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Industrial policy intensity, technological change, and productivity growth: Evidence from China

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ABSTRACT

China has employed various industrial policies and science & technology (S&T) policies in its effort of catching up with the world technology frontier. This paper evaluates the effect of China's industrial policies and S&T policies with a newly constructed measurement of policy intensity and a national database of firm surveys. We argue that whether China's industrial policies and S&T policies contribute to productivity growth in an industry is conditioned by the relative development stage of that industry to that of the world frontier. Specifically, we argue that China's industrial policies and S&T policies contribute to greater productivity growth in globally emerging high-tech industries than in domestically catching-up and domestically mature industries. We then provide empirical evidence for our hypotheses. Our study identifies a new driver behind China's economic success in the past decades.

1. Introduction

Industrial policy has had a long history (Chang, 2003; Peres and Primi, 2009). After the Second world war, most developed economies have put little emphasis on industrial policy. In contrast, many East Asian and Latin American economies (e.g., Japan, South Korea, Singapore, China, and Brazil), have ardently pursued various forms of industrial policy, with very different outcomes.

Any consensus on industrial policy, however, has been elusive.[1] Opponents emphasize government incompetence in information sifting, corruption, and rent-seeking when crafting and implementing industrial policies. Proponents tend to single out the few successful cases in East Asian. Hampered by the lack of quality data, however, neither side has had a convincing case. As a result, much of the existing literature on industrial policies has been theoretical and rhetorical, without solid empirical evidence.

As a country striving for catching up with the developed world, China has experimented with different industrial policies with a wide range of sectors over an extended period of time, with both successes and failures. This fact makes China an ideal choice for assessing the effect of industrial policies. This study takes a first step in assessing the overall effect of China's industrial policies from 2000 to 2012. Our contribution is threefold.

First, we outline a theoretical framework for understanding how industrial policy and an industry's characteristics interact to shape the effect of China's industrial policy. We begin by casting China's industries into three types according to their relative development stages versus the world's technological frontier: *Domestically Mature* industries (industries where both China and the world frontier are at the mature stage, or Type I industries hereafter), *Globally Emerging* high-tech industries (emerging new industries where China is at the ferment stage, while the world frontier is at also the ferment or take off stage, or strategic emerging industries or Type II industries hereafter), and *Domestically Catching-up* industries (industries where China is either at the ferment or take off stage, whereas the world frontier is at the mature stage, or Type III industries hereafter). We then argue that China's

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[1] E.g., Rodrik (2008), Nunn and Trefler (2010), Harrison and Rodríguez-Clare (2010), Lee (2013a & 2013b), Stiglitz et al (2013), Warwick (2013), Harrison (2014), Aghion et al. (2015). See also section 2 below.

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industrial policy contributes to greater productivity growth in Type II industries than in Type I or Type III industries.

Second, we construct an aggregate measure of China's industrial policy intensity at the four-digit industry level and combine it with a less-explored dataset on China's firm-level characteristics and productivity to empirically evaluate our hypotheses. In our benchmark econometric analysis with panel fixed effects regression and a wide range of alternative specifications, we obtain broad and consistent support of our hypotheses. Our research thus enriches the existing literature that evaluates the effect of China's industrial policy with various policy instruments (see Section 2 below).

Third, we introduce a spatial econometric model to disentangle the effects of policies into direct effects and indirect (or spillover) effects. Today's firms and industries are closely connected in productions network, industrial policy for one industry may also impact firms in other industries through linkages. It is therefore natural to ask whether the productivity gain of a firm in a particular industry is spurred by policies targeted at the industry per se or by policies targeted at other industries. We show that even after controlling for spillover effects, China's industrial policies still have significant direct effects upon the industries being targeted.

The rest of the article is structured as follows. Section 2 surveys the existing literature on industrial policy. Section 3 provides background of China's industrial policy. Section 4 outlines our theoretical arguments and derives empirical hypotheses. Section 5 introduces our data, key variables, identification strategy, and econometric models. Section 6 reports our core empirical results based on a regression-differences-in-differences design, along with a series of robustness checks and heterogeneity tests.[2] Section 7 draws implications and concludes.

2. Industrial policy and empirics: A brief review

For Warwick (2013), industrial policy is "any type of intervention or government policy that attempts to improve the business environment or to alter the structure of economic activity toward sectors, technologies or tasks that are expected to offer better prospects for economic growth or societal welfare than would occur in the absence of such intervention…" In contrast, for Chang (1994), industrial policies are "policies aimed at particular industries (and firms as their components) to achieve the outcomes that are perceived by the state to be efficient for the economy as a whole".

Apparently, Warwick's definition is "horizontal" and broader whereas Chang's definition is "vertical" (or selective) and narrower, even if we admit that "even the most 'general' policy measures favor some sectors over others" (Rodrik, 2008; Crafts and Hughes, 2013; Chang et al., 2016). Here, we opt for a narrow and selective (or vertical) definition. More concretely, we classify a policy document as an industrial policy only if it outlines some developmental goals for an industry (or industries) such as expanding capacities, encouraging export, reducing import, upgrading technologies, supporting R&D, increasing productivity, and setting other competiveness goals.

Another issue is whether S&T policies should be included as parts of industrial policy. Crafts and Hughes (2013) argue that S&T policies may also impact productivity growth hence should be regarded as integral parts of industrial policy. This is particularly true for China, as its S&T policies are patently designed for advancing its competitiveness in targeted industries. Therefore, our exercise also includes China's S&T policies as parts of its industrial policies.

Our definition of industrial policy thus includes tax breaks, tariffs, subsidies, export credits, and policies that target FDI and technology transfer. Moreover, our definition of industrial policy also includes S&T policies, which have traditionally been left out of the existing literature on industrial policies (see also Harrison and Rodríguez-Clare 2010).

Although the debate on industrial policies might have been raging on since Alfred Marshall, much of the discussion has been more theoretical. Despite some outstanding in-depth case studies (e.g., Amsden, 1989; Haggard, 1990; Wade, 1990), solid econometric evidence on the effect of industrial policy has been lacking, due to the lack of quality data.

More recently, with the availability of better data on industrial policies, econometric studies on the effect of industrial policies have become more visible. For example, examining tariff structures from 63 countries, Nunn and Trefler (2010) find that tariffs that protect skill-intensive sectors are positively correlated with long-term GDP growth. Nunn and Trefler, however, do not engage with the broader debate on industrial policy, and tariffs are only one instrument of industrial policy.

Turn to China-specific studies, Boeing (2016) 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 but are neutral in later periods. Interestingly, Boeing (2016) also uncovers that this "crowding-out effect is not prevalent for repeated recipients of R&D subsidies, high-tech firms, and minority state-owned firms." (See also Boeing et al., 2016) Guo et al. (2016) studies the effect of a particular government support program (Innofund) upon small to medium Chinese firms and concludes that firms supported by the fund tend to produce more innovations than firms not supported. Interestingly, Guo et al. (2016) also observes that decentralization in the allocation of the Innofund significantly improves the performance of the fund and its supported firms. With a structural innovation approach, Howell (2017) scrutinizes the effect of public subsidies (as an integral component of China's industrial policies) upon several dimensions of innovation by Chinese firms with panel data from China Annual Report of Industrial Enterprise (2001 to 2007). He discovers that public subsidies promote innovation in the higher technology industries but hinders economic performance in both lower and higher technology industries.[3] More recently, with a panel of manufacturing firms from 2008 to 2011 from China's State Administration of Taxation, Chen et al. (2020) investigates the effect of income tax cuts for R&D investment by firms (above certain thresholds) upon firms' R&D expenditures. These authors find that despite the fact that relabeling accounts for 24.2% of the reported R&D, firms' productivity increases by 9% when their real R&D doubles.

Several recent studies are more relevant to ours. Aghion et al. (2015), using data from China that are different from ours, reports that "industrial policies allocated to competitive sectors or that foster competition in a sector increase productivity growth." Due to the lack of systematic data on China's industrial policy, however, Aghion et al. (2015) mostly focuses on trade policies such as tariffs, export subsidies, FDI policies, and tax holidays (see also Du et al., 2014). While trade policy is certainly an important component of China's industrial policy, it is only part of it (for a recent review, see Harrison, 2014).

Kalouptsidi (2018) tries to gage the magnitude of the Chinese government's subsidies to its shipbuilding industry and then measure the effects of these subsidies. She 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. Her study, however, is limited to one particular sector and its implications are necessarily limited.

Taking advantage of the unique econometric opportunities provided by South Korea's "Heavy Chemical Industry (HCI)" drive under Park Chung-Hee (1973–1979), Lane (2019) examines both HCI's short-term

[2] Additional robustness checks, supporting background information, and technical details such as spillover estimation and TFP estimation are reported in the online supplementary materials.

[3] To some extent, Howell's (2017) results corroborate our own results. See also Howell (2020).

and long-term effects with a difference-in-difference method. Lane finds that the HCI, as a classical "big-push" industrial policy, "significantly shifted [Korea's] economic activity to capital-intensive industry, a shift which continued after the interventions were retrenched [after Park was assassinated in October 1979]." Overall, Lane estimates that "real output of industries targeted by the HCI big push grew 80 percent more relative to non-targeted manufacturing industries during the policy period." He also finds that HCI had a strong positive effect upon industries with forward linkages with industries targeted by HCI and a weak negative effect upon industries with backward linkages with industries targeted by HCI. Echoing earlier qualitative studies (e.g., Amsden, 1989; Haggard, 1990), Lane concludes that HCI drive had a long-lasting and positive impact upon South Korea's economic development, both directly and indirectly (cf. Lee, J. W., 1996).[4]

Our study extends those of Lane (2019), and to a lesser extent, Aghion et al. (2015), and Kalouptsidi (2018). However, our study differs from them in three key aspects.

First, rather than considering the effect of particular policies targeted at one or a few industries, this paper examines a wide range of industries (72 four-digit code industries in total) heavily favored by China's industrial and S&T policies, which include not only low-tech industries (e.g., textiles, iron and steel), but also medium-to-high skilled ones (e.g., basic chemicals, machinery), and high-tech "strategic emerging industries" (hereafter, SEIs) (e.g., computer related manufacturing and services, mobile telecommunication, biotech).

Second, to our knowledge, we are the first in bringing S&T policies into the empirical literature on industrial policies. In fact, China's top decision-makers have explicitly identified industrial policies and S&T policies as two mutually reinforcing pillars of achieving technological catching-up. In contrast, previous studies have tended to focus on either industrial policies or S&T policies alone (e.g., Boeing, 2016; Boeing et al., 2016; Chen and Naughton, 2016; Guo et al., 2016; Howell 2017; Zhi and Suttermier, 2014; Zhi and Pearson, 2017). We find this synergy between (traditional) industrial policies and S&T policies to be a key cause behind China's rapid technological catching-up.

Third, we advance a new theoretical perspective for evaluating the effects of industrial policy. We hypothesize that the type of the targeted industry is a critical factor that conditions whether a country's industrial policy can succeed or not. In particular, we single out an industry's relative development stage to the world's technological frontier as a key factor.

