The Interplay between Innovation and Marketing: Evidence from the Pharmaceutical Industry*

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Abstract This paper examines the long-standing question about the interplay between firms' innovation and marketing decisions. We develop new perspectives that emphasize the relationships of different marketing activities to innovation and the dynamics of their relationships. Exploiting detailed data on firm-level expenditures and innovation outcomes (patents and new drug applications) and a quasi-experimental policy setting in China during 2009–2018, we examine how firms respond to policy-induced innovation incentives in China's pharmaceutical industry. We find that as regional innovation policy reforms in China led to increased pharmaceutical R&D investments, firms significantly reduced non-ad marketing expenditures. However, firms raised future advertising expenditures when past R&D input generated innovation outputs. Our results indicate that while firm innovation substitutes non-ad marketing activities, advertising and innovation are dynamic complements. Our findings also underscore the importance of understanding the (unintended) impact of innovation policies on marketing activities.

Keywords: innovation, marketing, R&D incentives, informative advertising, pharmaceutical industry

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1 Introduction

"The business enterprise has two—and only two—basic functions: marketing and innovation."

– Peter Drucker, *The Practice of Management*, 1954.

Both innovation and marketing are central to business success and firm growth. As innovation activities are often recognized as the driving force for long-run economic prosperity (Solow 1957; Romer 1990), from both business and social points of view, it is imperative to understand the interplay between these two important investments. However, two seemingly opposite views exist regarding their relationship. On the one hand, innovation and marketing are often considered substitutes, as both can increase firms' competitiveness and contribute to market expansion by, for instance, influencing the perceived quality of a product (e.g., Grossmann 2008; Cavenaile and Roldan-Blancoz 2021). On the other hand, informative marketing activities such as advertising can foster innovation, as they deliver essential information—especially information about new products—to the market (Nelson 1974). Meanwhile, existing studies provide mixed empirical evidence, and their inferences based on observed correlations between firm R&D and marketing expenditures raise concerns about underlying endogeneity problems. In this paper, exploiting detailed firm-level data and the unique institutional setting of China, we offer new insights into the innovation–marketing relationship by examining firms' marketing responses to policy shocks that increase the incentives for innovation. To guide our empirical investigation, we develop new perspectives that emphasize the relationships of different marketing activities to innovation and the dynamics of their relationships.

In examining the interplay between innovation and marketing, it is often overlooked that marketing encompasses a variety of activities that serve distinct functions and that often differ substantially. Although this point is definitional in marketing and is increasingly understood in related fields, it has yet to be incorporated into research on the innovation–marketing interaction. In fact, research often treats marketing as a single-function activity by using aggregate measures of marketing expenditures. This issue is often related to empirical restrictions that researchers face, such as data limitations; for instance, in standard financial reporting, different firm marketing expenses are usually lumped into a single category of "Selling, General and Administrative Expense" (SG&A).[1]

In this study, we separately consider and measure advertising from other marketing activities. As advertising is often a major tool for firms to disseminate product information to the market, it is of unique importance among marketing activities. The essential informative function of advertising has been not only stressed in the academic literature but also long recognized by industries. One of the earliest and best-known examples in pharmaceuticals is Merck's direct-to-consumer (DTC) advertising of *Proscar*—a drug for treating benign prostatic hyperplasia—that circumvented physicians and directly targeted patients (a practice previously prohibited in the US.) and led to huge commercial success (Berndt 2005). We posit that due to the important role of advertising, especially in selling new products, advertising should complement innovation activities, in contrast to other sales activities that are more likely to substitute innovation. Furthermore, because the innovation process is dynamic, the demand for advertising should occur late in the process, such as when R&D investments start to generate innovation outcomes unknown to market participants. While our information-based dichotomy of advertising and non-ad marketing might still overlook the myriad forms and functions of marketing in reality, we view it as a crucial and necessary step towards a more complete understanding of the interplay between innovation and marketing.

To address the issue of spurious correlation, we examine how firms adjust their marketing variables in response to policy shocks that increase the incentives to innovate. Conceptually, firms' marketing responses to innovation incentives are revealing of the strategic relationships between innovation and different marketing activities. The basic idea of this correspondence is analogous to using cross-price effects to define substitute/complement goods in the consumer choice context. In Section 2, we clarify the conceptual issues surrounding our approach. Altogether, we hypothesize that if non-ad marketing and innovation are strategic substitutes, firms should reduce non-ad marketing efforts in response to an external policy change that incentivizes R&D investments. Meanwhile, firms should increase advertising when past R&D input results in tangible innovation outcomes.

To empirically test our hypotheses, we study China's pharmaceutical industry, which provides a natural setting for our research question. First, the pharmaceutical industry is typically R&D- and marketing intensive. Its dependencies on patent protection and drug approval administration

1. See, for instance, the 2003 *Standard & Poor's Compustat User's Guide.*

also allow researchers to better observe firms' activities along the business process. In this study, we build a novel dataset of publicly traded pharmaceutical firms in China. The dataset includes detailed firm-level information on R&D and marketing expenditures, patent status, and other financial variables of 171 firms for 2010–2018. Moreover, we collect additional data on new drug registrations from an official source to directly measure the outcomes of pharmaceutical innovation. Second, using the data of listed firms in China gives us another unique advantage. In early 2010, the Chinese regulatory authority required all publicly traded firms listed in China's A-share markets to disclose detailed expenditure information—including itemized marketing expenses—in their annual financial reports. This institutional feature allows us to separately examine different marketing expenses that are typically lumped into SG&A elsewhere.

Third, to overcome the identification hurdle caused by the simultaneity of firms' innovation and marketing decisions, we exploit a unique quasi-experimental setting in China. Specifically, in 2008, China introduced a third amendment to its patent law, and triggered by the national law amendment, provinces in China one by one introduced new local laws and regulations on patent protection and R&D promotion. These policy reforms were meant to reflect the updated content of the national law and to lay out the legal foundation for policy implementation by relevant local government agencies. They also include regional policy packages specifically aimed at promoting innovation activities, such as tax benefits for R&D, subsidies for patent application, and patent prizes. More important to our empirical design is the staggered introduction of the innovation policies. This setting provides both chronological and spatial variations that facilitate causal identification of the policy effects. We argue that the regional innovation policies are plausibly exogenous—i.e., there is no systematic confounding variable specifically related to local pharmaceutical firms that coincides with the launch of provincial policies. One of the most important reasons for this is that local governments face complicated political constraints and mixed economic incentives in launching these policies—for instance, an enhanced patent protection system can both incentivize innovation activities and hurt the counterfeiting product industries that are crucial to China's local economies—so it is actually *a priori* unclear how and why the introduction of the innovation policies should be correlated with any unobserved factors such as local economic conditions. In Section 3, we present a detailed discussion of the rationales behind the local policy-making process in China and descriptive evidence to support our identification assumption.

Using a difference-in-differences (DID) strategy, we find that the provincial innovation policies have large positive impacts on both firms' R&D investments and innovation outputs in China's pharmaceutical sector. Our results suggest that the innovation policies led to a substantial increase of 17.5% in firms' R&D expenditure, or approximately CNY5 million per firm.[2] Two to four years following the policy implementation, the number of successful new patent applications by a firm had risen by 34% or 3.8 units per firm, and the likelihood of a firm having a new drug registration increased by 10 percentage points. However, we find that the likelihood of a firm filing a supplemental drug application for minor product changes did not increase, which suggests that the innovation policies resulted in significant product development instead of marginal product modifications.

To explore the causal links between innovation and marketing, we apply our DID strategy to examine different marketing expenditures. We find that following the policy implementation, firms reduced non-ad marketing expenditures by approximately 17% on average, but starting two years afterward, firms increased advertising expenditures by 50%. The time points at which these changes occurred match those at which the firms increased R&D expenditure and generated more innovation outputs. Furthermore, we show that the policies have had no significant effect on firms' external financing and that the policy effects on marketing expenditures do not depend on their financing status. These results help rule out the story that the changes in firm marketing expenditures were driven by financial factors. Our main results survive a series of tests for parallel trends and robustness, in which we consider alternative regression specifications, different variable constructions, and placebo tests with randomly generated policy years or treatment status.

Our study directly addresses current research on the innovation–marketing interaction. Our results to some extent reconcile a few conflicting findings in this literature. For instance, Kaiser (2005) finds that in the German service sector, innovative firms are less likely to advertise. Cavenaile and Roldan-Blancoz (2021) find that large firms substitute advertising (as measured by firms' SG&A expenses) for R&D, using data on listed US firms in 1980–2015. The substitutability between R&D and advertising is also stressed by important marketing papers, such as Mizik and Jacobson (2003). However, Matraves (1999) documents a positive relationship between industry R&D level and advertising expenditure for pharmaceuticals in the UK. Askenazy et al. (2016) find a positive

2. USD1 = CNY6.61 in 2018.

correlation between firms' R&D stock and marketing expenditure in multiple industries using French data. A separate strand of the marketing literature examines the complementary roles of R&D and advertising in firm performance (e.g., Srinivasan and Hanssens 2009; Joshi and Hanssens 2010; Steenkamp and Fang 2011; Jindal and McAlister 2015). In this study, exploiting detailed firm-level data, we break down the SG&A measure of "advertising" used in the literature and isolate the advertising component from other marketing activities. We show that the different components of marketing interact differently with innovation, and such relationships can be contemporaneous or dynamic. Our findings suggest that some earlier findings based on the correlational approach might be driven by confounding factors (e.g., market size, as suggested by Matraves 1999) and the coarse measure of advertising.

Our study is closely related to several strands of economics and marketing literatures on advertising. We borrow important insights from early economic models of informative advertising (e.g, Nelson 1974) and prominent works in marketing that stress the essential role of advertising in new product diffusion (e.g, Horsky and Simon 1983; Kalish 1985; Narayanan and Manchanda 2009). Scholars have identified the lack of detailed marketing data as a major setback for business research (Hanssens et al. 2009; Katsikeas et al. 2016). Although the SG&A variable is often used as a proxy for firm total marketing expenditures, recent research indicates that such a coarse measure can be problematic. For instance, Ptok et al. (2018) demonstrate that SG&A lacks construct validity as a measure of advertising expenses but serves as a reasonable proxy for selling effort. Markovitch et al. (2020) show that using SG&A may lead to questionable inferences about the effect of marketing expenditures on firm performance. Taking advantage of China's special financial reporting rules, we examine detailed marketing expenditure data and demonstrate the importance of separately considering advertising from other marketing expenses in empirical analysis. By empirically examining the pharmaceutical industry, our study is also related to the pharmaceutical marketing literature, with extensive prior research focusing on how various marketing strategies affect demand (e.g., Manchanda and Chintagunta 2004; Fischer and Albers 2010; Ching and Ishihara 2012; Chan et al. 2013).[3]

Lastly, our study broadly contributes to the large literature on innovation. Existing studies have focused on important external factors (e.g., product-market competition (Aghion et al. 2005) and

3. See also the literature review by Kenkel and Mathios (2012).

financial market conditions (Amore et al. 2013; Cornaggia et al. 2015)) and internal factors (e.g., managerial incentives (Manso 2011)). This study examines an underexplored side of innovation: its strategic interplay with other business decisions. As our empirical design exploits regional innovation policies in China, this paper is related to the vast literature on R&D subsidies and tax incentives for innovation (see David et al. 2000 for a critical review of the literature), and especially to recent studies of tax reforms and innovation in China (Chen et al. 2021; J. Cai et al. 2018). We show that regional IP protection and R&D promotion policies can have substantial unintended effects on firms' marketing activities.

