,t-k} + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt}, \tag{14}$$

where k is the lag order of policy intensity, and other symbols have the same interpretations as above. The empirical results and analysis of models (13) and (14) is presented in Section 5.3.1 below.

Finally, according to the characteristics of nine SEIs, this paper further explores the heterogeneity of the effect of industrial policy intensity on firm TFP in different types of industries. According to scholars such as Rogers (2003)[20] and Hall (2005)[13], the development process of an industry is an S-shaped curve, which can be roughly divided into three stages: ferment, take-off, and maturity. Mao et al. (2021)[16] conclude by empirically examining the impact of China's industrial policy intensity on the TFP of Chinese firms that, the position of an industry in China's domestic development stage relative to the industry's global frontier determines the effectiveness of relevant industrial policies Compared with domestically catching-up industries and domestically mature industries, the effect of government support for globally emerging industries is much better. The logic given in the article is that for developing countries like China, many domestic industries started later than the developed countries. When China tries to catch up with the global frontier, it is likely to reach technology limits. A series of obstacles might arise, such as lack of decision power in the global value chains, invisible ceiling set up by international competitors (such as changing industry technical standards), etc., making the government inefficient in providing policy support to such industries, and even leading to redundancy and waste of resources. But for globally emerging industries, industry entry barriers have not yet been established, and all countries are trying to seize the new opportunities. Supportive policies for those industries will greatly help domestic firms to gain a foothold in the fierce global competition, and also the potential and space for future improvement of firm productivity is much greater than that of former type of industries.

China's plan for cultivating and supporting SEIs is based on the domestic development stage of industries. As discussed before, we divide the nine SEIs into two types: globally emerging industries (GEIs) and domestically emerging industries (DEIs). Our previous definitions of GEIs and DEIs are not operationally friendly. Here we give a more specific criterion to classify the SEIs: whether the industry nowadays is at the stage of rapid technological iteration and has not yet formed a unified global industry standard or technical benchmark. The industry is classified as GEI if the answer is yes, and DEI otherwise. Specifically, the globally emerging type includes "Artificial Intelligence", "Frontier New Materials", "New-energy Automobile Industry", "New Energy Industry", and "Energy Conservation and Environmental Protection Industry". The domestically emerging type includes the rest of the second-level categories. Among the 10,728 observations, GEIs account for 19.85%, and DEIs account for 80.15%. When building our model, the interaction term of key explanatory variable and the dummy variable of industry type is added to explore the heterogeneity of industrial policy effect, as Eq. (15)-(16):

$$\begin{aligned}\ln(\text{tfpop})_{ijpt} &= \alpha + \beta policy_{jt} + \gamma(policy_{jt} \times GEI_j) + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi + \mu_j \\ &\quad + \lambda_p + \nu_t + \epsilon_{ijpt}, \qquad (15)\\ \ln(\text{tfpop})_{ijpt} &= \alpha + \beta policy_{j,t-k} + \gamma(policy_{j,t-k} \times GEI_j) + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi \\ &\quad + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt}. \qquad (16)\end{aligned}$$

Here GEI_j is the dummy variable for the globally merging industries (DEI serves as the benchmark group); β is the coefficient of policy effect on the productivity level of the firms in the benchmark group; γ is the marginal effect of policy on the productivity level of the firms in DEIs; so, $\beta + \gamma$ represents the net effect of policy on the productivity level of the firms in DEIs; other symbols have the same interpretation as the benchmark model. The empirical results and analysis of models (15)-(16) are presented in Section 5.3.2 below.