3. China's industrial policy: A brief background

China has a long history of economic planning. When crafting its industrial policy in the post-1978 period, China has mainly followed the selective model of its East Asian neighbors (Japan, Singapore, and South Korea). More concretely, a number of industries were first selected and then different packages of policy instruments were employed to help the targeted industries achieve their competiveness goals.[5]

In 1986, China began to adopt a more ambitious approach regarding industrial policy that closely followed the "national innovation system" in OECD countries (Lundvall and Borrás, 2006). China's program targeting SEIs, as dictated by successive initiatives known as "863 plan" (also known as "National High-tech R&D Program", released in March 1986), "973 plan" (also known as "National Key Basic Research Program", released in March 1997), and "Medium and Long-term Plan for Science and Technology (2006–2020)" (released in March 2003) were explicit in its method of picking key technologies and industries: closely following those identified by leading economies such as OECD countries (Chen and Naughton, 2016; Zhi and Pearson, 2017).[6] The initiatives on SEIs thus have been specifically designed to promote rapid technological catching-up and even leapfrogging by Chinese industries and firms to "seize the commanding heights of the new technological revolution" (Wan Gang, minister of Ministry of Science and Technology, MoST hereafter, quoted in Chen and Naughton, 2016).

Under Premier Zhu Rongji (1998–2003), economic planning, including industrial policies, took a brief hiatus in part because the central task of the government was to promote a more market-based economy and rein in hyperinflation. Under Premier Wen Jiabao (2003–2013), however, a dramatic revitalization, institutionalization, and rationalization of industrial policy and S&T policy resulted.[7] Several aspects are notable.

First, the organizational apparatuses for economic planning, including crafting industrial policy, were streamlined. In particular, a powerful super-planning agency, the National Reform and Development Commission (NDRC), was created. A central task for the NDRC is to initiate and coordinate major industrial and economic policies among different ministries (e.g., Ministry of Education, Ministry of Finance), other government agencies (e.g., the central bank, and state-owned commercial banks), and industries. In addition, a new and more powerful Ministry of Science and Technology (MoST), in charge of crafting S&T policies, was also created. Moreover, industrial policies and S&T policies that were previously decoupled under Primer Zhu Rongji became much more closely coordinated.

Second, processes of policymaking were also more institutionalized and streamlined. MoST is responsible for initiating and drafting S&T policies by consulting with scientists. Meanwhile, although the top leadership has the final say, NDRC is responsible for initiating and drafting industrial policies by gathering input from scientists, economists, local governments, and other ministries. Moreover, key policies, such as the Medium and Long-term Plan for Science and Technology (2006–2020) and the SEIs initiatives, were to be issued by the top leadership and to guide overall industrial policy for a significant period of time. All these measures have ensured policy continuities within a significant time horizon.

Our data on China's industrial policies and S&T policies cover this crucial period of more intensive and ambitious industrial policy and S&T policy in China (2000–2012). China at the start of this period was still a developing country with limited resources. As such, China's industrial policy was very selective: only a handful of industries were selected for policy intervention, and the majority of others were largely skipped. What are these policy-focused industries? We sift them out using the Government Document Information System database (Huang et al., 2015), which includes all the policy documents issued by China's governmental agencies at the ministry level and above (e.g., the State Council).[8] Specifically, for each year from 2000 to 2012, we first screened for documents of industrial policy using keyword searching and machine matching. We then verified them by reading and coding the actual documents. Our finest level of industry classification is the four-digit code system of the National Bureau of Statistics (NBS) adapted

[4] Somewhat relatedly, Liu (2019) develops a model of industrial policy situated in production networks and deduced that a state may have valid rationale to subsidize upstream sectors. He then went on to show that this has indeed been the case for both South Korea in the 1970s and contemporary China. Yet Liu did not provide any empirical evidence for the question of whether industrial policies by South Korea and China have had any positive effects upon targeted industries.

[5] Only recently has China begun to experiment with horizontal industrial policies (Jiang and Li, 2018).

[6] For instance, the "863 Plan" was explicitly modeled after Europe's Eureka initiatives and United States' "Strategic Defense Initiative" (i.e., "Star Wars") under Ronald Reagan.

[7] This part of our discussion draws from the more detailed discussion by Liu et al. (2011), Heilmann and Melton (2013), and Chen and Naughton (2016).

[8] The dataset actually contains all documents after 1952. Because the data for our key dependent variables (i.e., firm level performance) run to 2012 only, we only utilize the policy data from 2000 to 2012 in our analyses.

from the ISIC Rev.3 coding standard (for additional details on data, see online supplementary material B). For each verified industrial policy document, we sort out which four-digit industries are specifically cited as policy targets in the document. Eventually we have a list of 72 four-digit industries that are specifically targeted in the industrial policy documents.[9] The main purpose of this paper is evaluate the performance of China's industrial policy on these targeted industries with theoretical framework and empirical validation.

4. Theory and hypotheses

We now outline a theoretical framework for explaining why and when China's industrial policies may succeed or fail. Our central argument is that the effect of industrial policy on an industry's productivity growth depends on (1) the timing of a policy, (2) the attributes of a policy; and (3) the attributes of the industry. Our theoretical arguments center on how these factors shape the possibility of catching up via innovation by firms in different industries.

Our argument combines and extends the arguments advanced by Lee and Malerba (2017) and Pellegrino and Savona (2017). The former stressed that within any specific industry, three sets of factors (technological, demand, and institutional/policy) affect the catch-up cycles of the industry whereas the latter argued that both financial and non-financial factors (e.g., knowledge and demand side factors) are critical in shaping firms' innovation efforts even though much of the existing literature focuses on financial obstacles. We also draw elements from Lee's (2013a) notion of "short-cycle technology sectors" (i.e., sectors in which the pace of technological change is more rapid).

Our research focuses on the period of 2000–2012, the maximum period that we are able to collect our empirical data for this study. By 2000, China has experienced with market reform for more than two decades and successfully integrated into the global production network for more than a decade. Yet China's per capita GDP in 2000 was only $1768 (in 2010 constant USD), about one twenty fifth of that of the United States then. In 2000, therefore, China was clearly a developing country in its catching-up stage, i.e., on average its technology has risen appreciably from the bottom but is still far from the world's technology frontier. We reason that the relative development stage of China's industry with respect to the world frontier plays a key role in determining the effectiveness of China's industrial policy.

According to the S-curve theory, the life cycle of an industry's technological development has three stages: ferment, take-off, and maturity (Rogers, 2003; Hall, 2005; Papazoglou and Spanos, 2018). Combing the S-curve theory with the fact that technologies in developing countries often lag behind those in developed countries, we can then classify industries in a developing country such as China into three types according to their development stage relative to that of the industrial world frontier: (1) Domestically Mature (Type I), for which the industry of China and that of the world frontier are both at mature stage; (2) Globally Emerging (Type II), 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; and (3) Domestically Catching-up (Type III), 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 (Table 1A provides a simplified characterization of the distribution of China's industries relative to the world frontier).

Domestically mature industries (Type I) are thus industries with low technological entry barrier and slow technological progress. Examples include food catering, textile, shoes, iron and steel, and others. In these industries, the most critical competitive edge is labor cost and logistics.

Globally emerging industries (Type II) are the emerging high-tech industries that are at the world technological frontier with a rapid pace of technological change: they are what Lee (2013a) called "short-cycle technology sectors".[10] Importantly, both OECD and China have identified these industries as "strategic emerging industries". Examples of globally emerging industries include biotech, telecommunication equipment, computer manufacturing, computer systems and services, data processing, electronics, software and services, mobile telecommunication, and satellite imaging and transmission.

Domestically catching-up industries (Type III) include the majority of the medium-to-high skilled manufacturing industries in which China has gained substantial technological improvement since its Reform and Opening-up in 1978 but is still far off the technological frontier. Examples of domestically catching-up industries include basic chemicals, special chemicals, boilers, metal-working machinery, bearings, gears, ovens and smelting furnaces, weighing and packaging equipment, electricity transmission and distribution, and switch and control equipment. (Table 1B displays the list of industries in our sample.)

The ideal goal of industrial policy is to promote productivity (and hence competitiveness) of firms in targeted industries. Since productivity improvement is underpinned by successful innovation, industrial policy should aim to reduce obstacles of innovation, which can be either financial or non-financial, or from the supply side or the demand side. Below, we address a factor that is widely discussed (i.e., financial support) and three others that have received less attention (i.e., technological limit, glass ceiling, and creating market demand).

Much of the existing literature is centered upon the traditional investment cash-flow model, focusing on the relationship between financial constraints and firm's R&D investment (see Hall, 2008 for a review). Briefly, due to the high uncertainty, asymmetry and risk of the return of R&D, firms facing financial constraints are less likely to engage and succeed in innovation (Savignac, 2008). Here is where financial support provided by industrial policy (such as subsidies and tax credits) kicks in. In a nutshell, financial support reduces marginal cost, and a full or partial pass-through of cost reduction to output prices will result in lower prices, while mark-ups per product are at least not reduced.

However, whether financial support translates into significant productivity growth is contingent on the financial constraint faced by the firm. If a firm is financially constrained, financial support leads to technological upgrading because the support reduce the marginal cost of R&D and the profit margin increases. A firm that is not financially constrained, however, may not enhance its R&D and no productivity growth results despite support.

Non-financial obstacles are just as important as financial ones in constraining firms' innovation effort (Pellegrino and Savona 2017). Technological limit is perhaps the most obvious non-financial factor that constrains innovation, and the three types of industries in developing countries such as China face different technological incentives and constraints.

Domestically mature industries have been in existence for centuries and the technology level of these industries has approached a natural limit, rendering the return of additional R&D efforts immaterial. With financial support, firms in domestically mature industries mostly increase physical output and seek to capture a greater market share rather than invest in R&D for technological innovation. In contrast, with financial support, firms in both domestically catching-up and globally emerging industries have more incentives in investing in R&D, because technologies in these industries still have significant room for

[9] A four-digit industry is targeted in a policy document if it is directed cited in the document. If a four-digit industry is not cited or is only indirectly cited, we deem it not targeted. By indirect citation we mean that a broader category of industries which contains the four-digit industry is cited. For example, "manufacturing" is a broad category that contains textiles (1810), clothing (1820), etc.

[10] Lee's (2013a) notion of "short-cycle technology sectors", however, is broader than our notion of SEIs here. In this paper, we will use Type II industries and SEIs interchangeably.

improvement.

Another non-financial factor to firms' innovation comes from the power asymmetry within the structure of the global value chains (GVC). This is particularly true for domestically catching-up industries, which are typical GVC industries. While Chinese firms in these industries are an integral part of the global production network, the GVCs of these industries are dominated by leading firms in developed countries.

Consider the innovation process in a globalized production network, organized by a lead firm in a developed country in the form of such as FDI with a host developing country. The lead firm divides the whole production process into two parts: the less profitable and low-skilled part versus the more profitable and high-skilled part. The lead firm assigns the low-skilled part to a follower firm in the developing country, which will follow the instruction and protocol to finish the assigned tasks. The lead firm retains the high-skilled part. At first, firms in developing countries are far behind in technology and can only perform low-skilled tasks with low productivity. To facilitate the whole production process, the lead firm shares some of the technology know-how of the low-skilled tasks with the follower firms, but keeps its core technological know-how and innovation efforts for the high-skilled tasks as business secret. Nevertheless, the follower firms, once acquired the technology know-how of the low-skilled tasks, can engage in innovation toward the high-skilled tasks and become the competitors of the leader firm, and the lead firm knows this possibility.