The rest of this paper is organized as follows. In Section 2, we present our conceptual arguments and state our hypotheses. In Section 3, we provide background information about the 2010–2018 provincial innovation policy reforms in China and its pharmaceutical industry. In Section 4, we describe our dataset and perform preliminary analysis. In Section 5, we describe our empirical strategy and present the empirical results. Section 6 concludes.

2 Conceptual Framework

Innovation and different types of marketing activities. Marketing broadly encompasses any activity that firms undertake to generate and increase sales revenue. In the marketing process, firms inform consumers, boost market sales, and expand their sales channels through activities such as advertising, sales promotion, personal selling, and relationship building. However, in thinking about the interplay between innovation and marketing, various distinct marketing activities are often considered as serving a single function. For instance, Mizik and Jacobson (2003) argue that advertising, broadly representing all marketing strategies, is associated with the value appropriation aspect of the business process, as opposed to R&D, which represents the value creation aspect. In important economic models, innovation and marketing are often considered substitute strategies, as both can drive revenue by affecting the market perception of product quality (Grossmann 2008; Cavenaile and Roldan-Blancoz 2021).

However, as advertising is often the most important way to deliver product information to the market, it has a unique role in the business process. The informative function of advertising often makes it indispensable in selling new products. Advertising not only informs the market about the existence of a new product and its price and attributes but, as an important strand of literature points out, it can also accelerate the adoption and diffusion of new products through its effects on innovators and early adopters in particular (e.g., Horsky and Simon 1983; Kalish 1985).

Following this idea, we consider advertising separately in studying the innovation–marketing relationship. First, due to its often essential role in the launch of new products, advertising should be more complementary to innovation activities than other forms of marketing. Second, as innovation takes time, the need for delivering new product information to the market through advertising should occur relatively late in the innovation process, such as when past R&D investments generate tangible outcomes that demand advertising. We refer to this lagged change in advertising incentives as the *dynamic complementarity* between R&D and advertising. However, for other presumably less informative marketing activities, we do not expect such a time-specific, dynamic relationship. Notably, the dichotomy between advertising and non-ad marketing expenses is also common in the empirical literature when detailed expenditure data are available (e.g., Ptok et al. 2018; Markovitch et al. 2020).

The setting of our empirical investigation is the pharmaceutical industry, which is well-known for its high R&D and marketing intensities. For instance, pharmaceutical companies in the US annually spend 11%–15% of their revenue on R&D and 21%–40% on marketing and sales activities (Schweitzer and Lu 2018). Letting the market know about product improvements and innovation is essential to this industry, and pharmaceutical firms achieve this through personal selling to physicians (i.e., detailing), advertising in professional journals, and DTC advertising.[4] At the same time, due to the often complex market institutions for selling drugs and medical products, firms devote significant efforts to maintaining and expanding sales channels, including relationship-building with various parties like insurance companies, physicians, and regulators/governments. Notably, the increasing importance of sales channel marketing is by no means specific to pharmaceuticals; in many other markets for consumer goods, the modern process from production to consumption is often indirect and involves a number of intermediaries, such as wholesalers, retailers, brokers/agents, and trade platforms. Our focus on pharmaceuticals should shed light on the general understanding of firms' interrelated business strategies.

4. Besides the above-mentioned works in the large pharmaceutical marketing literature, see, e.g., Kenkel and Mathios (2012) and Schweitzer and Lu (2018) for reviews of the marketing practices in pharmaceuticals.

Strategic relationship and policy responses. According to Milgrom and Roberts (1990), two business choice variables are complements if increasing one variable raises the return to the other variable. It follows that for complementary strategies, their expenditures should be positively correlated, and this idea motivates the correlation-based approach to empirically examine the innovation-marketing relationship. However, in empirical implementation, the correlation-based approach can be subject to serious endogeneity problems, as both innovation and marketing decisions are often the results of other unmeasured factors, such as market size (Matraves 1999).

We propose to study the strategic relationship between innovation and marketing by examining firms' marketing responses to a positive shock to firm R&D. In the Online Appendix, we sketch a simple model of firm innovation and marketing to illustrate the idea behind our approach. Intuitively, it is analogous to the definition of product complementarity/substitutability in the consumer choice context. In particular, for goods that are substitutes (complements) at the consumption level, a positive demand shock to one good reduces (raises) the demand for the other.[5] In our business decision context, if non-ad sales activities substitute innovation efforts, we expect firms to adjust their marketing expenditures downward in response to an external policy change that incentivizes R&D investments, and vice versa.

Notably, our interpretation of the policy responses hinges on that firms do not simultaneously make other important adjustments. In our context, a potential confounding variable is firms' external financing choice, which may be strategically related to both R&D and marketing activities. While it is hard to construct alternative stories that explain why external financing, or any other strategic variable, could cause exactly opposite policy effects on advertising and non-ad marketing, in the empirical section we offer additional evidence showing that such a concern is unsupported.

2.1 Main hypotheses

We formulate the following hypotheses on the interplay between innovation and marketing activities:

- *Distinction between advertising and non-ad marketing.* The relationship between innovation and advertising may differ from that between innovation and other non-ad marketing activ-

5. In fact, in the consumer choice context, the related notions of gross and net substitutes/complements are defined according to the cross-price effects.

ities. An innovation policy change that increases R&D investments causes firms to reduce non-ad marketing expenditures if innovation and non-ad marketing are strategic substitutes.

- *Dynamic complementarity between innovation and advertising.* Innovation policies cause firms to increase advertising expenditures at the point in time when R&D investments generate innovation outputs.

In the empirical section, we directly test these hypotheses using a quasi-experimental policy setting in China and detailed, firm-level expenditure data from China's pharmaceutical industry.

3 Institutional Background

3.1 Province-level innovation policies in China

The empirical strategy of this study takes advantage of the staggered introduction of province-level innovation policies in China, which followed the third amendment to the country's patent law in 2008. The third amendment brought a number of important changes to China's IP protection system, including increased infringement damages, heightened patentability standards, and clarified rules on patent joint-ownership and double patenting.[6] It also introduced the Chinese version of the "Bolar exemption"—a legal provision that allows generic drug producers to use patent-protected knowledge and materials for R&D purposes without a license. The national policy reform triggered a series of new laws and regulations at the province level. During 2009–2018, approximately two-thirds of China's mainland provincial governments adopted new policies on patent protection and innovation promotion. These policy packages—which we simply refer to as "innovation policies"—were like many other market-oriented reforms in China whereby the central government set the general guidelines, and local governments were encouraged to experiment and implement policies based on local conditions (Xu 2011). Legally, they have the status of lower-level, local laws that are intended to reflect the updated content of the national law and layout the implementation details.[7]

6. See "Patent Law of the People's Republic of China (2008 Amendment)," available at http://www.lawinfochina.com/display.aspx?id=7289&lib=law. See also Zhuang (2014)'s review of the historical development of China's patent law.

7. See China's Legislation Law (http://lawinfochina.com/display.aspx?id=19023&lib=law), especially its article 73. The first article of each province's policy document explicitly states that they are "formulated in accordance with the Patent Law of China" and with the particular objectives to "promote inventions" and "improve the innovative capabilities [of the society]," which echo Article 1 of China's 2008 patent law. See, e.g., the 2009 regulations of

In China, local implementation is often key to the overall effectiveness of nationwide policies. For instance, in the context of patent promotion, for firms to receive the tax benefits for R&D expenditures introduced by the central government, they must complete a lengthy administrative process, working with both local tax bureaus for application and local departments of science and technology for careful on-site inspection and verification (Chen and Yang 2019). Without local policies for implementation, it would be difficult to coordinate different local government divisions to bring to life central-government policies. The series of new and revised local innovation policies specify the local government divisions (e.g., tax, commerce, and science and technology) that should take part in the policy implementation and grant them the legal authorization to fulfill their duties.

We review all of the policy documents and compare them with their earlier versions to identify novel content.[8] In Table A.2, we summarize the main points of each province's policies. We also read the policy documents of selected local departmental regulations for specific implementation details. In summary, these new policy tools can be divided into two types. The first type includes policies and regulations for stronger patent and IP protection, such as increased patent infringement penalties and new policy frameworks for patent transfer and brokerage. It is established in the literature that IP protection and patent systems are crucial for promoting innovation activities, especially in the pharmaceutical industry (Schankerman 1998). The second type of policy tool are direct R&D and patent incentives, such as tax benefits and innovation subsidies. In many provinces, the local policies statutorize a "super deduction" policy for R&D expenses. Under this policy, firms can claim an extra tax deduction equal to 50% of their R&D expenses, enabling them to effectively save 12.5% in eligible R%D expenses (as the corporate tax rate is 25% in China).[9] The overall tax benefits can be sizable, and according to Lennox et al. (2015), it is not unusual for a firm's tax savings to exceed its tax payment. For direct subsidies, first, provincial governments provide reimbursements for firms' costs associated with patent application. Second, firms can

Jiangsu Province (http://www.lawinfochina.com/display.aspx?id=12246&lib=law), and the revised, 2013 regulations of Beijing (http://www.lawinfochina.com/display.aspx?id=16917&lib=law).

8. The policy documents are available through the website of China's State Intellectual Property Office at http://pss-system.cnipa.gov.cn (under "Policies and Regulations") and comprehensive legal databases in China, such as PKULaw.

9. There are also province-specific tax benefits. For example, in Fujian, 150% of the capitalized R&D expenditures of firms in the software industry can be amortized over 2 years instead of 10 years. In Zhejiang, expenses for hiring external R&D personnel and experts, which are not eligible for super deduction by the central-government policy, are exceptionally considered as eligible R&D expenses. See the official news release at http://www.gov.cn/xinwen/2016-04/05/content_5061276.htm.

receive a monetary reward for each successful patent application. For domestic patents, the reward is usually between CNY2,000 and CNY8,000 per patent grant, and for foreign patents, it can be up to CNY40,000 per patent. Other innovation incentives include special regional prizes—which often amount to a few hundred thousand Chinese yuan—and patent pledge bank loans. In this paper, we provide an assessment of the overall effectiveness of these policies in promoting R&D inputs and generating innovation outputs.