5.2 Dynamic Panel Data Model and GMM Estimation

The RDID method used in the benchmark model is a panel data model with multiple fixed effects. To address potential omitted confounders that vary with both time and individuals, Angrist and Pischke (2009)[3] suggest that the lagged term of explained variable can be added to the fixed effect model as one of the explanatory variables to build dynamic panel data model. The system GMM model set in this paper for dynamic panel data is as Eq. (17), where L and M are positive integers, representing the lag order of the explained variable and the key explanatory variable, respectively:

$$\begin{aligned}\ln(\text{tfpop})_{ijpt} = \alpha + \sum_{l=1}^{L} \psi_l \ln(\text{tfpop})_{ijp,t-l} + \sum_{m=0}^{M} \beta_m policy_{j,t-m} + \sum_{m=0}^{M} \gamma_m policy_{j,t-m} \times GEI_j \\ + X_{it}'\eta + Z_{jt}'\theta + W_{jpt}'\phi + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt}\end{aligned} \tag{17}$$

5.3 Benchmark Results

Now we are ready to present our empirical results to evaluate the validity of our two hypotheses. .

5.3.1 Industrial Policy Intensity and Firm TFP

Table 3 reports the RDID model results with SEI policy intensity as key explanatory variable and firm TFP as explained variable. Column (1) displays the results for the benchmark model, and columns (2) to (4) replace the key explanatory variable, i.e., industrial policy intensity, with its first, second, and third order lagged term, respectively. We can see from columns (1) and (2) that, one increase in the number of industrial policies leads to an overall increase of firm TFP by 0.0251%   0.0308%, which is a significant positive effect. This is consistent with our first hypothesis H1. Meanwhile, the effect of industrial policy has a delay effect within 1 year, and the effect become insignificant when the policy has been implemented for 2 or 3 years. This is also consistent with the fact that China's industrial policy is usually of short-termed nature.

5.3.2 Industrial Policy Intensity, Industry Type and Firm TFP

In order to explore the difference of productivity performance affected by industrial policies between firms in globally emerging industries and domestically emerging industries, Table 4 below shows the results of models with industrial type interaction term. Column (1) display the contemporary industrial policy effect. The coefficient for policy represent the industrial policy effect on the benchmark group, i.e., the domestically emerging industries. The estimates for this coefficient is 0.000046, with a standard error of 0.0001. This means that China's industrial policy has a positive yet insignificant boosting effect on productivity for firms in the domestically emerging industries, which is consistent with the first part of hypothesis H2. The net effect term captures the industrial policy effect on the globally emerging industries. Its estimated value is 0.000705, with a standard error of 0.0001, which means that China's industrial policy has a positive and significant boosting effect on productivity for firms in the globally emerging industries, confirming the second part of hypothesis H2. The positive interaction term coefficient of column (1) indicates that the TFP of firms in globally emerging industries is more stimulated by contemporary industrial policies compared with the benchmark group, with marginal benefit 0.0659%, and net benefit as high as 0.0705%. According to the results of columns (2)-(4) in Table 4, in terms of marginal benefit, the delay effect lasts longer for globally emerging industries and reaches the maximum in the following year 3.

5.4 Robustness Checks

5.4.1 Robustness Test for Industrial Policy Intensity

The measurement of industrial policy intensity of benchmark model is the number of policies. In the robustness test, we replace key explanatory variable with the number of related keywords of industries. Generally, the more addressed the keywords of an industry and its related field in policy documents are, the more likely the industry and relevant products

Table 3: Industrial Policy Intensity and Firm TFP

Dependent: lntfpop	(1)	(2) k = 1	(3) k = 2	(4) k = 3
policy	0.000251**			
	(0.0001)			
policy_lag1		0.000308***		
		(0.0001)		
policy_lag2			0.000107	
			(0.0001)	
policy_lag3				-0.000018
				(0.0001)
Intercept term	1.722802***	1.703704***	1.679099***	1.643527***
	(0.03)	(0.0329)	(0.0366)	(0.0425)
Firm-level control variables	Yes	Yes	Yes	Yes
Industry-level control variables	Yes	Yes	Yes	Yes
Province-industry level control variables	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Within R-Square	0.4318	0.4228	0.417	0.408
Number of observations	10728	9122	7588	6120

Note 1: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

Note 2: Firm-level control variables include firm age, total asset size, ROA, asset-liability ratio and the ratio of total R&D expenses to total sales revenue, and firm ownership type (with state-owned firms as the benchmark group); industry-level control variables include industry agglomeration indicators of four regions in China (with the eastern region as the benchmark group); the province-industry level control variables include average size of firms (measured by total firm assets), average profitability (measured by ROA), average asset-liability ratio, average ratio of R&D expenditure to total revenue, and average total factor productivity within each province-industry group. Due to space limitations, the results of the above control variables are not fully displayed.