In the beginning, China's firms were at very low level of technological stage. After joining the production network, China's firms will receive some transfer of technologies and trainings from the lead firms. The productivity of China's firms can rise swiftly.

The follower firms in China, however, may soon approach a technological ceiling that is hard to break through. On one hand, the technology embedded in the low-skilled part is mostly mature and has very limited room of improvement. Significant productivity increase has to come from moving from low-skilled tasks to high-skilled tasks, which require substantial effort in innovation. Because follower firms have yet to conduct indigenous R&D, however, they lack the capacity for indigenous innovation.

On the other hand, envisioning follower firms as potential competitors, a lead firm typically erects implicit barriers (e.g., changing the standard of product) to protect its core competitiveness advantages. Such barriers are termed *glass ceilings*, and they exacerbate the difficulty of the follower firms' innovation breakthrough (Gereffi et al., 2005; Phillips, 2017; Lema et al., 2018).

For follower firms in domestically catching-up industries, therefore, industrial policy instruments such as subsidies may lower some innovation barriers but are unlikely to be a game changer. Lead firms generally have more latitude than the host country and follower firms. For example, the lead firms may choose to relocate the low-skilled tasks to another developing country which is willing to offer better terms.

The situation for globally emerging industries is different. There exists little well-established task-segmentation within these industries. Most critically, 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 bet right whereas firms in developed countries bet wrong, Chinese firms can not only catch up with but also leapfrog over firms in developed countries. This is no fantasy. Samsung and Lucky Goldstar (LD) bet correctly on digital TV whereas Sony and Toshiba bet wrong with high-definition analog TV, and the result has been that South Korea has now dominated the entire high-resolution display sector (Lee, 2013a). The fate of Kodak and Polaroid versus digital camera tells a similar story.

Because globally emerging industries are all high-tech ones, firms in this type of industries in China have more potential for productivity growth than firms of domestically catching-up or domestically mature industries. Also, without successful lead firms to follow, or even if there is, the rapid pace of development in globally emerging industries makes it imperative for 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 now stand a better chance of making a breakthrough.

Nevertheless, the likelihood of innovation success for firms in globally emerging industries relies critically on market demand (Canepa and Stoneman, 2008; Gao and Rai, 2019). Lack of demand is an important non-financial obstacle to firm innovation (Pellegrino and Savona, 2017; Boon and Edler, 2018). This is especially severe for globally emerging industries 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.[11] 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 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), such double-whamming policies (i.e., both supply and demand) might have been decisive.

To summarize, our theory suggests that due to the interaction of both supply side and demand side factors, 1) for domestically mature industries, industrial policies are essentially inept for productivity growth; 2) for domestically catching-up industries (i.e., medium-to-high-tech industries with its GVCs dominated by developed countries), industrial policies have only limited effect on productivity growth; and 3) for globally emerging industries, industrial policies are the most effective for productivity growth.

The above theoretical derivation leads to two empirically testable hypotheses regarding the different effects of China's industrial policy across different targeted industries.

Our first hypothesis is that among all China's targeted industries, its industrial policy will have lesser effect on firms' productivity for domestically mature industries than for globally emerging and domestically catching-up industries.

H1. : Ceteris paribus, among all targeted industries, China's industrial policies that target its domestically mature (i.e., Type I) industries will have lesser effect upon productivity growth than its policies that target its globally emerging (i.e., Type II) and domestically catching-up (i.e., Type III) industries.

Our second hypothesis is that China's industrial policy will have larger effect on firms' productivity for globally emerging than for domestically catching-up industries.

H2. : Ceteris paribus, among all targeted industries, China's industrial policies that target its globally emerging (i.e., Type II) industries will have a greater positive effect upon productivity growth than its policies that target its domestically catching-up (i.e., Type III) industries.

[11] Costantini et al. (2015) and Gao and Rai (2019) provide supporting case evidence for this possibility, focusing on the biofuel industry in 35 economies and the photovoltaic industry in China, respectively.

5. Sample, data and method

5.1. Sample and data

5.1.1. Sample

To test our hypotheses, we need data for three types of variables: independent (i.e., treatment) variables, dependent variables, and control variables.

Our key independent variables should capture the aggregate magnitude or intensity of China's industrial policy across industry and time. For this, we have constructed an original dataset that contains yearly observations of China's industrial policy intensity for 72 four-digit industries from 2000 to 2012. This dataset is based on the Government Document Information System database, as mentioned in Section 3.

We categorize the 72 four-digit industries into three types according to the type definitions in Section 4 (Table 1A). Within the 72 industries, 9 belong to Type I (with the first two-digit codes of 18, 32, and 67), 20 to Type II (with the first two-digit codes of 26, 27, 40, 60, 61, and 62), and 43 to Type III (with the first two-digit codes of 26, 35, and 39). In total, we have coded 6533 policy documents. On average, 78 policies are issued to a single industry annually over 2000–2012, in which about two are issued at the level of China's State Council or above (i.e., the highest level of the decision-making bodies in China), 12 by MoST or NDRC, and the rest by other ministries or ministry-level agencies. Of the 78 policies per year on average, 62 policies are issued by a single agency, while 16 are jointly issued by multiple agencies.

For our dependent variables, we rely on the *National Tax Survey Database* (NTSD), jointly developed by China's State Administration of Taxation and Ministry of Finance in 1985 for the purpose of collecting tax-related information from firms across the country. NTSD provides essential information on our dependent variables and control variables.

NTSD's data before 2005, however, are not so useful because both the sampling methods and the indicators were experimental and changed frequently. In 2005, NTSD finally settled down with a fixed sampling method and a set of indicators. We therefore use the data in NTSD from 2005 to 2012. During this period, nearly 120,000 firms are randomly sampled from the nationwide pool of taxpayers every year, using stratified random sampling.[12] These firms represent about 10% of the annual total output and tax revenues in China, and 48% of the firms sampled are in the manufacturing sector; 45% in the service sector; and the rest in agriculture (1%), mining (2%), and construction (4%).[13]

Aside with stable sampling and indicators, NTSD from 2005 to 2012 are also less likely to suffer from misreporting. Since 2005, after stratified and randomly sampled annually, the subjects (i.e., sample firms) are required to use a specific electronic system for submitting information of survey, and the electronic system is equipped with some built-in functions automatically checking completion and accounting consistency of the information filled in by the surveyed firms. In the meantime, local tax bureaus supervising these surveyed firms are responsible for completion and quality of the survey. Before presenting the information of survey to the final NTSD, local tax officers in charge of the survey are asked to do additional checks such as comparing the survey data with tax return files of the firms filling the survey forms, and misreporting information will greatly raise risk of the firms being audited.

The NTSD dataset is different from the more widely used Annual Survey of Industrial Firms (ASIF) or officially *China Industrial Enterprise Database* (CIED) and the *China Economic Census Database* (CECD) produced by NBS.

The CECD dataset is reported every five years, which renders it far less fine-grained and useful for our purposes here. The NTSD dataset also has several key advantages over the CIED dataset. First, whereas the CIED dataset covers only manufacturing firms, the NTSD dataset covers all sectors, including high-tech service sectors such as satellite data transmission, which is of critical interest to us. Second, the CIED dataset is a censored dataset: it includes all SOEs but only non-SOEs with five million RMB annual sales or more. In contrast, the NTSD dataset is compiled by a stratified random sampling method and covers firms of all sizes. The NTSD dataset is thus much more representative than the CIED dataset. Also, as shown by Bai et al. (2014), a censored dataset has important drawbacks for statistical estimation. Third, the NTSD dataset is an annual dataset that covers 2005 to 2012, which is the critical period for our empirical investigation. In contrast, even though the CIED dataset is an annual dataset, most scholars use the CIED data only from 1998 to 2007 because its quality after 2007 is suspect.[14]

Liu and Mao (2019) used the same NTSD data from 2005 to 2012 to explore the effect of China's VAT reform on firm investment and productivity. Section 2 of their paper introduces the process of survey in detail.

5.1.2. Key independent variables

Our key independent variable is the intensity of the industrial policy, measured as the weighted number of industrial policies received by an industry in a given year (i.e., *number_w* in our econometric exercises below).

We acknowledge that (weighted) policy number is not a perfect measure of the magnitude of China's industrial and S&T policies, as different policies may have different goals and instruments. To corroborate our results, we therefore also use the subsidy, one particular type of industry policy, in our econometric analysis.[15] There is a weak positive correlation between the weighted number of policy and the amount of subsidy (the Pearson correlation coefficient is 0.063), suggesting that there is indeed a positive relationship between the two.

However, subsidy or other forms of financial support is just one instrument of China's industrial policy package and only addresses the supply side. As argued above, both supply side instruments such as subsidy and demand side instruments such as public procurement contribute to firms' productivity change. A narrow focus on financial support may miss a larger chunk of reality and actually hinder our understanding of China's industrial policy instruments (see section B3 of the online supplementary material B for a detailed introduction). Based on these considerations, we believe that the weighted number of policies (i.e., policy intensity) is a reasonable proxy for uncovering the systematic effect of China's industrial policy, at least for the critical first step we are now undertaking.

We construct our key independent variable as follows. First and perhaps unsurprisingly, most China's policy documents address several industries rather than a single industry. We count each mentioning of an industry in a policy document as a policy toward that industry. As a result, the 6533 policy documents we have coded contain more than

[12] Firms are stratified into deciles, according to their total sales. Firms are then randomly sampled and required to provide relevant information through an electronic system. The system will only let a firm pass until the firm has submitted complete and adequate data. Such a rigorous procedure provides quite robust proofs against incomplete, inadequate, and even fabricated data.

[13] The composition of industries within the NTSD database has been stable over time and is consistent with the overall industrial structure in China. For instance, with data from the NBS of China (http://data.stats.gov.cn/easyquery.htm?cn=C01), from 2005 to 2012, the average share of the secondary sector (mainly the manufacturing) and that of the tertiary sector in gross domestic production have been 46.35% and 43.44%, respectively. The distribution of firms in our sample matches these figures quite closely. The proportion of firms from the agriculture sector is low because China abolished most of the taxes in agriculture in 2006.

[14] This explains why even very recent studies only use data from 1998 to 2007 (e.g., Hsieh and Song, 2015).

[15] Indeed, as indicated by several key industrial polices, subsidy is often secondary to market support such as governed procurement and R&D tax rebates. Information available from authors upon request.

12,611 policies targeting different industries. Second, China's bureaucracy is hierarchical, just like any other state. In a highly centralized state such as China, industrial policies issued by agencies with higher bureaucratic ranking carry more political weight and economic power than those issued by agencies with lower raking.