Timing of the regional innovation policies. Ideally, our estimate of the effects of China's innovation policies would have a clean causal interpretation if their rollout across provinces had been random. However, given the non-randomness of the policy assignments—as in most observational studies—we must carefully discuss why the staggered introduction of the innovation policies can be treated as exogenous shocks to China's pharmaceutical firms. Specifically, exogeneity of the policies requires that the policy implementation in each province not be correlated with any unobserved factor that affects drug producers in that locality.

In Figure 1, we show the introduction of the new policies by provinces during 2009-2018 (see Appendix Table A.1 for more details). Based on the figure, there is no discernible geographical pattern to the timing of the policy introduction. For instance, as of 2012, the first seven adopting provinces include both more developed coastal provinces (e.g., Guangdong and Jiangsu) and less developed central-western provinces (e.g., Shaanxi and Gansu). We further check the correlations of the policy timing with selected local economic variables. Appendix Table O.1 shows the regression results, which include three groups of explanatory variables: GDP and GDP per capita, sectoral shares of GDP, and total imports and exports. The results show that none of the economic indicators have any significant correlation with the timing. In particular, there is no evidence that more (or less) developed provinces introduced the policy earlier.

[Figure 1 about here]

Rationales behind the regional policy-making process. Since no study has examined the political economy of innovation policy making in China to our best knowledge, we draw on existing scholarly works in public policy to underscore some of the most important underlying motives. From a politico-economic perspective, it is unclear *a priori* whether and how local economic conditions would correlate with the timing of the policies. A key objective of China's local governments is fostering economic development, which is crucial for local officials' promotions (Li and Zhou 2005). However, because the R&D incentive programs are usually coupled with stricter IP protection regulations in the policy packages, provincial governments face mixed incentives in bringing these upgraded policies to life. On the beneficial side, a better IP protection system is key to a healthy market environment, especially in the longer term. In China's context, it has been documented that the improvement in IP protection has helped attract foreign direct investments (Awokuse and Yin 2010). On the disadvantageous side, stronger IP protection may hamper local economic activities (e.g., Qian 2007), especially where the local economy heavily depends on the counterfeit goods industry—in the early 2000s, it was estimated that counterfeiting accounted for 8% of China's GDP (Chow 2006).[10] For this reason, some local governments are reluctant to bring in tougher IP protection regulations. In addition, local governments have strategic considerations regarding the adoption of policies that generate significant inter-regional spillovers. In particular, stricter anti-counterfeiting law enforcement in one province can drive the counterfeit industry to neighboring regions. Although there is no scientific evidence of this motive in China's innovation policy making, this strategic motive and the related issue of inter-regional competition are the main theme of a large body of literature on China's economic institution (e.g., Xu (2011)) and are empirically tested, for instance, in the context of local environmental policies (H. Cai et al. 2016). Moreover, other political factors—often unrelated to local economic conditions—such as political factions (Tsou 1995) and political cycles (McGregor 2010), may have also contributed to the differences in timing of the innovation policies.

Our empirical evidence indicates that the reform timing was largely consistent with the key features of China's policy environment. In the following sections, we show further evidence that (i) the timing of policies is not correlated with the average pre-policy pharmaceutical R&D level in a province and that (ii) there is no pre-reform trend in firms' R&D or any other main outcome variable.

3.2 China's pharmaceutical industry

Since the 1980s, the sales and production of pharmaceuticals in China have experienced double-digit growth. From 2008 to 2018, the total industry revenue increased from approximately CNY908

10. For the effects of counterfeiting in China, see, e.g., Qian (2008).

billion (US$130 billion) to CNY2,426 billion (US$350 billion), accounting for 2.6% of China's GDP.[11] In China, domestic pharmaceutical producers typically produce generic drugs, chemical compounds, traditional Chinese medicines (TCMs), and other medical products (Jiang et al. 2001). In the early 2000s, there were approximately 5,000 firms in the industry, of which 90% were generic drug producers.

Despite the growing importance of China's pharmaceutical sector, until recently, its innovation level was low. For instance, between 2005 and 2008, the ratio of R&D spending to sales revenue among pharmaceutical firms was 1% to 2% on average, whereas this ratio was around 15% to 18% for pharmaceutical companies in major developed countries (Sun et al. 2008). Meanwhile, Chinese pharmaceutical firms spend disproportionately more on sales and marketing. In our sample of listed Chinese firms, the ratio of R&D to total marketing spending is approximately 1:3.5. In comparison, based on 2003–2012 data, pharmaceutical companies in the US spend 30% to 100% more on R&D than on marketing and promotional activities (Schweitzer and Lu 2018).

Over the past decade, the innovation level of China's pharmaceutical companies has increased. Innovation scholars have characterized the last two decades as a period of "imitative innovation" and the beginning of independent innovation for this industry (Ding et al. 2011). Figure 2 shows this trend of increasing average R&D spending by the firms in our sample from 2008 to 2018.

Not only innovator drugs but also TCMs and generic drugs rely on China's patent system for IP protection. Although the core substances of a generic drug are not patentable, generics producers in China often protect their innovation outcomes through patents in peripheral areas, such as manufacturing techniques, which are commonly referred to as "process innovations". For example, lopinavir is a drug used to treat HIV and it is sold under the brand name Kaletra. The patents on lopinavir's basic substances were held by Abbott Laboratories and expired in 2016. However, as of 2014, there were 149 patent applications in China related to lopinavir from various applicants including both multinational firms and domestic producers. These applications covered chemical intermediates, drug preparations, and medical usage (Yang et al. 2015). Zhang and Nie (2021) document that in 1993–2009, about 60% of all pharmaceutical invention patents in China involve process innovation. Compared with innovator drugs, the development cycle for generic drugs and TCMs is also significantly shorter. In China, the process from generic R&D to production typically

11. China's National Bureau of Statistics. See also Jiang et al. (2001) and Sun et al. (2008).

takes two to three years.[12] Patent applications are made at different stages in the process. In fact, pharmaceutical innovators conventionally disclose information and file patent applications early in the research process, for both ethical and regulatory reasons (Lakdawalla 2018).

4 Data and Descriptive Statistics

4.1 Data sources and variable construction

4.1.1 Firm data

We use data on publicly traded pharmaceutical manufacturing firms (CSRC industry code C27) in China's A-share markets from 2010 to 2018. In January 2010, China's financial regulatory authority required all listed firms to disclose detailed expenditure information in their annual financial reports.[13] This regulatory change provides a unique opportunity to separately examine firms' expenditures on different types of marketing activities.

Our primary data source is the China Stock Market and Accounting Research (CSMAR) database, a standard database for Chinese business research similar to Compustat in the US. The CSMAR data include firm-level information on R&D, patent applications and grants, and other financial variables. To avoid sample selection problems, we drop all firms that first appear in the database after the policy implementation in their home provinces. We also drop all firms in the three provinces that introduced new policies before or during the first year of our sample period (i.e., 2010). We use additional information from another financial database, Choice Data, for selected variables (e.g., the number of employees). The resulting dataset is an unbalanced panel of 171 Chinese pharmaceutical firms over nine years.

R&D and patents. We consider both the R&D inputs and innovation outputs of the firms. For our research design, it is crucial to examine those variables separately, as we have specific predictions of how different marketing activities relate to different phases of innovation. When we need to calculate R&D spending directly from the financial reports, we use the sum of R&D expense from the category "Administrative Expense" and capitalized R&D expenditures from the

12. See China Bond Rating Coporation (2017)'s industry report on pharmaceuticals in China.

13. See "Announcement No.1 [2010] of China Securities Regulatory Commission–Preparation Rules for Information Disclosure by Companies Offering Securities to the Public No. 15–General Provisions on Financial Reports (2010 Revision)," available at http://www.lawinfochina.com/display.aspx?lib=law&id=9034 (English translation).

category "Intangible Assets," following the literature (e.g., Acharya and Subramanian 2009) and China's accounting standards.

One of our main measures of innovation output is the number of patents filed by a firm in a given year that are eventually granted. As we are interested in measuring real innovation outcomes, we focus on successful patent applications to avoid the issue of low-quality patenting. Based on our data, it takes two years on average for a patent application to be approved. China grants three types of patents: invention, utility model, and design. In the main analysis, we consider all three types of patents as innovation. For robustness, we use other patent measures and obtain similar results (see Section 5.5).

Our main analysis examines firms' future innovation outcomes in $t+2$ to $t+4$, which represents two to four years after the policy implementation in a province. This is motivated by the observation that the development cycle for generic drugs in China typically takes two to three years. Recently, Zhang and Nie (2021) find an immediate surge in patent applications related to specific insurance-covered diseases one year after the implementation of a nationwide public health insurance program in China in 2003. In Section 5.3, we conduct an event study analysis to examine the full dynamics of the policy effects. It transpires that the estimated effects on patents are also most significant three and four years after the policy implementation.

Marketing variables. Taking advantage of China's financial reporting rules, we separate various items under the broad category of "Sales and Marketing Expense" into separate groups.[14] The first group is expenditure on advertising, which includes not only traditional media advertising but also participation in exhibitions—a presumably more informative marketing activity. The other broad category—which we refer to as non-ad marketing expenditure—includes expenses for consultation and conferencing, agency fees, ETCs, and others. We use these expenses to measure spending on sales efforts that contain comparatively less information about new products. Notably, among these expenses, ETCs are often used to measure corporate corruption, especially in the Chinese context (H. Cai et al. 2011; Fang et al. 2018). Conference expenses also belong to this category, as they have been used prevalently to bribe doctors and government officials in China.[15]

14. For practical reasons, we do not separate total marketing expenditure into more than two categories. Listed firms in our sample often have different labels for their expenditures; for instance, some firms choose to report "conference expenses" and "market promotion expenses" separately, whereas others combine such information under a single category.

15. See https://www.ft.com/content/79d2c1d8-e542-11e5-bc31-138df2ae9ee6 and https://www.bloomberg.com/

Although we emphasize the difference between the two types of marketing expenditure in this study, our categorization is not perfect. It is easy to imagine that in reality, what we associate with advertising, such as trade-fair participation, may involve efforts to persuade customers, not only to inform them. Nonetheless, we consider our two measures as substantially different and suitable proxies for the two distinct marketing concepts featured in our conceptual framework. Recent marketing studies also divide total marketing expenditure into advertising and other sales expenses (Ptok et al. 2018; Markovitch et al. 2020). In Section 5.5, we check the robustness of our main results by using alternative variable definitions.