Table 4: Model of Industrial Policy Intensity and Firm TFP with Interaction Term of Industry Types

Dependent: lntfpop	(1)	(2) k = 1	(3) k = 2	(4) k = 3
policy	0.000046			
	(0.0001)			
policy×GEI	0.000659***			
	(0.0002)			
policy_lag1		0.000162		
		(0.0001)		
policy_lag1×GEI		0.000489**		
		(0.0002)		
policy_lag2			-0.000012	
			(0.0001)	
policy_lag2×GEI			0.000406*	
			(0.0002)	
policy_lag3				-0.00016
				(0.0001)
policy_lag3×GEI				0.000671**
				(0.0003)
Net effect	0.000705***	0.000651***	0.000395*	0.000516*
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Intercept term	1.734987***	1.712122***	1.683776***	1.647592***
	(0.0301)	(0.033)	(0.0367)	(0.0425)
Firm-level controls	Yes	Yes	Yes	Yes
Industry-level controls	Yes	Yes	Yes	Yes
Province-Industry level controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Within R-Square	0.4328	0.4234	0.4175	0.4088
Number of obs.	10728	9122	7588	6120

Note: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

are to be valued and supported by the government. Therefore, the robustness test models for industrial policy intensity, are set as Eq. (18):

$$
\begin{aligned}
\ln(\text{tfpop})_{ijpt} &= \alpha + \beta word\_cnt_{jt} + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt}, \\
\ln(\text{tfpop})_{ijpt} &= \alpha + \beta word\_cnt_{jt} + \gamma(policy_{jt} \times GEI_j) + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi + \mu_j \\
&\quad + \lambda_p + \nu_t + \epsilon_{ijpt},
\end{aligned}
\tag{18}
$$

where $word\_cnt_{jt}$ is the keyword frequency of industry j in year t, and other symbols have the same interpretation as above. Table 5 shows the results of robustness test for industrial policy intensity. The coefficient of key explanatory variables in Column (1) shows that there is also a significant positive relationship between the frequency of industrial policy keywords and firm TFP. Though the coefficient is much smaller than that of the benchmark model, it is reasonable because it represents unit effect of keyword count, not policy count. Column (2) adds the interaction term of industry type. The conclusion is consistent with the benchmark model above. In addition, we also test the model with lagged terms of the keyword count, and the results are not significant. The possible reason is that, unlike the release of the policy document, the delay effect caused by a single keyword is negligible.

5.4.2 Robustness Test for Firm Productivity Level

We take the robustness test for firm productivity level from two perspectives. One is to use different methods to calculate firm TFP. Another is to replace TFP with output per worker as an alternative measurement of firm productivity level. From the first perspective, the models are set as Eq. (19):

$$
\begin{aligned}
\ln(\text{tfpopacf})_{ijpt} &= \alpha + \beta policy_{j,t-k} + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt}, \\
\ln(\text{tfpopacf})_{ijpt} &= \alpha + \beta policy_{j,t-k} + \gamma(policy_{j,t-k} \times GEI_j) + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi \\
&\quad + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt},
\end{aligned}
\tag{19}
$$

where $\ln(\text{tfpopacf})_{ijpt}$ is the natural log of firm TFP calculated by OP method with ACF correction and other symbols have the same interpretation as above (Here k can be 0, 1, 2,

Table 5: Robustness Test Model for Industrial Policy Intensity

Dependent: lntfpop	(1)	(2)
word_cnt	0.000009*	0.000005
	(0.0000)	(0.0000)
word_cnt × GEI		0.000032**
		(0.0000)
Net effect		0.000037**
		(0.0000)
Intercept term	1.723823***	1.727561***
	(0.03)	(0.0301)
Firm-level controls	Yes	Yes
Industry-level controls	Yes	Yes
Province-industry level controls	Yes	Yes
Time FE	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Within R-Square	0.4316	0.432
Number of obs.	10728	10728

Note: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

and 3). Table 6 shows the results. Column (1)-(4) show that after changing the calculation method of firm TFP, the conclusion is consistent with our benchmark model. Overall, the intensity of industrial policy has a significant positive relationship with the explained variable, and there is a one-year delay effect; the results of Column (1)-(4) in Table 7 with industry type interaction term also show that the delay effect of policy release lasts longer for globally emerging industries.