We rank the agencies that promulgate industrial policy according to three levels. The first level includes the Politburo of the Chinese Communist Party (CCP), the CCP's Central Committee, and the State Council. These three organs occupy the top echelon of state power in China. Although policies issued by them will be relatively few, they should carry the most weight. The second level includes NDRC and MoST because these two agencies are the main agencies that craft industrial policy. As a result, firms and local governments pay great attention to policies issued by these two agencies. The third level includes all other ministries or agencies of the central government (e.g., the Ministry of Commerce, Ministry of Finance, People's Bank of China). Although policies issued by these agencies are also important, they are mostly derived from the industrial policy issued by the State Council, NDRC, or MoST.

For simplicity, we assign a weight of three to a policy issued by agencies at the first level (e.g., the State Council), two to a policy issued by agencies at the second level (i.e., NDRC or MoST), and one to a policy issued by agencies at the third level. The value of *number_w* is thus the weighted sum of the number of policies received by an industry in a given year.[16] In our robustness checks, we also use the original (i.e., unweighted) number of the policy (variable: *number_o*) or the number of policies from NDRC/MoST as alternative explanatory variables to verify our main results. Our results hold throughout the robustness analyses.

Consistent with our theory, Type I industries should have the fewest number of policies. In contrast, both Type II and Type III industries should have been given priority by policymakers. Moreover, because more of China's industries belong to the Type III category, more policies should have been directed toward Type III industries than Type II industries. In our limited sample, we have picked those Type I and Type III industries that have received substantial policy attention but left out those that have received little policy attention.

Within this limited sample, if we can show that policies targeting Type II industries have a more powerful positive effect upon firms' TFP from Type II industries than policies targeting either Type III or Type I industries, our results should be all the more convincing. The left out industries are mainly Type I industries or Type III industries that are not essentially different from the included Type I and Type III industries in terms of technological complexity. It is unlikely that the productivity growth of firms in the excluded industries would be higher than firms in the included Type I and Type III industries, if equal policy intensity were applied to the excluded industries (as the included industries). Rather, it might be more plausible that firms in the excluded industries were less responsive to industrial policy interventions (imagine that policy makers may have learned from past experience or experience from other countries that only certain industries are responsive to industrial policy). Therefore, if we were to use the whole sample, it's likely that the estimated positive effect of industrial policy on TFP growth by Type II industries would be more significant when compared to Type I and Type III industries. Therefore, more likely than not, the results reported below may underestimate other than overestimate the positive effect on Type II industries of China's industrial policy.[17]

5.1.3. Dependent variables

Our key dependent variable for capturing firms' performance is firms' TFP, the most direct measure of productivity. Besides TFP, we also use output (e.g., sales) and investment (i.e., fixed assets) as alternative indicators for firms' performance in our robustness checks.

TFPs are estimated from firm level production data and relevant price data. The former are available in NTSD, while the latter come from NBS' annual *China Statistics Yearbooks* and the 122-sector input-output sheet issued in 2002. These two datasets provide key information on industry-level price indices such as output, fixed-asset investment, and province-industry growth rate of capital stock. These indices are essential for netting out the impact of inflation and estimating TFP by adjusting a firm's book capital. All other dependent variables and control variables are all from NTSD.

We perform some data cleaning before estimation. First, because China changed its 4-digit industry codes in 2011, we unify the pre-2011 industry classification codes and the post-2011 codes by converting the latter into the former. Second, we unify the administrative codes for firms' locations (mainly counties), which have experienced changes, to the 2007 standard codes.[18] Third, we drop problematic observations, such as those with missing or nonsensical values in terms of firms' age, assets, output, and number of employees. Fourth, we treat (i.e., "winsorize") outliers in our key variables that are within 1% of the top or bottom of the sample by using the *winsor* command in STATA. We calculate the TFP values with three methods: Olley-Pakes (OP) (Olley and Pakes, 1996), the Levinsohn-Petrin (LP) (Levinsohn and Petrin, 2003), and OLS (i.e., Solow residuals), with related variables deflated by a series of price indices (for details, see section B1 of the online supplementary material B and Liu and Mao 2019).[19]

5.1.4. Control variables

We control for a host of firm-specific, industry-specific and province-industry-specific control variables in our baseline models and robustness checks.

Our benchmark firm level controls include the following basic characteristics: (1) firm age; (2) firm ownership types, include whether the firm is state-owned or not, whether the firm is foreign or not, whether the firm is owned by capitals from Hong Kong, Macao or Taiwan or not, whether the firm is incorporated or not, whether the firm is a domestically owned private firm or not, and whether the firm is of other domestic firm; (3) whether the firm has benefited from the value-added tax (VAT hereafter) reform from 2004 to 2009, as well as whether the firm has been benefited from the corporate income tax (CIT hereafter) reform in 2008, two major reforms that have surely impacted firms' overall performance (for details of these two reforms and our

[16] The fact that policies issued by different agencies not only overlap with (and often reinforce) each other but also carry different weight means that using dummy variables to capture the different policies is not a tenable option. Because results with the weighted number of policies are easier to interpret, we report them in the main tables. In our baseline specification, we do not use the natural log of the weighted number of policies as the key explanatory variable for two reasons. First, compared to the coefficients in front of the natural log of the weighted number of policies, the coefficients in front of the weighted number of policies are much easier to interpret, i.e., to what extent a firm's performance will change due to a one-unit increase in the weighted number of policies. Second, it will cause loss in observations if we use the natural log of the weighted number of policies, as some industries in some years received no policy. To avoid loss of observation in these years, we can make zero into one and then take the natural log, but doing so may lead to other biases.

[17] Hence, examining all the industries will require far more effort, without necessarily adding much insight.

[18] From 1994 to 2012, about 670 county-level regions and areas (out of nearly 3,000 total) in China changed their area code.

[19] We use the same methods as those in Liu and Mao (2019) to calculate firm level TFP. Briefly, when estimating TFP, we deploy real values of variables including output (i.e., total sales), valued added, capital stock (i.e., net value of fixed assets), investment (i.e., current increase in fixed assets), the number of employees, wage, and intermediate input. First, we provide price indices for output and input, which are necessary for acquiring real values of the key variables required in TFP estimation. Second, we calculate firm-year adjusted capital stock using the standard method of Brandt et al. (2012). For details, see the online supplementary material B of this study, as well as Appendix B of the online appendix in Liu and Mao (2019).

coding, see online supplementary material B),[20] and additional control variables such as R&D investment expense, firm size, and exports.

To untangle policy effects on productivity from market power, we also control for the markup, a widely used measure of market power. The firm-level markup is calculated as the ratio of the output elasticity for a variable input to input revenue share (De Loecker and Warzynski, 2012). We use materials and intermediate inputs as our variable inputs, as these inputs can be adjusted more flexibly than capital or labor. The output elasticity of inputs is computed using the estimated coefficient of production function, and we adopt the semi-parametric approach developed by Olley and Pakes (1996) to estimate the production function. The input revenue share is the ratio of expenditure on intermediate materials to total revenue, which represents the marginal cost of production. The intuition behind the calculation is that the output elasticity for a variable input should equal its corresponding expenditure share in total revenue (i.e., markup equals one) when the market is perfectly competitive (and so price equals marginal cost).

Industry-level controls consist of industry-level characteristics that capture industry agglomeration. Specifically, we divide all provinces in China into four regions (east, central, west, and northeast), and use the shares of an industry's total sales in these regions (among the total sales of the industry of all four regions) as indicators, and we use the share in East China as the reference group, meaning only three shares will be used in the regression.

Controls at the province-industry level consist of a number of province-industry average characteristics and performance, including the province-industry average size (measured as total assets), profitability (measured as return on assets), debt-asset ratio (i.e., a firm's total liabilities versus total assets), R&D spending, and province-industry average performance (TFP, output, and investment). These variables are calculated by averaging firm-level data within the same two-digit industry and the same province. We label these controls collectively as "born advantages" (for a particular industry within a particular province). When calculating the competition pressure faced by a firm, we exclude the firm itself.[21]

Our whole sample consists of 54,263 observations from 2005 to 2012, in which Type I, Type II, and Type III industries make up 26.46%, 14.19% and 59.35% of the total observations, respectively. Summary statistics for the dependent variables, independent variables and control variables are reported in Table 2.

5.2. Econometric strategies

To identify the effect of China's industrial policy on firm productivity (and output and investment), we use a regression-differences-in-differences (RDID) with panel data (See Section 4.3). We believe that the regression coefficients of our benchmark models are reliable estimates of the treatment effects of industrial policy, for the following reasons.

First, there is substantial degree of exogeneity of China's industrial policy which largely rules out selection bias and reverse causality. By definition, industrial policy cannot possibly be random treatment.

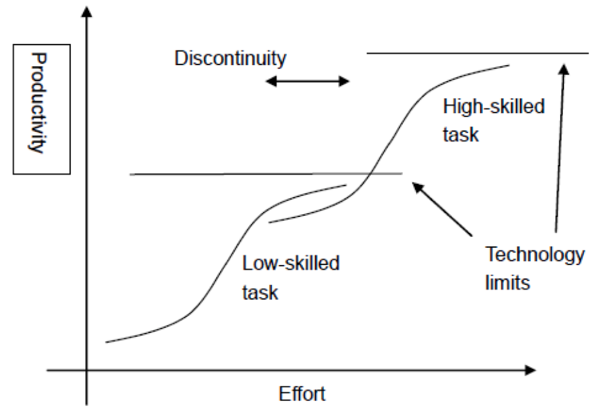

Fig. 1. S-curve for Type III industries.

However, most of China's industrial policy has been drafted by bureaucrats with extensive consultations with scientists and economists, with little input from industries and firms. This is especially true for Type II industries (Liu et al., 2011; Zhao, 2012; Zhi and Suttmeier, 2014; Chen and Naughton, 2016; Zhi and Pearson, 2017). Moreover, when picking SEIs, China essentially follows OCED's lead (see fn. 4 above).

Most importantly, most Type II industries (i.e., SEIs) simply did not exist in China before China's industrial policy came along to target these industries. For instance, before 1994, wind turbine manufacturing in China was non-existent. Yet, with major policy initiatives between 1997 and 2007, China has since created a wind turbine manufacturing industry that now dominates the world market (Ru et al., 2012). The same can be said about electric car, high-speed train, mobile phone, solar panel, and LED display. Thus, China's industrial policy toward SEIs has really attempted to "create" these industries from scratch.[22]

The lack of treatment selection bias is supported by data. If there were selection bias, we would see industries with higher levels of productivity to receive more or less industrial polices. This is not the case. Most evidently, Type III industries, which have received the highest level of industrial policy treatment, only have a medium level of average productivity. Formally, the correlation coefficient between the industry-level policy intensity and the previous year industry level TFP is 0.07. This suggests only weak if not negligible treatment selection bias.

Second, because the above exogeneity argument is only suggestive, we control for a large list of potential confounders in our econometric exercises in order to achieve reliable identification. Thanks to the rich panel data structure with cross-industry, cross-region, and cross-time observations, we are able to control a long list of factors (both observable and unobservable) in our RDID design to alleviate the potential omitted variables bias.

Specifically, we control for firm/industry level time-invariant fixed effects, time fixed effects, besides a list of firm level characteristics, industry level characteristics, and provincial-industry level characteristics. The time-invariant fixed effects address potential selection bias caused by omitted time-invariant confounders. The time fixed effects address potential selection bias caused by omitted firm/industry-invariant confounders.