Other variables. To analyze the effect of the innovation policies on firms' external financing, we construct four measures. The first is the KZ-index, following Kaplan and Zingales (1997), which provides a relative measure of reliance on external financing. The second measure is the log amount of long-term debt of a firm. The third measure is an indicator variable of whether a firm has raised new long-term debt in year t, and the fourth measure is a binary variable indicating whether a firm has raised new external equity. A firm is counted as having raised new debt (or new equity) if its new long-term debt (or new external equity) exceeds 5% of its total assets in a year. The last two measures are used by Xu and Yano (2017) to study financing decisions of listed firms in China.

Last, our control variables include firm size measured by the log of total assets ($LnAssets$) and the log of the total number of employees ($LnEmployee$); asset tangibility, $PPEAssets$, measured by net property, plant, and equipment divided by total assets; capital expenditure ratio, $CAPEXAssets$, measured by capital expenditures divided by the book value of total assets; LEV, the ratio of total liabilities to total assets; growth opportunities $TobinQ$; and corporate liquidity, $CashRatio$, measured by the ratio of corporate cash to current liabilities. We include more details on the variable definitions in Appendix A.1.

4.1.2 Drug registration data

Data of new drug registration are newly collected from the website of the Center of Drug Evaluation (CDE) under China's National Medical Products Administration (NMPA).[16] The official website has a publicly accessible database of the registration information for all drugs and medical

news/articles/2016-03-24/novartis-agrees-to-settle-sec-china-bribe-case-for-25-million.

16. http://www.cde.org.cn.

products in China since the mid-2000s. As mandated by the "Provisions for Drug Registration" issued in 2007, drug producers in China need to file an application for authorization for clinical trials in the research stage and a separate application for marketing approval before final production. The database records all requests for clinical trials and marketing approval. As of late 2020, there are more than 200,000 records.

In this study, we focus on the registration requests for marketing approval. Those requests mainly fall under two broad categories, which can be literally translated as "new drugs" and "imitative drugs" and roughly correspond to the new drug application (NDA) and the abbreviated new drug application (ANDA) in the US, respectively.[17] The "new drug" category covers any new-to-China drugs and re-launched old products with major modifications (in terms of formula, dosage, and usage). Both categories include not only common medications (prescription and over-the-counter) but also vaccines, blood products, dietary supplements, and TCMs.

We use the names of the applicants to match the official records to a list of publicly-traded pharmaceutical firms and their subsidiaries (downloaded from our financial database) for each year between 2010 and 2018. The drug registration data are then aggregated to the firm level and merged with the main dataset.

Variables of new drug development. To obtain direct evidence on new product development, we construct a binary variable, $NewDrug$, indicating whether a firm has any successful drug registration requests—including both new-to-market and imitative products—in a given year. We construct another binary variable, $SupApp$, indicating whether a firm has any supplemental applications for non-substantial changes in an existing drug. As such requests reflect marginal changes that do not take much innovation effort (e.g., changes of packaging), we use it in a placebo test to check whether the policy interventions led to merely minor changes to existing products.

4.2 Summary statistics

Table 1 provides the summary statistics of the main variables. Treatment firms are defined as firms whose headquarter is in a province that introduced new innovation policies during 2010–2018. Excluding three provinces that introduced new policies before or during 2010, we have 124 treated

17. In Chinese, "imitative drugs" and "generic drugs" are the same word. However, we intentionally make a distinction here because the Chinese "imitative drug" category also contains copycat TCM products, which are not generic drugs by definition. Outside China, TCMs are often regulated as food.

firms from 17 provinces and 47 non-treated firms from 11 provinces. Except for the province of Ningxia, each province is home to multiple publicly traded pharmaceutical firms. Note that the panel is unbalanced due to the entry of newly listed firms and missing data for some variables. In a robustness check, we include additional observations with missing control variables, and our main results continue to hold.

On average, the firms in our sample spend CNY81.4 million (approximately USD12 million) annually on R&D. The standard deviation is CNY130 million, which implies a large degree of dispersion in R&D spending across firms. The average R&D intensity is between 2% and 3%, which is consistent with the estimated 1% to 2% for all drug producers in China (Sun et al. 2008). The average number of successful patent applications is around 15, and the standard deviation is 34.5. As shown in Figure O.2, the distribution of the patent variable is highly right-skewed.

Among all three types of pharmaceutical patents, most ($> 95\%$) are inventions. The mean of $NewDrug$ is 0.353, indicating that approximately one-third of the firms have successful new drug product registration in a year. Given that the mean of *SupApp* is 0.387, on average, firms have a slightly bigger chance to apply for making a minor change to existing products.

The firms in our sample spend disproportionately more on marketing: on average, they spend CNY350 million (approximately USD52 million) on all sales and marketing activities. Advertising expenses account less than 20% of all marketing expenditures on average, whereas non-ad marketing expenditures account for more than 80%. The marketing variables have large variances. For instance, the mean of non-ad marketing expenditures is around CNY290 million, and the standard deviation is CNY542 million.

[Table 1 and Figure 2 about here]

Figure 2 plots the trends of the average R&D and marketing expenditures of our sample firms. For both the treated and non-treated firms, their average R&D and non-ad marketing expenditures have substantial growth over time. For R&D, we have two more years of available data before 2010. The average R&D expenditures of the two groups are largely comparable between 2008 and 2011, and their average non-ad marketing expenditures are also similar up to 2012. From the graphs, three patterns are particularly noteworthy. First, the average R&D spending of the treated firms grows faster than that of the non-treated firms. In fact, by 2018, the treated firms on average spend roughly 30% more on R&D than the non-treated firms. Second, whereas the average non-ad marketing expenditure of the treated firms has a higher growth rate initially, the average expenditure of the untreated firms grows faster after 2016 and catches up by 2018. Third, although the non-treated firms consistently have a higher level of advertising expenditure over time, the average advertising expenditure of the treated firms has larger growth after 2015/2016. In the next section, we rigorously examine to what extent these patterns can be attributed to the provincial innovation policy reforms after 2009. Before moving to describe our empirical strategy, in the next part, we examine more closely the correlations between our key variables of interest.

4.3 Correlation between R&D and marketing expenditures

Existing research uses a correlation-based approach to examine the relationship between innovation and marketing decisions. Following that approach, we also find a positive correlation of 0.70 between firm R&D and total marketing expenditure in our sample of pharmaceutical firms in China, as shown in Appendix Table O.3. In column 1 of Table O.3, the estimated coefficient of 0.778 is the elasticity of total marketing to R&D spending, and it is highly significant. Similar positive correlations emerge for ad and non-ad expenditures separately (columns 4 and 7). However, when we add firm-level control variables to account for firm characteristics that potentially affect both marketing and R&D, the correlations become visibly smaller (columns 2 and 5).

These seemingly persistent patterns of positive correlation are in line with existing findings based on data from the UK (Matraves 1999) and France (Askenazy et al. 2016) that use a similar correlational approach. To further examine the potential endogeneity problem, we employ the commonly used instrumental variable (IV) strategy for panel data by using lagged R&D as an instrument. When we apply the IV method, the estimated elasticity of total marketing to R&D expenditure decreases further (0.183) and is no longer significant. We also find similar changes for both ad and non-ad marketing expenditures. Taken together, the IV estimates indicate that there is no significant relationship between firm R&D and either marketing variable—a conclusion in sharp contrast to our findings based on OLS. To emphasize, we do not attempt to argue for the validity of the IV approach in our context; instead, we use that to illustrate the endogeneity issue of the correlation-based approach and hence to underscore the importance of finding exogenous shocks. We in this paper employ a different strategy to investigate the relationship between innovation and marketing, as described in the next section.

5 Empirical Strategy and Results

5.1 Research design

We examine how pharmaceutical firms in China respond to regional policies that incentivize innovation. As is explained in Section 2, the logic of our approach is as follows: while the regional innovation policies should induce firms to invest in more R&D and generate innovation outputs, the extent to which firms adjust their marketing strategies in response informs us about how innovation and marketing decisions interact in the business process. We are particularly interested in examining (i) how different types of marketing activities are related to firm innovation, and (ii) how dynamics matter for the innovation-marketing interaction.

Exploiting the staggered provincial innovation policy reforms following the third amendment of China's patent law in 2008/2009, we use a DID estimation strategy that allows for different timing of the treatment. This empirical setting alleviates the common problem of potential unobserved factors coinciding with a policy shock that directly affects firm behaviors. Specifically, we use the following baseline specification to run OLS regressions:

$$y_{i,t+N} = \beta_0 + \beta_1 Policy_{i,t} + X_{i,t}\gamma + \omega_i + \theta_t + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t+N}$ is an innovation or marketing variable of firm i in year $t+N$ with N denoting time lag. Our main variable of interest, $Policy_{i,t}$, is a binary indicator that equals 1 if the province where firm i is located has new innovation policies in t, and 0 otherwise. $X_{i,t}$ is a set of firm-level control variables described in Section 4.1.1. ω_i and θ_t are firm and year fixed effects that capture any time-invariant, firm-level heterogeneity and yearly, industry-wide shocks (including the impact of the Bolar's exemption as part of the national law), respectively. We cluster the standard errors at the province level to account for with-in province correlation in model errors.

For the patent variables, which are count data, we estimate a fixed-effect Poisson model with the following conditional mean:

$$\mathbb{E}(Patents_{i,t+N}|\mathbf{X}_{i,t}) = \exp(\beta_1 Policy_{i,t} + X_{i,t}\gamma + \omega_i + \theta_t), \tag{2}$$

which is analogous to the specification of equation (1).

5.1.1 Validity of the design

Our identification strategy rests on the assumption that the cross-province timing of the innovation policies was unaffected by the past R&D expenditures of pharmaceutical firms in a province. We have already shown that local economic conditions are not correlated with the timing of the policy roll-out (Appendix Table O.1). Figure O.1 further shows that the average pre-policy R&D level of firms in a province does not explain the timing of the policies. When we regress the year of the policy introduction on the average pre-policy R&D expenditure, the coefficient is 0.015 and insignificant (p-value = 0.96). We also use a probit regression to check whether the policy introduction can be explained by the average pre-policy R&D expenditure, and the estimated marginal effect is small (0.044) and indistinguishable from zero (z-value = 1.01).