Table 6: Robustness Test for Firm Productivity Level (1)

Dependent: lntfpopacf	(1)	(2) k = 1	(3) k = 2	(4) k = 3
policy	0.000528**			
	(0.0002)			
policy_lag1		0.000638**		
		(0.0002)		
policy_lag2			0.00016	
			(0.0002)	
policy_lag3				-0.00008
				(0.0002)
Intercept term	1.175879***	1.143679***	1.087306***	1.018171***
	(0.0628)	(0.0689)	(0.0763)	(0.088)
Firm-level control variables	Yes	Yes	Yes	Yes
Industry-level control variables	Yes	Yes	Yes	Yes
Province-industry level control variables	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Within R-Square	0.3241	0.3025	0.3072	0.3218
Number of observations	10728	9122	7588	6120

Note: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

From the second perspective of robustness test for firm productivity level, the models

Table 7: Robustness Test for Firm Productivity Level (2)

Dependent: lntf-popacf	(1)	(2) k = 1	(3) k = 2	(4) k = 3
policy	0.000151			
	(0.0002)			
policy×GEI	0.001215***			
	(0.0003)			
policy_lag1		0.000341		
		(0.0002)		
policy_lag1×GEI		0.000995**		
		(0.0004)		
policy_lag2			-0.00007	
			(0.0002)	
policy_lag2×GEI			0.000792*	
			(0.0004)	
policy_lag3				-0.0003
				(0.0003)
policy_lag3×GEI				0.001178*
				(0.0005)
Net effect	0.001366***	0.001336***	0.000722*	0.00085
	(0.0003)	(0.0003)	(0.0003)	(0.0005)
Intercept term	1.198330***	1.160795***	1.096439***	1.025276***
	(0.063)	(0.0691)	(0.0764)	(0.0881)
Firm-level controls	Yes	Yes	Yes	Yes
Industry-level controls	Yes	Yes	Yes	Yes
Province-industry level controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Within R-Square	0.325	0.3032	0.3078	0.3225
Number of obs.	10728	9122	7588	6120

Note: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

are set as Eq. (20):

$$
\begin{aligned}
\text{lnrevpw}_{ijpt} &= \alpha + \beta policy_{j,t-k} + X_{it}'\eta + Z_{jt}'\theta + W_{jpt}'\phi + \mu_j + \lambda_p + \nu_t + \epsilon_{ijpt}, \\
\text{lnrevpw}_{ijpt} &= \alpha + \beta policy_{j,t-k} + \gamma(policy_{j,t-k} \times GEI_j) + X_{it}'\eta + Z_{jt}'\theta + W_{jpt}'\phi + \mu_j \\
&\quad + \lambda_p + \nu_t + \epsilon_{ijpt},
\end{aligned} \tag{20}
$$

where $\text{lnrevpw}_{\text{ijpt}}$ is the natural log of the output per worker, and other symbols have the same interpretation as above (Here k can be 0, 1, 2, and 3). Tables 8 and 9 show the results of models using firm output per worker instead of TFP as explained variable. The intensity of industrial policies positively affects firm output per worker, and the effect is more pronounced to globally emerging industries with longer lasting time.