Of course, there can still be time-varying confounders that cannot be captured by the fixed effects above. Fortunately, Angrist and Pischke (2009, p. 243–246) have shown that the fixed effects estimates (the benchmark) and the lagged dependent variables estimates provide reliable bounds of the true treatment effects, even if additional

[20] The VAT reform was implemented in four waves across the country and allowed specific industries in specific regions to receive credit for their fixed assets investment. Within our sample, 48.7% of the firms benefited from the VAT reform. The CIT reform, which aims to reduce tax burden of domestic firms and help them compete fairly with foreign enterprises, unified the statutory tax rate of corporate income tax for domestic and foreign firms. Domestic firms, therefore, are the main beneficiaries of this reform. We code one if a firm is a domestic firm in year 2008 or later, and zero otherwise. Within our sample, 45.6% of the firms have benefited from the 2008's CIT reform. For details, see online supplementary material B.

[21] Given that there are N firms in industry j and province p at year t, we calculate the value of indicators of competition pressure for firm i by averaging the values of an indicator across the N-1 firms without the firm i.

[22] Indeed, China's NBS released its first industry classification coding system for SEIs only in 2012. This fact reinforces our argument that China's industrial and S&T policies that targeted SEIs have worked mostly because they have attempted to "create" rather than to "pick" winners in these industries.

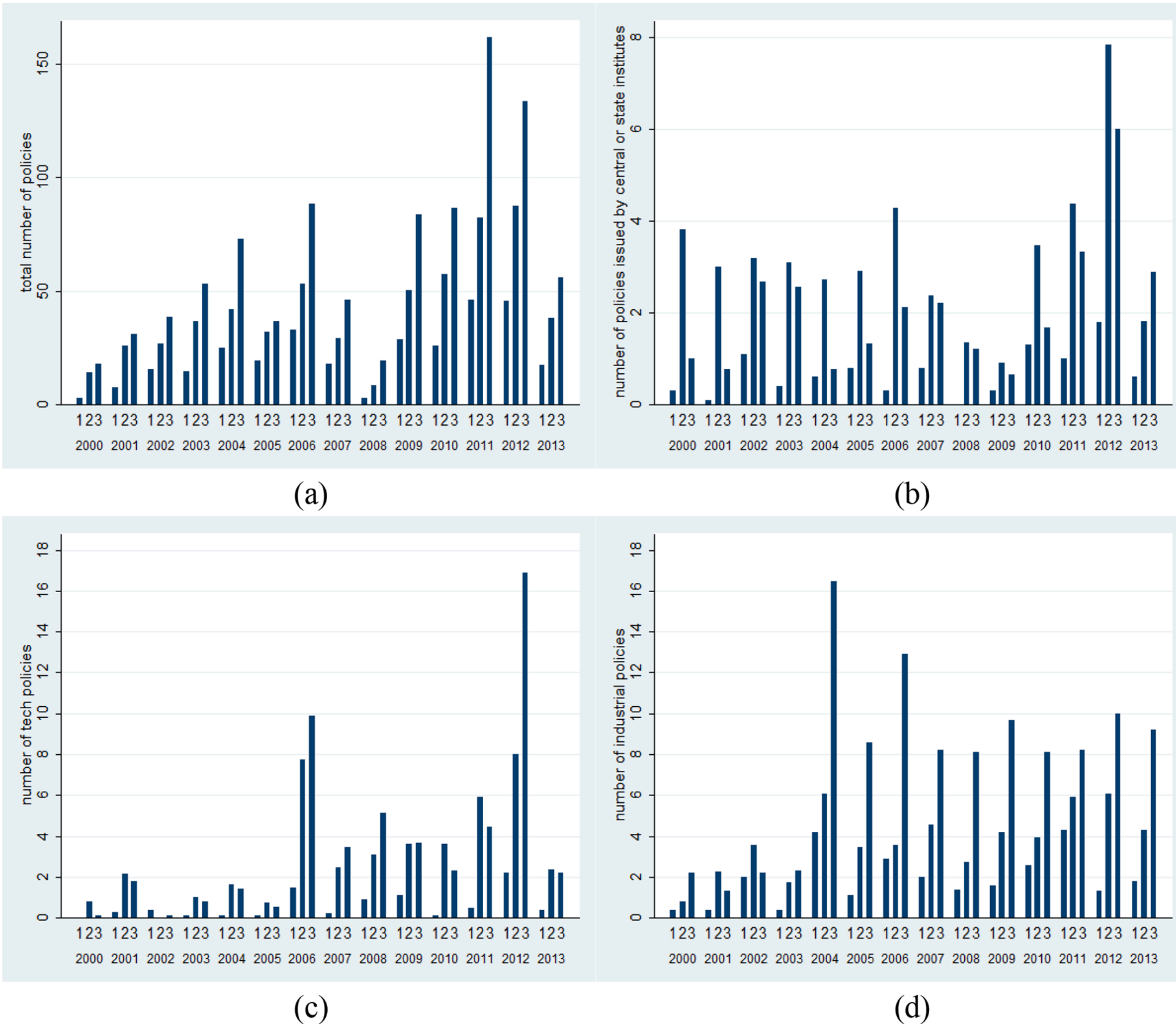

Fig. 2. Distribution of Number of Policies Issued by Different Agencies.
Notes: There are two *x* axes. The lower one is year, and the upper one is the type of industry (1=type I; 2=type II; 3=type III). The *y* axis is number of policies. Graph (a) is the aggregate number of policies, (b) is the number of policies issued by the State Council or above, (c) is the number of policies issued by NDRC, and (d) is the number of policies issued by MoST, respectively.

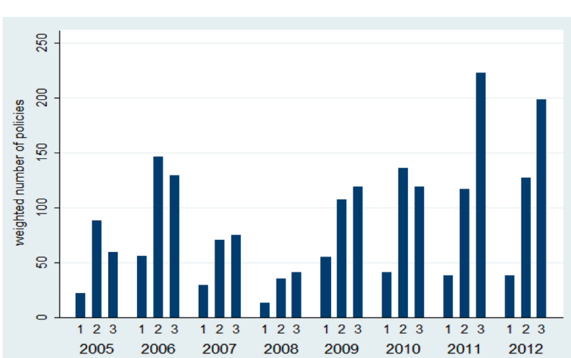

Fig. 3. Distribution of Weighted Number of Policies.
Notes: The *y* axis is weighted number of policies. For other notes, see Fig. 2.

time-varying confounders that cannot be captured by the fixed effects exist. We therefore follow their recommendation to include the lagged dependent variables to further control for omitted time-varying confounders as additional robustness checks.

Third, to further reinforce our argument, we deploy up to three year lags of the policy intensity (i.e., *number_w_lag1* to *number_w_lag3*) as independent variables in the benchmark regressions. Although it is conceivable that outcome variables (e.g., TFP) may impact current policies, it is highly improbable that outcome variables can impact policies made three years earlier. The results with lagged policy intensity are almost identical to that with contemporary policy intensity (Table 3 below), which indicates that reverse causality, if present in the benchmark models, is inconsequential.

Overall, our econometric challenges are quite similar to the minimum-wage studies where states change their minimum wages to affect labor market outcomes. Our empirical identification of the effects of industrial policy thus follows the RDID design, commonly used in minimum-wage studies (Allegretto et al., 2011).

Specifically, the industrial policy is a variable with different "treatment intensity" across industries and time (Angrist and Pischke 2009, p.234). The econometric model is thus a panel regression model with multi-level fixed effects:

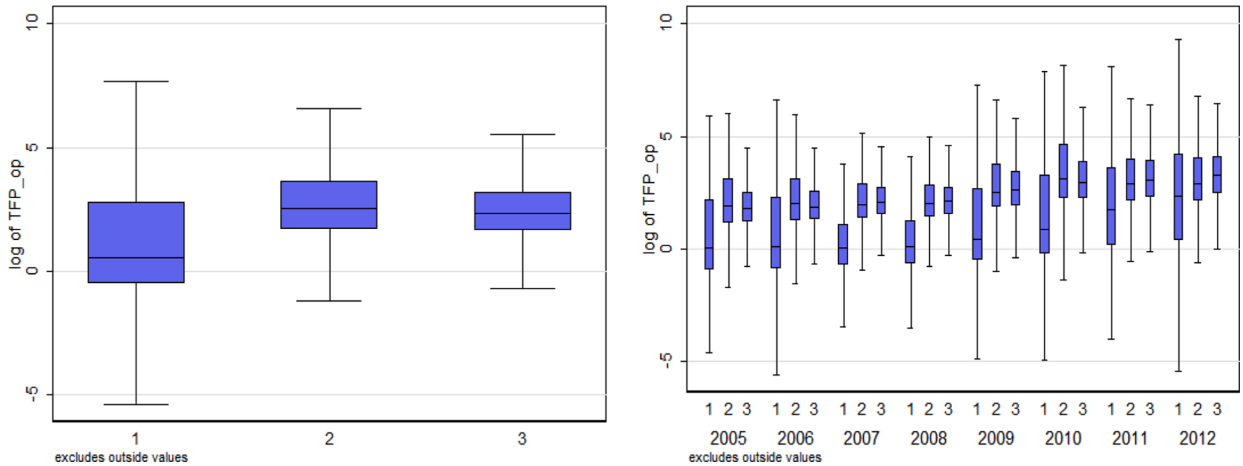

Fig. 4. Difference in TFP across the Three Types of Industries.
Notes: The *y* axis is natural log of firm-level TFP, estimated with the OP method (Olley and Pakes 1996). For other notes, see Fig. 2.

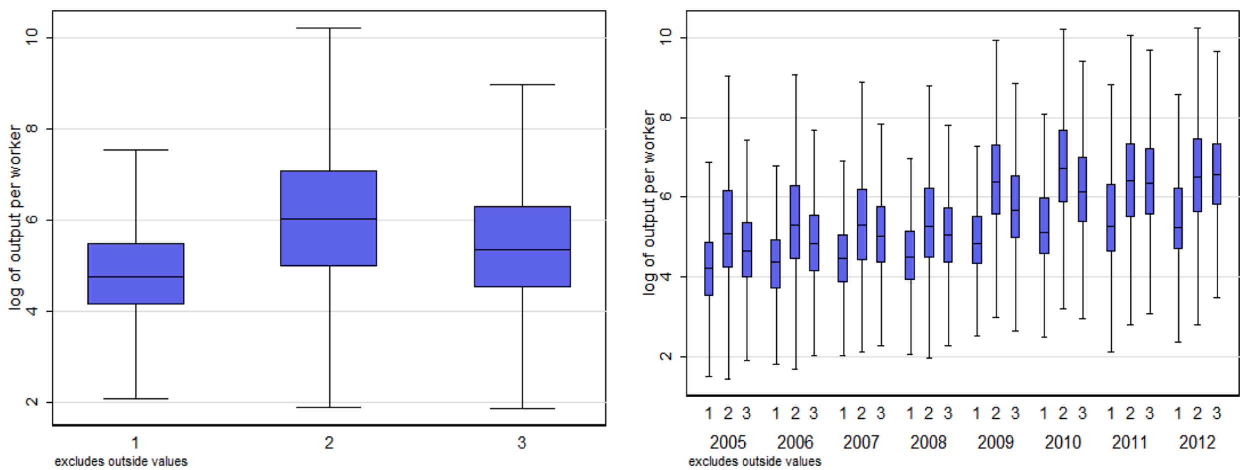

Fig. 5. Difference in Output per Worker across the Three Types of Industries.
Notes: The *y* axis is natural log of firm-level output (i.e., total sales) per worker. For other notes, see Fig. 2.

$$y_{ijpt} = \alpha + \beta \text{policynumber}_{jt} + \gamma_1(\text{policynumber}_{jt} \times \text{TypeII}_j) + \gamma_2(\text{policynumber}_{jt} \times \text{TypeIII}_j) + X_{it}^{'}\eta + Z_{jt}^{'}\theta + W_{jpt}^{'}\phi + \mu_i + \upsilon_p + \nu_t + \lambda_{pt} + \varepsilon_{ijpt}. \tag{1}$$

In Eq. (1), y_{ijpt} is the dependent variable, that is, TFP, output, or investment of firm *i* at year *t*, in industry *j* and province *p*. We use TFP values calculated via the Olley-Pakes (OP) method (Olley and Pakes, 1996) in our baseline models, with TFP values calculated via the Levinsohn-Petrin (LP) method (Levinsohn and Petrin, 2003) and OLS (i. e., Solow residuals) methods in robustness checks.