Another related concern is that any difference in innovation and marketing activities between the treatment and control firms after the treatment event may be driven by differences in firm characteristics unrelated to the policy interventions. In Table O.2, we make univariate comparisons between the treatment and control firms' characteristics in 2008. On average, the treatment firms tend to be larger in size and have a higher leverage ratio and more patents, whereas the control firms have a higher Tobin's Q. However, based on column 4, which shows the p-values, none of the differences is statistically significant. To alleviate any remaining concern, first, we explicitly control for all of these covariates in our regressions. As we show later, the inclusion of these control variables does not affect our main results. Second, we examine the pre-treatment trends in the key innovation and marketing variables of the two groups. In short, we find no evidence of any pre-trend in firms' R&D, patent status, and marketing expenditures before the policy introduction (see Figure 3).

5.2 Main results

5.2.1 Positive effects on R&D and innovation outputs

R&D spending. We begin by showing that the provincial innovation policies successfully incentivized firms to increase R&D spending. In Table 2, column 1, in which the regression does not include any control variable, the estimate for *Policy* is positive (0.161) and statistically significant at the 10% level. Column 2 includes a set of firm-level controls to account for important time-varying determinants of innovation. Following the literature, we use the variables with a one-year lag. Three covariates, namely, the total assets, the debt-to-asset ratio, and the capital expenditure ratio, are significantly correlated with R&D spending. The coefficient for *Policy* (0.164) is similar to the estimate in column 1, and its significance level increases. Controlling for the covariates also does not substantially increase the explanatory power of the regression model, as the R-square only increases marginally (from 0.843 to 0.859). Overall, our estimates indicate that the implementation of the innovation policies is associated with a 17.5% ($\approx e^{0.161} - 1$) increase in firms' total R&D spending, whether we include firm-level control variables or not. Evaluated at the mean R&D level in 2010, this increase is CNY4.9 million (USD0.7 million) per firm. Figure 3a further supports our causal interpretation by showing that no pre-trend pattern existed for R&D investments.

[Table 2 about here]

Patents. Next, we examine the policy impacts on future innovation outputs of affected firms. This is crucial because according to our conceptual framework, the regional policies that provide R&D incentives lead to increased future advertising expenditure only if the initial R&D investments result in tangible outcomes to advertise. Columns 3 and 4 of Table 2 show that the estimates for patents are positive and significant. The effects hold with and without firm-level control variables. The results suggest that the policy introduction is associated with a 34% ($\approx e^{0.296} - 1$) increase in the number of successful patent applications in $t + 2$, which is about 3.8 new patents per firm. Later in Figure 3b, we verify the parallel-trend condition for patents.

The results show that the innovation policies led to more innovation outputs starting two years after the policy roll-out. Considering the long product development cycle for new drugs, the rapid response of patent applications in China might seem surprising at first. Nonetheless, it is consistent with previous findings based on the establishment of public health insurance programs in the US.

(Blume-Kohout and Sood 2013) and China (Zhang and Nie 2021). For instance, Zhang and Nie (2021) find an immediate increase in specific disease-related patent applications in 2004 after the implementation of a major rural insurance program in 2003. There are at least two reasons for this fast response of patent applications. First, in China and elsewhere, it is conventional for pharmaceutical firms to file patent applications early in the development process (Lakdawalla 2018). Second, specifically in China, most innovation activities are imitative innovations that take less effort and time. For instance, it is reported that the typical development cycle for generic drugs takes two to three years in China (China Bond Rating Coporation 2017). As noted earlier, although the core substances of a generic drug are not patentable, generics manufacturers in China often protect their innovation outcomes through process patents in peripheral areas, such as manufacturing techniques and drug preparations. For other important pharmaceutical products in China, such as TCMs, their development cycle is also significantly shorter than innovator biochemical drugs.

New drug registration. To obtain direct evidence on product development, we use newly-collected data on drug registration in China. In Table 3, we first look at $NewDrug$, which indicates whether a firm has any successful request for new product registration. To emphasize, this indicator variable covers not only novel biochemical drugs but also generic products, major modifications of existing drugs, and other medical products (e.g., TCMs and biologics). The estimates indicate that the policies are associated with a 9 to 15 percentage point increase in the likelihood of a firm having a new drug registration three or four years after the policy reforms. Such effects hold with and without firm-level control variables.

[Table 3 about here]

This direct evidence of the policy effect is consistent with our previous finding on patent outcomes. Taken together, our results are consistent with the documentation that the research-to-production process for generic drugs on average takes two to three years in China. In our sample, approximately 80% of the firms are mainstream, non-TCM drug producers, and all of them produce generic drugs.[18] The rest of them specialize in TCMs. Given that new drug registration in China also includes TCMs and re-marketed old drugs with modified formulas, it is not surprising

18. The few Chinese pharmaceutical firms known for innovator drugs became publicly listed relatively late in the past decade, so they are not included in our sample. They are Alphamab Oncology, BeiGene, Betta Pharmaceuticals, Chipscreen Biosciences, and Innovent Biologics.

that the firms had been able to launch new products so quickly after the initial increase in R&D investments.

As a placebo test, we also examine *SupApp*, which indicates whether a firm has any request for minor changes in an existing product (e.g., new packaging). In columns 5 to 8, the estimated coefficients are positive but insignificant. This suggests that the policy interventions had been effective for reasons other than firms re-marketing old products with only minor modifications.

In summary, we have established that the regional innovation policies are positive shocks to firm R&D and that they lead to significant increases in innovation output of the pharmaceutical firms. Both the *direction* of the effects and the *timing* match our priors.

5.2.2 Marketing responses to the innovation policies

We now examine the marketing responses of the affected firms and report the DID results in Table 4. For each variable, we use two specifications—with and without the firm-level control variables.

Non-ad marketing. In columns 1 and 2, the estimates imply a strong negative impact of the policies on non-ad marketing: the introduction of the innovation policies is associated with an immediate drop of 17% ($\approx e^{-0.190} - 1$) in non-ad marketing expenditure of the affected firms. In other words, firms responded to the innovation policies by substantially cutting their non-ad marketing expenditure. However, this negative effect does not apply to the advertising expenditure of the affected firms (see Figure 3c). As shown in Section 5.5, the result continues to also hold when we consider alternative measures of non-ad marketing. For instance, the policy reforms are associated with a 1.5-percentage-point decrease in non-ad marketing intensity. Overall, our findings indicate a significant substitute relationship between R&D and non-ad marketing.

In this study, our measure of non-ad marketing also contains elements that are considered rent-seeking in the Chinese context (i.e., ETCs). Xu and Yano (2017) find that China's recent anti-corruption campaigns had led to reductions in ETCs and significant increases in corporate innovation. Our findings largely complement theirs. They are particularly important in the context of China's pharmaceutical sector, where low R&D intensity and widespread bribery have been the major concerns for practitioners and regulators.

[Table 4 about here]

Advertising. Columns 3 to 6 examine the policy effect on future advertising. In column 4, the estimate implies that the affected firms had spent 52% ($\approx e^{0.422} - 1$) more on advertising in $t+2$, which is two years after the enactment of the innovation policies. In column 6, the estimate for $t+3$ is positive, although its significance level is just below the 10%-threshold by a small margin (*p-value* = 0.11). Later, our event study estimates further confirm that the policy effects on advertising are concentrated around three to five years after the treatment event (see Figure 3c). This set of findings is consistent with the timeline of the policy effects on patents and product development.

In summary, our results regarding firm marketing provide strong support for the main hypotheses. Both the *direction* and the *timing* of the effects match our predictions on the dynamic complementarity between R&D and advertising. Previously in Section 4.3, we showed that the correlational approach yields very different results. Our empirical approach exploits quasi-experimental policy variations to examine the strategic responses of the affected firms. It also provides a transparent framework to understand the underlying dynamic interaction.

In the subsection below, we provide auxiliary evidence to further support the causal interpretation of our main findings.

5.3 Pre-policy trends and dynamic effects

One main concern about our findings above is that the firms in provinces that have new innovation policies might already have been on a trajectory of higher R&D investment. Nonetheless, Figure 2 shows that the average R&D spending of the treatment firms is not higher than that of the control firms in pre-reform years. We have also shown in Section 5 that the average pre-policy R&D level of the pharmaceutical firms in a province does not explain the policy adoption (or its timing). Here, we further address this concern by checking whether there are pre-treatment differences—in terms of their innovation and marketing variables—between the treatment and control firms. Specifically, we perform an event-study analysis to examine the dynamics of the policy effects by running the following regression:

$$y_{i,t} = \alpha + \sum_{k=-3}^{6} \beta^k \, \mathbb{1}(t - PolicyYear_i = k) + \gamma X_{i,t} + \theta_t + \omega_i + \varepsilon_{i,t}, \tag{3}$$

where $\mathbb{1}(\cdot)$ is an indicator function that equals 1 if the observation year minus the province-specific treatment year is exactly equal to k. The associated coefficients, β_{-3}, β_{-1}, ..., β_6, range from three years before the treatment year to six years afterward. We include the same set of control variables and fixed effects as in equation (1). In particular, this model does not impose any functional form restrictions on the pre- and post-treatment effects.

Figure 3 plots the estimated β_K coefficients and the 95% confidence intervals. It shows that the pre-treatment differences between the affected and non-affected firms for the innovation and marketing variables are largely indistinguishable from zero, indicating that firms in the treated provinces did not have a higher level of innovation or marketing expenditure before the implementation of the innovation policies. Panel (a) shows the dynamic policy effects on R&D. The parallel trend in R&D spending continues into the post-treatment years, and the positive difference between the affected and non-affected firms becomes most significant two to three years after the policy implementation. For the effects on patents, panel (b) shows a similar qualitative pattern.

In panel (c), the pattern for advertising spending looks similar to that for patents in panel (b). Specifically, the positive effects are most significant three to five years after the policy implementation. Lastly, panel (d) shows that the dynamic effects on non-ad marketing expenditure exhibit a downward trend over time, although the yearly effects are not precisely estimated. Importantly, the trend shown in this figure is almost a mirror image of that for R&D investments in panel (a), visualizing the opposite effects on R&D and non-ad marketing. Notably, the event study specification in the form of equation (3) does not suffer from the issues with two-way fixed effects DID designs emphasized in the recent econometric literature (e.g., de Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021). In particular, Goodman-Bacon (2021) recommends using the event study specification to address the issue. Therefore, the fact that our event study estimates are consistent with the baseline results offers additional support for the validity of our DID strategy.

[Figure 3 about here]

5.4 Heterogeneity in the policy effects by financing status

We interpret our main findings as evidence of the strategic relationships between innovation and various marketing activities. A potential confounding choice variable is a firm's external financing decision. Based on the provincial policy documents, most provinces have specific policies that facilitate R&D financing, such as IP pledge loans (see Section 3.1). Nonetheless, even if the policies did facilitate capital raising, it is hard to see why they would generate differential effects on advertising and non-ad marketing expenditures.