Table 8: Robustness Test for Firm Productivity Level (3)

Dependent: lnrevpw	(1)	(2) k = 1	(3) k = 2	(4) k = 3
policy	0.003221***			
	(0.0009)			
policy_lag1		0.002829**		
		(0.0009)		
policy_lag2			0.00124	
			(0.001)	
policy_lag3				-0.0008
				(0.0011)
Intercept term	4.468376***	4.485156***	4.740775***	4.664672***
	(0.2995)	(0.3245)	(0.3612)	(0.4186)
Firm-level controls	Yes	Yes	Yes	Yes
Industry-level controls	Yes	Yes	Yes	Yes
Province-industry level controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Within R-Square	0.3686	0.3756	0.3694	0.3677
Number of obs.	10728	9122	7588	6120

Note: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

Table 9: Robustness Test for Firm Productivity Level (4)

Dependent: lnrevpw	(1)	(2) k = 1	(3) k = 2	(4) k = 3
policy	0.001003			
	(0.001)			
policy×GEI	0.007149***			
	(0.0016)			
policy_lag1		0.000952		
		(0.001)		
policy_lag1×GEI		0.006296***		
		(0.0016)		
policy_lag2			0.00015	
			(0.0011)	
policy_lag2×GEI			0.003730*	
			(0.0017)	
policy_lag3				-0.0016
				(0.0012)
policy_lag3×GEI				0.00378
				-0.0024
Net effect	0.008152***	0.007248***	0.003875*	0.002229
	(0.0014)	(0.0015)	(0.0016)	(0.0022)
Intercept term	4.600656***	4.594126***	4.783961***	4.687587***
	(0.3006)	(0.3255)	(0.3617)	(0.4189)
Firm-level controls	Yes	Yes	Yes	Yes
Industry-level controls	Yes	Yes	Yes	Yes
Province-industry level controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Within R-Square	0.3699	0.3767	0.3698	0.368
Number of obs.	10728	9122	7588	6120

Note: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

5.4.3 Robustness test of dynamic panel data

As mentioned in Section 5.2 above, three-dimension fixed effects of industry, province and year in the benchmark model can only control confounding variables that only change with time or only with individuals. For confounders changing with both time and individuals, we build a dynamic panel data model by adding lagged explained variables and use the GMM method to estimate it. Table 10 below shows the results. The coefficients of key explanatory variables are significantly positive, indicating our conclusions above are robust.

Table 10: Robustness Test for Dynamic Panel Data

Dependent: lntfpop	(1)
lntfpop_lag1	0.438726***
	(0.1167)
policy_lag3	0.000227
	(0.0002)
policy_lag3×GEI	-0.000053
	(0.0006)
policy_lag4	0.000046
	(0.0002)
policy lag4×GEI	0.000981*
	(0.0005)
Intercept term	0.763904*
	(0.3374)
Firm-level controls	Yes
Industry-level controls	Yes
Province-industry level controls	Yes
Time FE	Yes
Industry FE	Yes
Province FE	Yes
p value for AR(1)	0.0000
p value for AR(2)	0.519
p value for Hansen Test	0.543
Number of observations	4786

Note: *, **, *** refer to 5%, 1% and 0.1% significant levels, respectively, and standard errors are in parentheses.

6 Conclusion

China has experienced remarkable growth in its strategic emerging industries during the past decade. In this paper we present China's industrial policy as one of the significant contributing factors of its rapid upgrading of strategic emerging industries.

We divide China's strategic emerging industries into two types: domestically emerging industries and globally emerging industries. Chinese firms in the former category usually lag decades behind their counterparts in the developed world, thus are restrained in technological break through by the glass ceiling set by the lead international firms, though they still enjoy the technological improvement of the whole production network. Chinese firms in the latter category usually lag years behind their counterparts in the developed world, and sometimes are even competing at the same level. That's a double edge for Chinese firms. The good part is that they won't suffer from the asymmetry of global value chain governance. The bad part is that they have to innovate by themselves as there is no role model or guideline to follow. Both the Chinese firms and OECD firms in the globally emerging industries are competing in the wild and facing the great uncertainty of failure.

As such, we argue that by patronizing firms' innovation effort from both the supply side (by the tools such as various forms of R&D subsidy) and the demand side (by the tools such as public procurement, sales rebate, etc.), a distinctive feature of China's multi-pronged industrial policy, Chinese state may stand a high chance of achieving its purpose.