The key explanatory variables are policynumber$_{jt}$ (i.e., the weighted number of policies, or *number_w*) and its interaction terms with the types of industry. Specifically, TypeII$_j$ and TypeIII$_j$ are dummies for Type II (i. e., globally emerging) and Type III (i.e., domestically catching-up) industries, respectively, and the reference group is Type I (i.e., domestically mature) industries. Their coefficients are β, γ_1, and γ_2.[23] β is the policy effect on a firm's performance in the reference industry, that is, the Type I industry. γ_1 is the marginal effect of policy on a firm's performance in a Type II industry, whereas γ_2 is the marginal effect of policy on a firm's performance in a Type III industry, compared to a Type I industry. $\beta+\gamma_1$ therefore captures the net effect of policies upon Type II industries, whereas $\beta+\gamma_2$ captures the net effect of policies upon Type III industries. $\gamma_1-\gamma_2$ measures the difference of policy effects between Type II industry and Type III industry.

Our observable control variables (Section 5.1.3) fall into three categories: the firm level characteristics vector (X_{it}), the industry level vector (Z_{jt}), and the province-industry level vector (W_{jpt}).

To deal with omitted unobservable confounders, we also control for four levels of fixed effects: μ_i is the firm-level fixed effects, υ_p is the province-level fixed effects, ν_t is the year fixed effects, and λ_{pt} is the province-year time trend. ε_{ijpt} is the random error, clustered at province-industry level, to allow for within province-industry error dependence.[24]

Intuitively, most policies need some time before their full effect can be realized. We therefore expect some time lag between policy input and performance outcomes. We estimate a lagged model as Eq. (2) below.

[23] Because the weighted number of policy is the key independent variable, both β and γ are semi-elastic.

[24] As another robustness check, we also control for industry-year fixed effects. Our baseline results remain essentially unchanged. The reason we do not control for industry-year fixed effects in the baseline models is that our baseline models have already controlled for a host of fixed effects that capture industry-level characteristics and clustered robust standard errors at the province-industry level. For brevity the results are omitted and are available upon request.

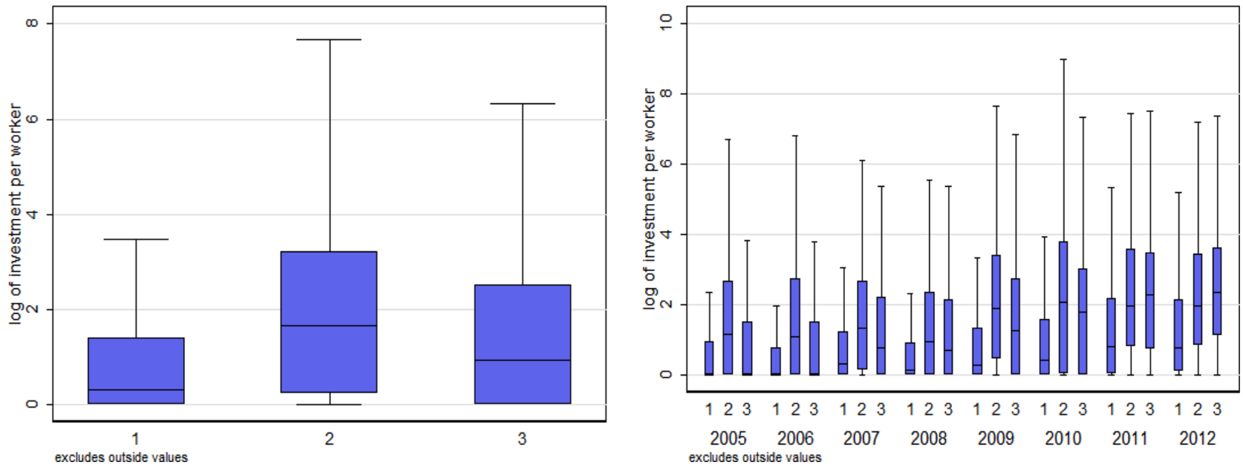

Fig. 6. Difference in Investment per Worker across the Three Types of Industries.
Notes: The *y* axis is natural log of firm-level investment (i.e., current increase in fixed assets) per worker. For other notes, see Fig. 2.

Compared to Eq. (1), Eq. (2) uses lagged but not current value of*policynumber*,[25] and other variables are the same.

$$y_{ijpt} = \alpha + \beta \text{policynumber}_{j,t-k} + \gamma_1 \left(\text{policynumber}_{j,t-k} \times \text{TypeII}_j\right) + \gamma_2 \left(\text{policynumber}_{j,t-k} \times \text{TypeIII}_j\right) + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi + \mu_i + \upsilon_p + \nu_t + \lambda_{pt} + \varepsilon_{ijpt}, \tag{2}$$

Following Angrist and Pischke (2009, p. 243–245), we introduce lagged dependent variables into the fixed effects model to account for time-variant or group-variant omitted confounders. We therefore also estimate Eq. (2) with lagged dependent variables, using the system-GMM method (Arellano and Bover, 1995), as a robustness check of the fixed effects findings (where *L* and *M* are positive integers):

$$y_{ijpt} = \alpha + \sum_{l=1}^{L} \psi_l y_{ijp,t-l} + \sum_{m=0}^{M} \beta_m \text{policynumber}_{j,t-m} + \sum_{m=0}^{M} \gamma_{1,m} \left(\text{policynumber}_{j,t-m} \times \text{TypeII}_j\right) + \sum_{m=0}^{M} \gamma_{2,m} \left(\text{policynumber}_{j,t-m} \times \text{TypeIII}_j\right) + X'_{it}\eta + Z'_{jt}\theta + W'_{jpt}\phi + \mu_i + \upsilon_p + \nu_t + \lambda_{pt} + \varepsilon_{ijpt} \tag{3}$$

Finally, because our data are unbalanced, we follow the labor economics literature (e.g., Allegretto et al., 2011) to replace the individual firm effects in Eq. (1) with the industry fixed effects; that is, we treat the individual-firm-level data not as panel data but as repeated cross-section data.

6. Results

6.1. Descriptive evidence

Our theoretical argument predicts that China's policymakers tend to "create (and pick) winners" to facilitate technological catch-up in both Type II and Type III industries with industrial policy. If our argument is correct, we should be able to identify some obvious empirical patterns with simple descriptive statistics.

First, both Type II industries and Type III industries should have received more policy attention than Type I industries. Moreover, Type III industries should have received far more attention than Type II ones because the former is more numerous. This is indeed the case.

Within our sample, from 2000 to 2012, the total number of policies targeting Type I industries is 2202, and on average, Type I industries receive 27.53 policies per industry. Meanwhile, the total number of policies targeting Type III industries is 5906, whereas the total number of policies targeting Type II industries is 4403, even though our sample includes six Type II industries but only three Type III industries. On average, Type II and Type III industries receive 50.03 and 82.03 policies per industry, respectively. Thus, on average, Type II industries have been targeted two to four times more than Type I ones, and Type III industries have been targeted four to six times more than Type I ones (Fig. 2a).

Second, we should expect that when policies are ranked according to the three levels of authority (i.e., above NDRC/MoST, NDRC/MoST, and other than NDRC/MoST), the pattern that more policies are directed to Type II and Type III industries than to Type I industries should still hold. Again, this is indeed the case, as shown in Fig. 2b, c, and d.

Third, with the weighted measurement of policy intensity, we expect the pattern that more policies are directed to Type II and Type III industries than to Type I industries to hold still. Again, this is indeed the case (Fig. 3).

Fourth, we should expect the TFP of Type II industries to be higher than that of Type III industries, and in turn, that of Type I industries. As shown in Figs. 4, 5, and 6, again this is indeed the case. Firms from Type II and Type III industries have significantly better performance, compared to those from Type I, whether measured in TFP, output per worker, or investment per worker. Importantly, TFP, output per worker, and investment per worker vary over time, thus providing sufficient variation for our subsequent empirical estimations.

6.2. Econometric results

6.2.1. Baseline results and robustness checks

Table 3 reports the results with firms' TFP as the dependent variable and the weighted number of policies as the key independent variable. Model 1 is without interaction terms between policies and types of industry and with only a minimal number of control variables. The average effect of industrial policy is positive but only marginally significant. Model 2 adds interaction terms between policies and types of industry to the equation. As shown, industrial policy has both positive marginal and positive net effects on firms' TFP from Type II industries,

[25] In subsequent analyses, we try different lags (i.e., k = 1, 2, or 3). When k = 4 or 5, our key results become insignificant under them (results not shown). A plausible explanation is that if an industrial policy does not have much effect in its first three years or so, it is highly unlikely that it will have much effect after that.

Table 2
Summary statistics of main variables (2005–2012, annual data).