To investigate whether the policy effects on marketing expenditures vary across firms with different financing status, we interact each of the four measures of external financing (as described in Section 4.1.1) with $Policy_{i,t}$ in equation 1 and report the estimates in Table 5. First, the estimates for $Policy$ carry the same signs as the main results, although they tend to be less precisely estimated. Second, the coefficients attached to the interactions are all small and insignificant. Third, the estimates based on different measures of financing are inconsistent with each other. For instance, the estimates suggest that firms having raised new long-term debt experienced a weaker positive effect on future advertising (column 3) but that firms having raised new equity experienced a stronger effect on future advertising (column 4).

We also the same DID method to test whether the innovation policies had directly affected firms' external financing. Table O.4 shows that the estimates on all four measures are small and insignificant. Together with the above findings, the results rule out the story that firms' marketing responses to the innovation policy reforms are driven by financial factors.

[Table 5 about here]

5.5 Additional placebo and robustness checks

Our identification strategy exploits both the time and spatial variation in the introduction of the province-level innovation policies. To threaten our identification, any confounding factors have to be unrelated to the provincial innovation policies but coincide with the timing of the policies, which we believe is unlikely. Nonetheless, we perform two additional placebo tests to alleviate this concern.

Random policy years. We showed in Section 5.3 that our results are not driven by concerns related to pre-trends. Here, our first falsification test further strengthens this point by testing the policy effects with randomly generated policy years. In particular, we hold the group assignment constant and randomly generate a policy year different from the actual year of policy introduction for each province in the treatment group. We then use the fictitious policy years to re-estimate the main specification. For each of the main variables, we repeat the exercise 500 times and examine the empirical distribution of the estimated coefficients of *Policy*. We find that the distributions are mostly centered around zero. For the placebo estimates for R&D, patents, and NDA (in $t+3$), the mean coefficients are in fact negative but close to zero (-0.001, -0.024, and -0.008, respectively). In most of the random draws, the placebo test yields estimates that are insignificant or smaller (in magnitude) than the original coefficients.

For non-ad marketing expenditure and advertising, the mean coefficients are 0.009 and 0.007, respectively. In approximately 95% of the random draws, the placebo test yields estimates that are insignificant or smaller (in magnitude) than the original coefficients reported in Table 4.This set of results shows that the actual policy years are crucial for our main results.

Random treatment status. Second, we hold the distribution of policy years (i.e., the number of provinces with new policy introduction in each year) constant and randomly put provinces into the treatment or control group. This random assignment gives us a false *Policy* variable, which we use to re-estimate the main specification. For each of the main variables, we repeat the exercise 500 times and examine the empirical distribution of the coefficient estimates. Again, we find that the resulting distributions are either centered around zero or markedly closer to zero than the results from Tables 2–4. For the placebo estimates for R&D, patents, and NDA (in $t+3$), the mean coefficients are closer to zero (0.052, 0.059, and 0.034, respectively). In most of the random draws, the placebo test yields estimates that are insignificant or smaller (in magnitude) than the original coefficients.

For non-ad marketing expenditure and advertising, the mean coefficients are -0.081 and 0.174, respectively. In more than 90% of the random draws, the placebo test yields estimates that are insignificant or smaller (in magnitude) than the original coefficients (in columns 2 and 4 of Table 4).

Taken together, the placebo tests further strengthen our confidence in the empirical strategy used.

Sample construction. For our main analysis, we focus on the observations with a complete set of covariates. For robustness, we include additional observations with missing firm-level control variables and estimate equation (1) with no covariates but with firm and year fixed effects. In Table 7a, the coefficients of *Policy* are largely the same as the baseline estimates reported in

Tables 2 to 4. For R&D and new drug registration, however, the significance level of the estimates falls below the 10% benchmark. We are not particularly concerned about these findings because (i) they indicate similar effects of the policies as do our main estimates, and (ii) based on a comparison of the results in Tables 2 and 3, we see that without controlling for firm-level characteristics, the DID estimation tends to yield less precisely estimated results in general. For other variables on patents and marketing expenditures, the coefficients are all significant. Overall, our main results are largely robust to the inclusion of out-of-sample observations, even though we do not control for important covariates in estimation.

Other outcome variables. We also consider alternative variable definitions for robustness checks. Column 1 of Table 7b includes salesperson salaries in the calculation of non-ad marketing expenditure, and the estimate remains negative and statistically significant. In column 2, we use the most restrictive definition of advertising by including only firms' reported advertising expenditure and excluding exhibition expenses. Notably, this drastically reduces the number of observations by two-thirds; nonetheless, the coefficient remains significant and quantitatively similar to the baseline estimate. Columns 3 and 4 use a broader and a narrower measure of patents by considering all patent applications (including those that were unsuccessful) and only the "invention" and "application" types of patents, respectively. The results are comparable to the baseline estimates. Finally, in columns 5 and 6, instead of examining whether a firm has a new drug application, we examine the log number of applications. In $t + 3$, the estimate is positive but does not reach the 10% significance level, and in $t + 4$, it is positive and highly significant. Again, they are in line with our main results.

[Table 6 about here]

6 Conclusion

In this paper, we offer new answers to the long-standing question regarding the interdependent relationship between innovation and marketing activities. Our key arguments are that advertising interacts differently with innovation than do other marketing activities and that advertising complements innovation input dynamically. Exploiting detailed data on firm expenditures and innovation outcomes and regional innovation policy reforms in China, we test our hypotheses in the context of China's emerging pharmaceutical industry. Our DID results show that in response to increased incentives for innovation, pharmaceutical firms lowered their non-ad marketing expenditures but raised future advertising expenditures when firms generated new patents and drug products. Overall, our analyses demonstrate the importance of separating marketing tools that are more relevant to product innovation from other business-expanding efforts.

Our findings have important implications for managerial decisions and public policy:

- Although a number of studies argue that public R&D incentives (e.g., subsidies) might crowd out private R&D investments (David et al. 2000), we show that in the context of a large emerging economy, regional innovation policies that include both IP system reforms and direct R&D incentives can successfully induce private R&D investments and lead to increased innovation outputs.

- Traditional views on the innovation–marketing interaction might oversimplify the relationship, as in reality, the different elements of marketing may interact differently with innovation.

- In a large emerging market like China, traditionally effective ways of connection building and market expansion—including activities that are sometimes rent-seeking—face challenges, as the new business and legal environments increasingly favor R&D inputs and more productive activities.

- As innovation is regarded as the engine of long-run growth, public policies aimed at regulating advertising activities should take into account the interactive effects of advertising on innovation efficiency.

In general, our approach integrates important insights from marketing research and practice into the analysis of the interplay between innovation and marketing. Possible extensions of this research include improving our measures of the marketing variables by exploring firm data at higher levels of granularity or modeling product market competition jointly with firms' innovation and marketing decisions. Such topics are important but beyond the scope of this paper. We leave these directions for future research.

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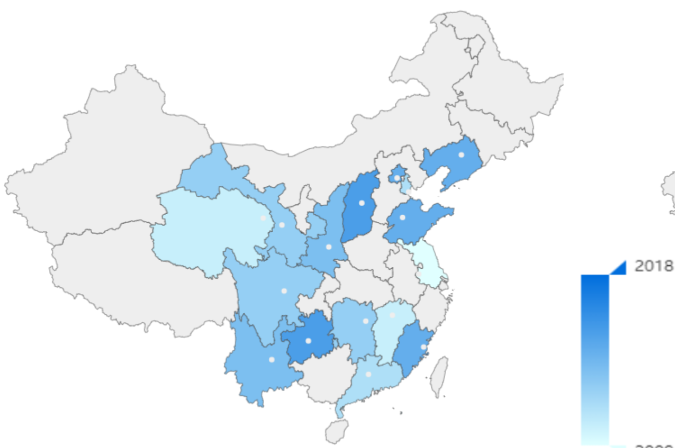
Figures and Tables

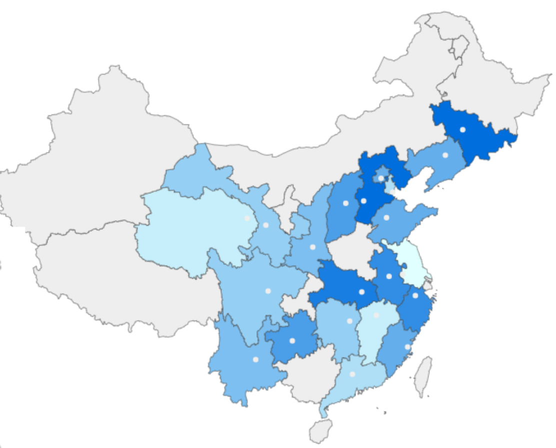
Figure 1: Roll-out of the provincial innovation policies in mainland China