Our empirical work using China's list companies in the strategic emerging industries during 2011-2020 adequately support our theoretical conjectures. Specifically, we find that China's industrial policy has significant promotion effect on firms' productivity (measured by total factor productivity) in the whole spectrum of strategic emerging industries. Moreover, we also find that the productivity promotion effects of China's industrial policy are both positive in domestically emerging industries and globally emerging industries, and the effect for the latter category is significantly larger than the former category.

Surely, industrial policy is not the unique factor that drives the booming of China's emerging industries. Take the artificial intelligence industry as an example. China's success in this field is clearly benefited not only from its industrial policy, such as loose regulation on data privacy, free data feeding by the government sponsored project (see Beraja, Yang, and Yuchtman, 2022)[17], but the international sharing of the computing platforms and algorithms, a result of decades of Free Software Movement and open source movement. Another example is China's electric car industry. Tesla shared a majority of its patents in June 2014, and Xpeng, Nio and Li Auto, three major brands of China's electric car industry today, were all established in the 2014-2015 period. It's anyone's guess that Tesla's patents played no role in the technology development of those and many other firms.

We also want to point out that China's success in the past decade is neither directly replicable by itself into the future nor by other countries in an arbitrary time period. Mao et al. (2021)[16] point out that the effect of industrial policy is contingent on the conjugation of three factors: when and where the policy is carries out, what attributes does the policy have, and what characteristics does the industry have. We believe that the theoretical and empirical analyses on China's industrial policy targeted at strategic emerging industries in this paper can provide valuable insights in interested industrial policy decision scenarios.

We use the total number of related policy documents to quantify the intensity of industrial policy on a particular industry. We also used the relative frequency of keywords in the documents as an alternative measure. However, certainly neither of them is a perfect choice. In light of the extremely complex and dynamic nature of China's industrial policy, it's perhaps a mission impossible to find a perfect measurement. Nevertheless, investigations that quantify exactly all policy instruments for a particular industry is an interesting topic for future study.

In our empirical studies we have followed the common practice to model the external forces that affect Chinese firms' productivity as time fixed effects. This of course over simplifies the complex scenarios. Exploration into the specific impact of various external drivers on the development of China's SEIs is also a promising avenue for future research.

References

[1] Daniel A Ackerberg, Kevin Caves, and Garth Frazer. Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451, 2015.

[2] Philippe Aghion, Jing Cai, Mathias Dewatripont, Luosha Du, Ann Harrison, and Patrick Legros. Industrial policy and competition. *American Economic Journal: Macroeconomics*, 7(4):1–32, 2015.

[3] Joshua D Angrist and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton university press, 2009.

[4] Philipp Boeing. The allocation and effectiveness of china's r&d subsidies-evidence from listed firms. *Research policy*, 45(9):1774–1789, 2016.

[5] Wouter Boon and Jakob Edler. Demand, challenges, and innovation. making sense of new trends in innovation policy. *Science and Public Policy*, 45(4):435–447, 2018.

[6] Brantly Callaway and Pedro HC Sant'Anna. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230, 2021.

[7] Alessandra Canepa and Paul Stoneman. Financial constraints to innovation in the uk: evidence from cis2 and cis3. *Oxford economic papers*, 60(4):711–730, 2008.

[8] Ling Chen and Barry Naughton. An institutionalized policy-making mechanism: China's return to techno-industrial policy. *Research Policy*, 45(10):2138–2152, 2016.

[9] Clément De Chaisemartin and Xavier d'Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96, 2020.

[10] Xue Gao and Varun Rai. Local demand-pull policy and energy innovation: Evidence from the solar photovoltaic market in china. *Energy Policy*, 128:364–376, 2019.

[11] Andrew Goodman-Bacon. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277, 2021.

[12] Di Guo, Yan Guo, and Kun Jiang. Government-subsidized r&d and firm innovation: Evidence from china. *Research policy*, 45(6):1129–1144, 2016.

[13] Bronwyn H Hall. Innovation and diffusion, 2004.