Variable name	Definition	Obs.	Mean	Std. Dev.	Min	Max
Dependent Variables: Firm-Level Performance						
lnTFP	Natural log of TFP using the OP method, in 1000 CNY	54,263	2.126	1.706	−2.133	6.249
lnoutputpw	Natural log of total sales per worker, in 1000 CNY	54,263	5.394	1.409	2.170	9.232
lninvestpw	Natural log of current increase in fixed assets per worker, in 1000 CNY	48,353	1.402	1.617	0	6.509
Key Independent Variables: Industry-Level Number of Policies and Industry's Type						
number_w	Weighted number of all policies	54,263	95.191	108.524	0	529
number_o	Original number of all policies	54,263	78.067	93.676	0	436
number_s	Number of state-level policies	54,263	2.350	3.833	0	32
number_td	Number of policies issued by MST or NDRC	54,263	12.422	13.003	0	69
number_so	Number of solely issued policies	54,263	62.190	77.355	0	377
number_m	Number of jointly issued policies	54,263	15.878	18.385	0	84
subsidy	Natural log of the total subsidies received	42,963	1.115	2.565	0	14.509
typeI	Dummy for a Type I industry	54,263	0.265	0.441	0	1
typeII	Dummy for a Type II industry	54,263	0.142	0.349	0	1
typeIII	Dummy for a Type III industry	54,263	0.593	0.491	0	1
Other Variables: Firm-Level Characteristics						
age	Firm's age	54,263	8.825	6.183	1	86
SOE	Dummy for a state-owned firm	54,263	0.037	0.188	0	1
Foreign	Dummy for a foreign firm	54,263	0.115	0.319	0	1
HMT	Dummy for a firm owned by capitals from Hong Kong, Macao, or Taiwan	54,263	0.073	0.261	0	1
Lshare	Dummy for an incorporated firm	54,263	0.046	0.208	0	1
Private	Dummy for a privately-owned domestic firm	54,263	0.358	0.479	0	1
ODomestic	Dummy for other domestic firm	54,263	0.372	0.483	0	1
assets	Total assets, in million CNY	54,263	296.563	907.588	0.115	6330.777
employ	Number of employees, person	54,263	321.706	756.108	2	4943
ROA	Return on assets (i.e., net profits/total assets)	54,263	0.036	0.109	−0.293	0.541
debt	Ratio of debt (i.e., total liabilities/total assets)	54,263	0.600	0.338	0	1.886
R&D	Ratio of R&D spending to total sales	54,263	0.005	0.034	0	3.822
lnwage	Natural log of total salaries per worker, in 1000 CNY	54,263	2.854	0.926	0	5.026
export	Ratio of exports to total sales	54,263	0.069	0.213	0	0.998
markup	Ratio of price to marginal cost	54,263	1.357	11.287	0.649	4.207
east	Dummy for a firm in East China	54,263	0.645	0.479	0	1
central	Dummy for a firm in Central China	54,263	0.137	0.344	0	1
west	Dummy for a firm in West China	54,263	0.136	0.343	0	1
northeast	Dummy for a firm in Northeast China	54,263	0.083	0.275	0	1
VATreform	Dummy for a firm in 2004–2009's VAT reform	54,263	0.487	0.500	0	1
CITreform	Dummy for beneficiary of 2008's CIT reform	54,263	0.456	0.498	0	1

Notes: We exclude two kinds of outliers, i.e., invalid observations and extreme values. The former include firms with missing or negative values of age, assets, output, or employment. We treat the latter by winsorizing 1% of upper and lower limits, respectively. For the method of calculating the weighted number of policies, see the note for Fig. 2 above. MoST and NDRC refer to the Ministry of Science and Technology and to the National Development and Reform Commission, respectively. For definition of Type I, Type II, and Type III industries, see the main text. When controlling for "born advantages," we use province-industry average values (excluding the firm itself) of assets, ROA, debt, and R&D to avoid endogenous correlation with the dependent variables (i.e., firm's performance). We also tried adding more control variables such as province-industry average values of lnwage and export. None of these variables is significant, and our baseline results do not change. Geographical variables, i.e., east, central, west, and northeast, are converted to indicators for industry concentration, which is defined as the extent to which an industry is concentrated in a region.

but not on firms' TFP from Type III industries (Type I industry is the reference group). These results hold as more control variables are added into the equation (models 3, 4, 5, and 6). Model 6 contains the full list of control variables and serves as the benchmark model. Models 7–9 use the same controls as model 6, but the independent variables are one to three year lags of the weighted number of policies, respectively. Both γ_1 and γ_2 are significantly positive in model 6 (and model 9), supporting our first hypothesis that industrial policy will have larger effects on Type II and Type III industries than Type I industries.

Also consistent with our expectation that policies need some time to exert their full impact, policies seem to have the most effect with a three-year lag (model 9).

Moreover, the difference between the policy effects upon Type II and Type III, $\gamma_1 - \gamma_2$, is consistently positive and significant across most models and in particular in models 6 and 9. These results strongly support our second hypothesis.

According to models 6 and 9 of Table 3, if the weighted number of policies increases by one, firms in Type II industries will experience 0.15 to 0.22 percentage total increase, or 0.05 to 0.10 percent net increase of TFP (natural log). This is a very significant positive effect.

One may notice that in some of the benchmark models, industrial policy delivers (sometimes statistically significant) negative effects on firm productivity, mainly for Type I industries. Our theory predicts that industrial policy has little potential to improve the productivity of firms in Type I industries. However, it does not preclude possible side effect of industrial policy in certain industries.

For example, as documented by several studies, China's industrial policy is one of the drivers of the emergence of zombie firms (i.e., firms that would go bankrupt due to poor earnings but survive with external support from government or financial sector) in many of China's industries, and the situation is most severe in the mature industries such as iron and steel, electrolytic aluminum, coal, cement and textile (e.g., Nie et al., 2016).[26] Hence, industrial policy has double-edged effects. On one hand, it serves to improve the competitiveness of the targeted industries. On the other hand, the excessive support can create overcapacity and zombie firms, which crowd out healthy firms and lead to reduced overall productivity. Our econometric results suggest that for Type I industries, the latter effect apparently outweighs the former effect. This possibility is also consistent with our theory.

We perform a host of robustness checks, including adding more

[26] Nie et al. (2016) reports that among all industries, the percentage of zombie firms in the iron and steel industry was the highest and reached a remarkable level of 51.43% in 2013, while the percentage in the computer related industries was among the lowest.

Table 3
Baseline results: Policies' effects on firm-level TFP, all industries.

Dependent Variable: lnTFP	(1)	(2)	(3)	(4)	(5)	(6)	(7) $i=1$	(8) $i=2$	(9) $i=3$
Independent Variables	FE	FE	FE	FE	FE	FE	FE	FE	FE
Key Explanatory Variables									
number_w	0.0003*	−0.0007	−0.0007	−0.0011*	−0.0008	−0.0010			
	(0.0001)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)			
number_*w* × typeII		0.0014**	0.0014**	0.0016**	0.0014**	0.0015**			
		(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)			
number_*w* × typeIII		0.0008	0.0008	0.0012*	0.0009	0.0011*			
		(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)			
number_w_lagi ($i=1$,2 or 3)							−0.0007	0.0004	−0.0013**
							(0.0005)	(0.0005)	(0.0006)
number_w_lagi × typeII ($i=1$, 2 or 3)							0.0009*	0.0002	0.0022***
							(0.0005)	(0.0006)	(0.0006)
number_w_lagi × typeIII ($i=1$, 2 or 3)							0.0006	−0.0006	0.0010*
							(0.0005)	(0.0005)	(0.0006)
Net Effect of number_w (or number_w_lagi)		0.0007***	0.0007***	0.0006**	0.0006***	0.0005**	0.0002	0.0006*	0.0010***
on a Firm in TypeII ($i=1$, 2 or 3)		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Net Effect of number_w (or number_w_lagi)		0.0001	0.0001	0.0002	0.0001	0.0001	−0.0001	−0.0002	−0.0003
on a Firm in TypeIII($i=1$, 2 or 3)		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Difference of Policy Effects between TypeII		0.0006***	0.0006***	0.0004*	0.0005**	0.0004**	0.0003	0.0007**	0.0012***
and TypeIII		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Firm's Basic Characteristics List A	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industrial Agglomeration	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
"Born Advantages"	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Key Tax Reforms	No	No	No	No	No	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-Square	0.0525	0.0557	0.0583	0.0596	0.0700	0.0714	0.0710	0.0712	0.0719
Observation	54,263	54,263	54,263	54,122	53,861	53,861	53,861	53,861	53,861

Notes: All columns use the method of Fixed-Effect Model (FE) for panel data. ***, ** and * refer to 1%, 5% and 10% significant levels, respectively. Robust standard errors clustered at province-industry level are in parentheses. For ownership, we use SOE as the reference. For age, we control natural log of age. For industrial agglomeration, we use agglomeration in East China as the reference. For born advantages, we control province-industry average characteristics, including natural log of total assets, ROA, debt, and R&D, as well as province-industry average level of TFP. All these variables exclude the firm per se and cover the rest of the firms in the same province and industry. Key tax reforms involve 2004–2009′s VAT reform and 2008′s CIT reform. Fixed effects include year and province-year trends, while firm, industry, and province fixed effects are automatically controlled, since we use the FE model. The reason we control province-year trends is that there exist large trade barriers among provinces due to the Chinese-style decentralization (see Young 2000; Xu 2011), and time-varying policies from provincial governments usually have greater impact on firms' activities. In Columns 7–9, we use one-year lagged, two-year lagged and three-year lagged values of the variable *number_w*, respectively. We also tried using four-year or five-year lagged values and found that coefficients of the variables of interest are insignificant. Net effect of *number_w* (or *number_w_lagi*) on a firm in typeII or typeIII means a test for the sum of coefficient of *number_w* (or *number_w_lagi*) and that of its interaction with typeII or typeIII. It is not meaningful, however, when neither of the coefficients is statistically significant. Firm's Basic Characteristics List A includes ownership and age.

control variables, using alternative independent variables (such as unweighted policy numbers, amount of subsidy, firm market power), using lagged independent variables in GMM regressions, using alternative measurements of TFP as alternative dependent variables, and correction the potential measurement error in the key independent variable with GMM involving higher order moments. Due to space limitation, these results are reported in our online supplementary material A. Here, suffice to say that our baseline results survive all these robustness checks. Altogether, our initial results strongly support our two empirical hypotheses.

6.2.2. *Using repeated cross section regressions*

In Table 4, we report results for models with a repeated cross-section framework. Specifically, we include industry fixed effects, not firm fixed effects. We also include, as in Table 3, the province fixed effects, the time fixed effects, and the province-time fixed effects. Standard errors are clustered at province-industry level. The results in Table 4 largely resemble the baseline fixed effects models.

To summarize, our hypotheses are supported by our benchmark empirical analyses and survive a host of stringent robustness checks listed above. We have also conducted additional validation analyses by using different key independent variables and/or different samples, plus a series of heterogeneity tests that cast doubt on some competing explanations (e.g., ownership, market power), all of which are well in line with our benchmark regressions. These empirical results and discussions are again to be found in the online supplementary material A.

6.2.3. *Controlling for spillover effects*

When gaging the impact of industrial policies, it is natural to ask: Was the productivity gain of a firm in a particular industry spurred by policies targeted at the industry per se or by policies targeted at other industries? More concretely, after controlling for (indirect) spillover effect, will China's industrial policies still have direct effects upon the targeted industries?

Table 5 present results from eight models of spillover effects, all with province-industry unit-specific fixed effects and time-fixed effects.[27] Models 1–4 use contemporary policy intensity (i.e., *policynumber*), and one to three-period lagged policy intensity as the explanatory variable, along with the spatial autoregressive terms, respectively. Models 5–8 adds a set of control variables discussed above to models 1–4, respectively.

Altogether, even controlling for spillover effects, the direct effects of policy intensity at current year and with lags are positive and highly significant (often at the level of $p<0.001$). The indirect effect of policy intensity is also positive and strongly significant, suggesting that on average, policies targeted at a particular industry also have positive spillover effect on the technological progress of the firms in other

[27] Models with unit-specific fixed effects deliver similar results. Due to its space limitation and technicality, we have put the more detailed explication of spillover models in the online supplementary material A.