(a) Year 2009

(b) Year 2012



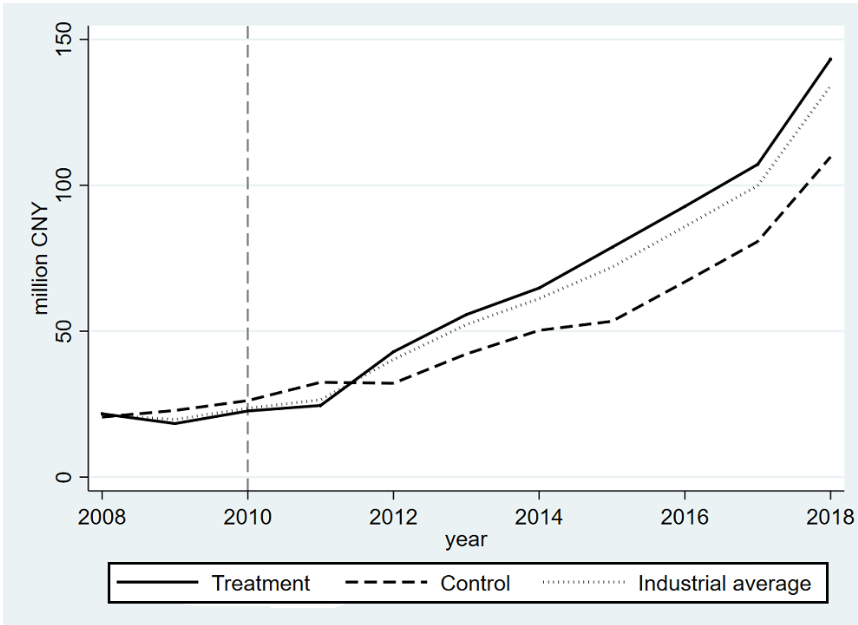
(c) Year 2015



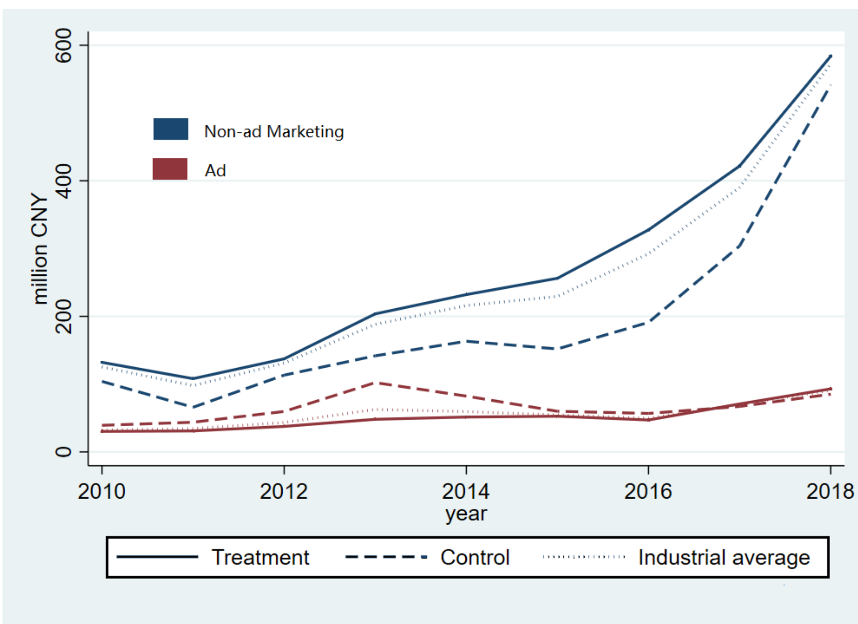
(d) Year 2018

Notes: The figures show the years in which the innovation policies became effective in mainland Chinese provinces, 2009–2018. Lighter (darker) colors denote earlier (later) years. See the Appendix Table A.1 for more details.

Figure 2: R&D and marketing expenditures of China's publicly listed pharmaceutical firms

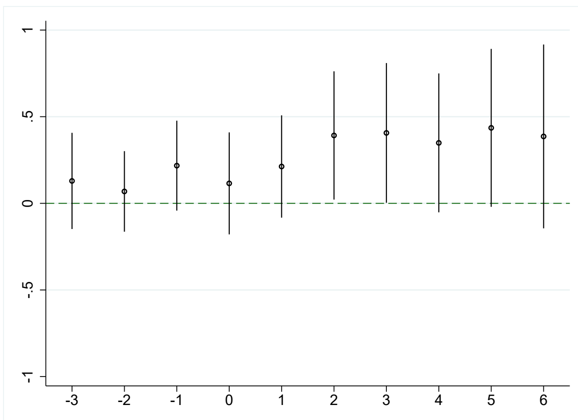


(a) R&D expenditure

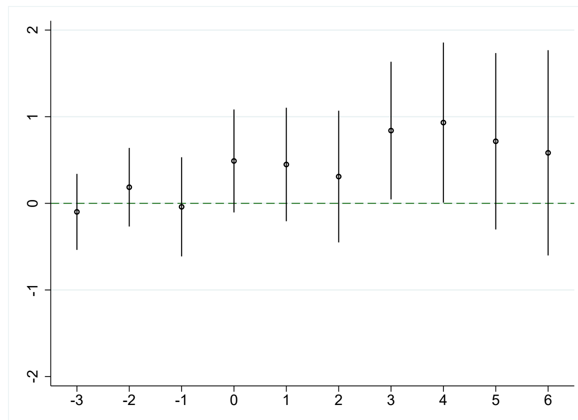


(b) Non-ad vs. ad expenditures

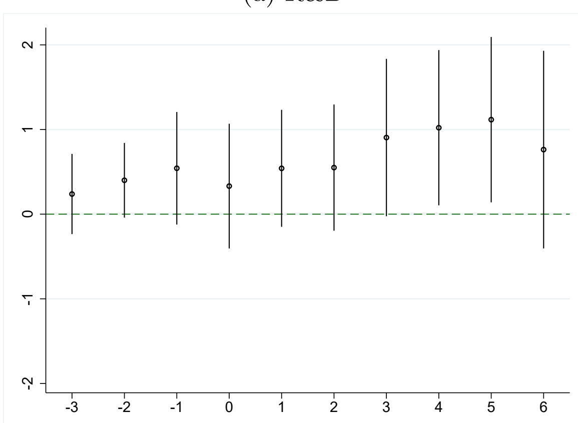
Figure 3: Parallel trends and dynamic effects



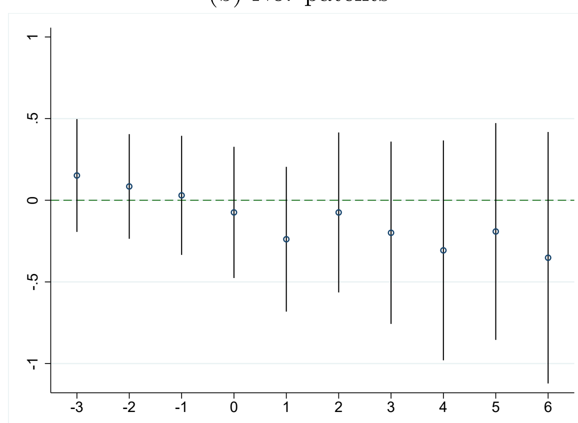
(a) R&D



(b) No. patents



(c) Advertising



(d) Non-ad marketing

Notes: These figures plot coefficients and 95 percent confidence internals from the event study specification described in Section 5.3. The coefficients are estimates from OLS regressions, and the standard errors are robust and clustered at the province level.

Table 1: Summary statistics of main variables

	obs	mean	sd	min	25%	median	75%	max
R&D (million CNY)	1002	81.447	130.032	0.1	18.63	41.973	87.538	1971.554
Patents	878	14.777	34.513	0	2	6	17	536
NewDrug	1160	0.353	0.478	0	0	0	1	1
SupApp	1160	0.387	0.487	0	0	0	1	1
Ad (million CNY)	845	59.243	140.57	0.003	2.688	11.92	53.017	2047.2
NonAdMkt (million CNY)	1111	289.333	542.587	0.012	24.465	104.326	324.823	5959.982
Assets (million CNY)	1160	3339.982	4477.441	17.829	900.738	1867.797	3902.618	50294.65
Employee	1160	3204.238	3795.674	28	881.5	1736.5	4090.5	28848
PPEAsset	1160	0.213	0.117	0	0.126	0.19	0.284	0.693
CAPEXAsset	1160	0.059	0.047	0	0.027	0.046	0.08	0.379
TobinQ	1160	2.94	2.552	0.883	1.665	2.276	3.315	40.1
LEV	1160	0.359	0.565	0.008	0.163	0.308	0.463	12.127
CashRatio	1160	0.023	0.068	-0.044	0.003	0.007	0.018	1.675
KZindex	1130	0.597	4.470	-13.135	-1.076	0.576	2.112	87.273
LongtermDebt (million CNY)	1160	139.157	432.882	0	0	0.379	82.215	6787.768
NewDebt	996	0.098	0.298	0	0	0	0	1
NewEquity	989	0.256	0.437	0	0	0	1	1

Notes: This table reports the descriptive statistics for the variables used in the baseline analyses, based on the sample of Chinese listed pharmaceutical firms from 2010 to 2018. The patent variable is for 2010-2017 only. All money values are in 2018 Chinese *yuan* (CNY). USD1 = CNY6.61 in 2018.

Table 2: Effects on R&D spending and patents

dependent variable	$LnR\&D_t$		$Patents_{t+2}$	
	(1)	(2)	(3)	(4)
$Policy$	0.161*	0.164**	0.234*	0.296**
	(0.082)	(0.076)	(0.126)	(0.140)
$LnAssets$		0.433**		-0.121
		(0.162)		(0.258)
$LnEmployee$		0.087		0.210*
		(0.101)		(0.119)
$PPEAssets$		-0.342		-0.621
		(0.388)		(0.784)
LEV		-0.823***		-0.998***
		(0.279)		(0.277)
$CAPEXAssets$		0.050**		-0.025
		(0.019)		(0.047)
$TobinQ$		-0.282		-0.493
		(0.225)		(1.352)
$CashRatio$		0.642		-1.426
		(0.545)		(1.442)
constant	16.122***	6.795***	–	–
	(0.184)	(2.995)		
Year fixed effects	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
N	1002	1002	792	792
Adjusted R^2	0.843	0.859	–	–

Notes: This table reports the regression results for R&D spending and patents. Estimates in columns 3 to 4 are estimated using the fixed-effect Poisson model. The variable definitions are in Appendix A.1. All control variables are lagged by 1 year. Robust standard errors clustered by province are displayed in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table 3: Effects on new drug registration

dependent variable	$NewDrug_{t+3}$		$NewDrug_{t+4}$		$SupApp_{t+3}$		$SupApp_{t+4}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Policy$	0.087*	0.094*	0.143**	0.152**	0.076	0.083	0.049	0.052
	(0.047)	(0.046)	(0.054)	(0.055)	(0.052)	(0.053)	(0.050)	(0.048)
$LnAssets$		0.078		0.090		0.073		-0.008
		(0.076)		(0.070)		(0.057)		(0.074)
$LnEmployee$		-0.044		-0.054**		0.013		0.016
		(0.044)		(0.021)		(0.023)		(0.027)
$PPEAssets$		0.021		-0.215		-0.017		-0.184
		(0.236)		(0.270)		(0.196)		(0.246)
LEV		0.007		0.018		0.020		0.042*
		(0.027)		(0.025)		(0.027)		(0.024)
$CAPEXAssets$		-0.170		0.448*		-0.240		0.571**
		(0.257)		(0.256)		(0.276)		(0.277)
$TobinQ$		-0.004		0.004		-0.001		-0.007
		(0.014)		(0.009)		(0.012)		(0.009)
$CashRatio$		0.190		0.453*		0.422*		0.297
		(0.308)		(0.259)		(0.215)		(0.182)
constant	0.461***	-0.803	0.415***	-1.034	0.482***	-1.096	0.488***	0.542
	(0.050)	(1.329)	(0.042)	(1.404)	(0.038)	(1.148)	(0.051)	(1.474)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
N	997	997	860	860	997	997	860	860
Adjusted R^2	0.525	0.524	0.529	0.533	0.541	0.543	0.547	0.548