[14] Anthony Howell. Picking 'winners' in china: Do subsidies matter for indigenous innovation and firm productivity? *China Economic Review*, 44:154–165, 2017.

[15] Myrto Kalouptsidi. Detection and impact of industrial subsidies: The case of chinese shipbuilding. *The Review of Economic Studies*, 85(2):1111–1158, 2018.

[16] Jie Mao, Shiping Tang, Zhiguo Xiao, and Qiang Zhi. Industrial policy intensity, technological change, and productivity growth: Evidence from china. *Research Policy*, 50(7):104287, 2021.

[17] David Y. Yang Martin Beraja and Noam Yuchtman. Data-intensive innovation and the state: Evidence from ai firms in china. *Review of Economic Studies*, Forthcoming.

[18] Steven Olley and Ariel Pakes. The dynamics of productivity in the telecommunications equipment industry, 1992.

[19] Gabriele Pellegrino and Maria Savona. No money, no honey? financial versus knowledge and demand constraints on innovation. *Research policy*, 46(2):510–521, 2017.

[20] Everett M Rogers, Arvind Singhal, and Margaret M Quinlan. Diffusion of innovations. In *An integrated approach to communication theory and research*, pages 432–448. Routledge, 2014.

[21] Luc Soete. 2 1 catching up in technology: entry barriers and windows of opportunity. 1988.

[22] Robert M Solow. Technical change and the aggregate production function. *The review of Economics and Statistics*, pages 312–320, 1957.

[23] Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199, 2021.

[24] J Tinbergen. Zur theorie der langfristigen wirtschaftsentwicklung(on the theory of long-term economic growth). *Weltwirtschaftliches Archiv*, pages 511–549, 1942.

[25] Zhang Yuwang. The impact of strategic emerging industry policies on business performance(in chinese). Master's thesis, Nanjing University, 2019.

[26] Xiao Z. Causal inference in panel data with a continuous treatment. Working paper, 2022.

[27] Qiang Zhi and Margaret M Pearson. China's hybrid adaptive bureaucracy: The case of the 863 program for science and technology. *Governance*, 30(3):407–424, 2017.

Table 11: Classification of strategic new industry categories and industry types

First-level directory	Second-level directory	Industry Type[1]
New generation of information technology industry	Next generation information network industry	DEI
	Electronic core industry	DEI
	Emerging software and new information technology services	DEI
	Internet and cloud computing, big data services	GEI
	Artificial intelligence	GEI
High-end equipment manufacturing industry	Intelligent manufacturing equipment industry	DEI
	Aviation equipment industry	DEI
	Satellite and application industry	DEI
	Rail transportation equipment industry	DEI
	Marine engineering equipment industry	DEI
New materials industry	Advanced steel materials	DEI
	Advanced non-ferrous materials	DEI
	Advanced petrochemical chemical new materials	DEI
	Advanced inorganic nonmetallic Materials	DEI
	High-performance fibers and products and composites	DEI
	Advanced new materials	GEI
	New material related services	DEI
Biological industry	Biomedical industry	DEI
	Biomedical engineering industry	DEI
	Biological agriculture and related Industries	DEI
	Biomass energy industry	DEI
	Other biological industries	DEI
New energy automobile industry	New energy vehicle manufacturing	GEI
	New energy vehicle devices, accessories manufacturing	GEI
	New energy vehicle-related facilities manufacturing	GEI
	New energy vehicle related services	GEI
New energy industry	Nuclear power industry	GEI
	Wind energy industry	GEI
	Solar industry	GEI
	Biomass and other new energy industries	GEI
	Smart grid industry	GEI
Energy conservation and environmental protection industry	Energy efficient industry	GEI
	Advanced environmental protection industry	GEI
	Resource recycling industry	GEI
Digital creative industry	Digital creative technology equipment manufacturing	DEI
	Digital cultural and creative activities	DEI
	Design services	DEI
	Digital creativity and integration services	DEI
Related service industry	New technology and innovation and entrepreneurship services	DEI
	Other related services	DEI

1 GEI stands for the global emerging category and DEI stands for the domestic emriging category, see section 3.2 for details of the classification method.