Table 4
Robustness checks for baseline results: repeated cross-section modeling.

Dependent Variable	lnTFP (1) FE	lnTFP (2) FE	lnTFP (3) FE	lnTFP (4) FE
Independent Variables				
Key Explanatory Variables				
number_w	0.0005** (0.0002)	−0.0050*** (0.0007)	−0.0032*** (0.0005)	
number_*w* × typeII		0.0051*** (0.0006)	0.0032*** (0.0005)	
number_*w* × typeIII		0.0055*** (0.0006)	0.0031*** (0.0004)	
number_w_lag1				0.0003 (0.0004)
number_w_lag1 × typeII				−0.0003 (0.0004)
number_w_lag1 × typeIII				0.0002 (0.0004)
Net Effect of number_w on typeII		.00005 (0.0003)	.00004 (0.00025)	.00005 (0.00027)
Net Effect of number_w on typeIII		.00045* (0.00023)	−0.00008 (0.00012)	.00050*** (0.00015)
Firm's Basic Characteristics List A	No	No	Yes	Yes
Industrial Agglomeration	No	No	Yes	Yes
"Born Advantages"	No	No	Yes	Yes
Key Tax Reforms	No	No	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Within R-Square	0.0003	0.003	0.051	0.051
Observation	54,263	54,263	53,861	53,861

Notes: In this table, we report regression results with repeated cross-section specification. Specifically, we include industry fixed effects not firm fixed effects. We also include as in Table 1 province fixed effects, time fixed effects and province-time fixed effects. Standard errors are clustered at province-industry level.

industries.[28]

7. Discussion and conclusion

Our central thesis is that the relative technological development stage of China's industry to that of the corresponding industrial frontier affects the effectiveness of its industrial policy on productivity. Our understanding of developmental stage is centered upon the joint distribution of the industries at different technological stages for both the developing country and the world's technological frontier, thus allowing us to integrate the technological S-curve theory and global value chain power asymmetry argument into our theoretical framework. We further contend that China's industrial policy targeting emerging industries might have worked precisely because China's policies began to encourage innovation in the emerging industries as China approaches the technological frontier after 25 years (1978–2002) of rapid catching-up via imitation. We then provide extensive evidence with unique and combined data while differentiating direct and indirect (i.e., spillover) effects of multi-pronged policy tools.

Our study yields important implications for two broader literatures: industrial policy and the role of comparative advantage for economic development in developing countries.

First, our study shows that industrial (and S&T) policy can indeed work. Our study further shows that the success of industrial policy is conditional on the relative stage of industry development compared to the international industrial frontier. To some extent, our results dovetail with the theoretical insight advanced by Acemoglu et al. (2006), who argue that when a country is in the early stage of development, it should encourage firms to adopt an investment-based strategy to facilitate the adoption or imitation of advanced technologies. As a country approaches the technological frontier, however, it should adopt a more innovation-based strategy.

Second, the success of industrial policy is not entirely about following the static or even latent comparative advantages, as Lin and his colleagues have advocated (Lin, 2012). Instead, by targeting emerging industries in which firms in developed countries also face greater uncertainty about technological direction, developing countries like China with considerable R&D capacities can indeed facilitate rapid technological catch-up by their domestic firms: Uncertainty over the technological future can be an important advantage for firms in developing countries. Thus, although a country's overall industrial policy should be comparative-advantage-following, well-crafted industrial policies that target selected emerging industries can work even though these policies defy comparative advantage.

Our study also suggests several directions for future inquiries.

First, standard models of industrial policies mostly assume two sectors: traditional (low-tech and capital-light) and high-tech (and capital-intensive). Yet, a two-sector model has not been the prism through which China's decision-makers look at China's industries: they see at least three categories of industries. Concurring with Ju et al. (2015), we believe that the traditional two-sector model often fails to capture the complex structure of real economies and the nuances associated with industrial upgrading (with or without industrial policies). Empirically, we believe that the two-sector simplification for the sake of modeling may not be appropriate for a more fine-grained understanding of the effect of industrial policies. Indeed, pooling all industries in econometric exercises when examining the impact of industrial policy may be a key reason why some earlier studies have failed to uncover any robust and significant effect of industrial policy consistently. As such, such models may not be ideal guide for designing effective industrial policies.

Second, our study is one of the few studies to incorporate S&T policies with industrial policies. This is especially important when examining countries with significant S&T capacities (e.g., Brazil, China, India, and Russia). We believe this is not only a key direction for further inquiries but also a critical lesson for countries with significant S&T capacities.

Third, most studies on industrial policy have focused on supporting policies as "carrots." The experience of east Asian development states, however, has long informed us that successful industrial policy should also contain "sticks," meaning that firms receiving support must achieve pre-set targets (e.g., absorbing key technologies, exporting) or face the consequences (Amsden, 1989; Wade, 1990). Inquiries along this logic will move us closer to the goal of establishing Aghion and Roulet's notion that "not only sectoral policies should be adequately targeted … they should also be properly governed" (2014, p.918). In our next project, we aim to examine whether and under what circumstances "carrots and sticks" really work better than "carrots" or "sticks" alone.

Finally, to fully understand the effect of industrial policy, in the context of China at least, we need to understand not only how firms respond to industrial policy but also how local governments respond to

[28] The spillover effect of lag 3 is significantly negative (model 8). How could there be negative spillover effects of a policy 3 years ago? Our explanation of this result is the same as the one we had for model (9) of Table 3, which has a similar result. Briefly, industrial policy had side effects in mature industries, i.e., it helped to create many zombie firms in upstream industries such as iron and steel and electrolytic aluminum, resulting in productivity depression in these industries. Since the transmission of changes among the production chains takes time, the negative effects may accumulate and emerge at the third year.

Table 5
Spillover effects estimation results: Cross-industry spillover.

Dependent Variable	lnTFP							
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
Independent Variables								
Key Explanatory Variables								
Direct Effects								
number_w	0.00132***				0.000919***			
	(0.000333)				(0.000274)			
number_w_lag1		0.000646				0.000952***		
		(0.000392)				(0.000303)		
number_w_lag2			−0.000944				−0.000470	
			(0.000535)				(0.000416)	
number_w_lag3				0.0000194				0.0000297
				(0.000601)				(0.000495)
Spillover Effects								
number_w	0.00596*				0.00552**			
	(0.00319)				(0.00245)			
number_w_lag1		−0.000415				0.00301***		
		(0.00367)				(0.000867)		
number_w_lag2			−0.00954*				0.00607***	
			(0.00535)				(0.00230)	
number_w_lag3				−0.0110**				−0.00513***
				(0.00527)				(0.00109)
ρ	0.0502	0.0861	0.0624	0.0587	−0.116	0.189*	0.285***	0.164*
	(0.0936)	(0.0906)	(0.0925)	(0.0928)	(0.106)	(0.0797)	(0.0713)	(0.082)
Firm's Basic Characteristics List A	No	No	No	No	Yes	Yes	Yes	Yes
Industrial Agglomeration	No	No	No	No	Yes	Yes	Yes	Yes
"Born Advantages"	No	No	No	No	Yes	Yes	Yes	Yes
Key Tax Reforms	No	No	No	No	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-Square	0.12	0.008	0.003	0.001	0.52	0.529	0.524	0.528
Observation	2392	2392	2392	2392	2392	2392	2392	2392

Notes: All models are estimated with both unit specific and time specific fixed effects. The main effects, spatial effects and the direct and spillover effects for other control variables are not reported. We don't include the interactions of policy number with the industry types, as both the direct and indirect effects are average effects across different units (thus industries). The standard errors are in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Columns (1)-(4) report results for models without controls, and columns (5)-(8) report results for models with all controls.

Table 1A
Industry type classification.

China / World Frontier	Ferment	Take-off	Mature
Ferment	Globally Emerging (Type II)		
Take-off	Globally Emerging (Type II)		
Mature	Domestically Catching Up (Type III)	Domestically Catching Up (Type III)	Domestically Mature (Type I)

Note. This table describes the distribution of China's industries at the beginning of the 21st century. Domestically mature (Type I) industries refer to the industries for which both China and the world technology frontier were at the mature stage of technological development. Globally emerging (Type II) industries refer to the industries for which China was at ferment stage while the world frontier was either at the take-off stage or also at the ferment stage. Domestically catching up (Type III) industries refer to the industries for which China was at ferment or take-off stage while the world frontier was at the mature stage.

the state's industrial policy. This will allow us to tie the literature on industrial policy to the literature on China's central-local relations.

Our results, however, may not be directly applicable to any other developing country. Existing literature has documented numerous failures of developing countries pursuing comparative advantage defying industrial polices when the time is not mature (e.g., Etzkowitz and Brisolla, 1999). The actual classification of relative stages for a developing country, as used in this paper, is also country and time specific. Indeed, our second hypothesis, H_2, is implicitly contingent on the fact that China has already experienced decades of catching up and accumulated significant capacity for venturing into the emerging industries. After two decades of investment in infrastructure, higher education, R&D, and learning from the developed economies, by the early 2000s, China has acquired substantial innovation capacity which empowered it to venture into the new industries. Moreover, by the early 2000s, 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. Without all these preconditions, China's industrial policies targeted at emerging industries might have also

Table 1B
Industries in our sample.

Type	Name	Classification Code
Domestically Mature/Type I: Mature Industries in both China and the world frontier		
	Textile, Clothing, Shoes, and Hats	1810, 1820, 1830
	Iron and Steel	3210, 3220
	Food Catering	6710, 6720, 6730, 6790
Globally Emerging/Type II: Strategic Emerging Industries (SEIs) as Identified by both OECD and China		
	Biochemistry and Biotech	2632, 2760
	Communication Equipment	4011, 4012, 4013, 4014, 4019
	Computer Manufacturing	4041, 4042, 4043
	Electronic Components	4051, 4052, 4053, 4059
	Mobile Telecommunication	6012
	Internet Information Services	6020
	Satellite Transmission Services	6040
	Computer Systems and Services	6110
	Data Processing	6120
	Basic Software and Services	6211
Domestically Catching Up/Type III: Industries that are underdeveloped in China but mature in the world frontier		
	Basic Chemicals	2611, 2612, 2613, 2614, 2619
	Specific Chemicals	2661, 2662, 2663, 2664, 2665, 2666, 2667, 2669
	Boiler	3511, 3512, 3513, 3514, 3519
	Metalworking Machinery	3521, 3522, 3523, 3524, 3525, 3529
	Bearings, Gears, Gearing, and Driving Elements	3551, 3552
	Oven and Smelting Furnace	3560
	Fan, Weighing, and Packaging Equipment	3571, 3572, 3573, 3574, 3575, 3576, 3577, 3579
	Electricity Transmission, Distribution, and Control Equipment	3921, 3922, 3923, 3924, 3929
	Lighting Fixture Manufacturing	3971, 3972, 3979

failed.

CRediT authorship contribution statement

Jie Mao: Resources, Formal analysis, Software, Writing – review & editing. **Shiping Tang:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision. **Zhiguo Xiao:** Conceptualization, Methodology, Formal analysis, Software, Writing – original draft, Writing – review & editing, Supervision. **Qiang Zhi:** Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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