Notes: This table reports the regression results for new drug product registration and supplemental application for minor changes to an existing product. The variable definitions are in Appendix A.1. Robust standard errors clustered by province are displayed in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table 4: Policy effects on marketing expenditures

dependent variable	$LnNonAdMkt_t$		$LnAd_{t+2}$		$LnAd_{t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Policy$	-0.217**	-0.190*	0.395	0.422*	0.346	0.330
	(0.100)	(0.111)	(0.244)	(0.237)	(0.220)	(0.202)
$LnAssets$		0.642***		0.631**		0.171
		(0.198)		(0.252)		(0.307)
$LnEmployee$		0.061		0.054		0.119
		(0.084)		(0.080)		(0.112)
$PPEAssets$		0.016		-0.486		0.944
		(0.497)		(0.830)		(0.676)
LEV		-0.836**		-0.644		0.290
		(0.382)		(0.702)		(0.632)
$CAPEXAssets$		-0.995		1.230		1.842
		(0.732)		(1.195)		(1.491)
$TobinQ$		0.064*		0.094*		0.066
		(0.034)		(0.052)		(0.060)
$CashRatio$		-1.881***		-0.698		-0.362
		(0.334)		(0.616)		(0.511)
constant	17.574***	4.117	15.678***	2.476	15.705***	10.749*
	(0.090)	(4.076)	(0.152)	(5.111)	(0.137)	(6.129)
Year fixed-effects	Y	Y	Y	Y	Y	Y
Firm fixed-effects	Y	Y	Y	Y	Y	Y
N	1111	1111	782	782	720	720
Adjusted R^2	0.831	0.845	0.795	0.804	0.795	0.797

Notes: This table reports the regression results for the two types of marketing expenditure. The variable definitions are in Appendix A.1. Robust standard errors clustered by province are displayed in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table 5: Policy effects on marketing expenditures interacting with financing status

	(1)	(2)	(3)	(4)
dependent variable		$LnNonAdMkt_t$		
$Policy$	-0.143	-0.103	-0.056	-0.020
	(0.124)	(0.121)	(0.131)	(0.149)
$Policy_t * KZindex$	0.001			
	(0.006)			
$Policy_t * LnLongtermDebt$		-0.010		
		(0.057)		
$Policy_t * NewDebt$			-0.095	
			(0.221)	
$Policy_t * NewEquity$				-0.158
				(0.117)
dependent variable		$LnAd_{t+2}$		
$Policy$	0.513**	0.376	0.326	0.277
	(0.247)	(0.242)	(0.217)	(0.231)
$Policy_t * KZindex$	-0.021			
	(0.018)			
$Policy_t * LnLongtermDebt$		0.007		
		(0.053)		
$Policy_t * NewDebt$			-0.056	
			(0.460)	
$Policy_t * NewEquity$				0.156
				(0.186)
Control variables	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y
Firm fixed-effects	Y	Y	Y	Y

Notes: This table reports the regression results of the heterogeneous policy effects on marketing expenditures. The variable $KZindex$ is calculated according to Kaplan and Zingales (1997). $NewDebt$ and $NewEquity$ are binary indicators of whether a firm has raised new long-term debt or new equity in a year. More information on variable construction is in Appendix A.1. All regressions include firm-level controls. Robust standard errors clustered by province are displayed in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table 6: Robustness results

(a) Out-of-sample observations

dependent variable	(1) $lnR\&D_t$	(2) $Patent_{t+2}$	(3) $NewDrug_{t+3}$	(4) $NewDrug_{t+4}$	(5) $lnNonAdMkt_t$	(6) $lnAd_{t+2}$
Policy	0.109	0.300**	0.052	0.078*	-0.221**	0.334*
	(0.074)	(0.118)	(0.039)	(0.046)	(0.103)	(0.188)
Control variables	N	N	N	N	N	N
N	1121	965	1557	1384	1234	939
Adjusted R^2	0.838	–	0.529	0.537	0.837	0.805

(b) Alternative outcome variables

dependent variable	(1) $lnNonAdMkt_t$	(2) $lnAd_{t+2}$	(3) $PatentApp_{t+2}$	(4) $IUPatent_{t+2}$	(5) $lnNewDrug_{t+3}$	(6) $lnNewDrug_{t+4}$
Policy	-0.153*	0.499*	0.257**	0.351**	0.104	0.210**
	(0.089)	(0.269)	(0.120)	(0.167)	(0.072)	(0.096)
Control variables	Y	Y	Y	Y	Y	Y
N	1111	274	802	792	997	860
Adjusted R^2	0.864	0.831	-	-	0.667	0.660

Notes: The tables report the coefficients of *Policy* for robustness checks. See Section 5.5 for more details. All regressions include year and firm fixed effects. Robust standard errors clustered by province are displayed in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Appendix

A.1 Variable definitions

R&D: A firm's research and development (R&D) expenditure, comprised of both R&D expenses and capitalized R&D expenditure.

Patents: The total number of a firm's patent applications filed in a given year that are eventually granted.

NewDrug: An indicator variable that equals 1 if a firm files a successful new drug registration application in a given year. In China, new drug registration covers new-to-China and imitative mainstream drugs, dietary supplements, traditional Chinese medicines (TCMs), blood products, and vaccines.

SupApp: An indicator variable that equals 1 if a firm files a successful supplemental application in a given year. In China, a supplemental application is for non-substantial changes (e.g., packaging) to existing drugs.

Ad: A firm's total advertising expenditure, including advertising expenditure and exhibition expenses.

NonAdMkt: A firm's total non-ad marketing expenditure, including promotional expenses, entertainment and travel costs (ETC), agency fees, and conference expenses. We exclude items related to miscellaneous selling expenses (e.g., transportation, electricity and other utilities, and depreciation expenses).

Assets: The book value of a firm's total assets.

Employee: The total number of employees of a firm.

PPEAssets: Net property, plant, and equipment divided by the book value of total assets of a firm.

CAPEXAssets: Capital expenditure scaled by the book value of total assets of a firm.

TobinQ: A firm's market-to-book ratio, calculated as [the market value of equity plus the book value of assets minus the book value of equity minus balance sheet deferred taxes] divided by the book value of a firm's total assets.

LEV: The book value of a firm's debt divided by the book value of total assets.

CashRatio: The ratio of a firm's cash and cash equivalents to its current liabilities.

KZindex: Kaplan-Zingales Index, a relative measure of reliance on external financing. It is calculated according to Kaplan and Zingales 1997 using our data of Chinese pharmaceutical firms.

LongtermDebt: The amount of long-term debt of a firm.

NewDebt: An indicator variable that equals 1 if a firm has raised new long-term debt in a given year. A firm is counted as having raised new debt if its new long-term debt exceeds 5% of its total assets in a year.

NewEquity: An indicator variable that equals 1 if a firm has raised new external equity in a given year. A firm is counted as having raised new external equity if its new equity exceeds 5% of its total assets in a year.

A.2 Provincial Innovation Policy Reforms in China, 2009–2018

Table A.1: Introduction of the new innovation policies in mainland Chinese provinces after 2008/2009

Province/ municipality	Document name	Issue time	Effective time	No. firms
(*excluded from our study*)				
Jiangsu	Regulations on Patent Promotion of Jiangsu Province (*new*)	2009.05	2009.10	14
Jiangxi	Regulations on Patent Promotion of Jiangxi Province (*new*)	2009.11	2010.01	5
Qinghai	Regulations on Patent Promotion and Protection of Qinghai Province (*new*)	2009.11	2010.03	2
(*included in our study*)				
Guangdong	Patent Regulations of Guangdong Province (*rev. ed.*)	2010.09	2010.12	23
Tianjin	Regulations on Patent Promotion and Protection of Tianjin Province (*rev. ed.*)	2011.01	2011.04	7
Hunan	Patent Regulations of Hunan Province (*rev. ed.*)	2011.11	2012.01	8
Sichuan	Regulations on Patent Protection of Sichuan Province (*rev. ed.*)	2012.03	2012.05	5
Gansu	Patent Regulations of Gansu Sichuan Province (*rev. ed.*)	2012.06	2012.08	3
Shaanxi	Patent Regulations of Shaanxi Province (*rev. ed.*)	2012.07	2012.10	4
Yunnan	Regulations on Patent Promotion and Protection of Yunnan Province (*rev. ed.*)	2012.11	2013.03	5
Shandong	Patent Regulations of Shandong Province (*rev. ed.*)	2013.08	2013.09	13
Beijing	Regulations on Patent Promotion and Protection of Beijing Municipality (*rev. ed.*)	2013.09	2014.03	14
Fujian	Regulations on Patent Promotion and Protection of Fujian Province (*rev. ed.*)	2013.11	2014.01	5
Liaoning	Patent Regulations of Liaoning Province (*rev. ed.*)	2013.11	2014.03	2
Shanxi	Regulations on Patent Implementation and Protection of Shanxi Province (*rev. ed.*)	2014.11	2015.01	3
Guizhou	Patent Regulations of Guizhou Province (*rev. ed.*)	2015.03	2015.05	5
Anhui	Patent Regulations of Anhui Province (*rev. ed.*)	2015.09	2016.01	4
Zhejiang	Patent Regulations of Zhejiang Province (*rev. ed.*)	2015.09	2016.01	26
Hebei	Patent Regulations of Hebei Province (*rev. ed.*)	2017.09	2017.11	3
Hubei	Patent Regulations of Hubei Province (*rev. ed.*)	2017.05	2017.09	6
Jilin	Patent Regulations of Jilin Province (*rev. ed.*)	2017.12	2018.01	7

Notes: Provincial-level governments that do not have a new policy package after 2008 include Chongqing, Guangxi, Heilongjiang, Hainan, Henan, Inner Mongolia, Ningxia, Shanghai, Tibet, and Xinjiang. Chongqing and Zhejiang had minor wording changes for their provincial regulations in 2010 and 2011, respectively. We do not count these two changes as new policy adoption. Overall, there are 124 firms in the treatment group and 47 firms in the control group. Ningxia has no observations.

Table A.2: Summary of the province-level innovation policy reforms

Policy content	Jiangsu	Jiangxi	Qinghai	Guangdong	Tianjin	Hunan	Sichuan	Gansu	Shaanxi	Yunnan	Shandong	Beijing	Fujian	Liaoning	Shanxi	Guizhou	Anhui	Zhejiang	Hubei	Hebei	Jilin
Direct incentives																					
Govt funding programs	+	+	+	+	O	+	+	O	O	+	+	+	+	+	+	O	O	+	+	+	+
Prizes for successful patents	+	+		+	O	+	+	+	+	+	+	O	+	+	+	+	O	+	+	+	+
Preferential tax	+	+		+	O	+	+	+	+	+	+	O	+		+			+	+		+
IP pledge loan	+	+		+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Priority in govt procurement		+		+	+	+	+		+				+					+		+	
Enhanced IP and patent protection																					
Increased govt penalties		+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Counterfeit reporting system					O				+	+	O	+	O	+		+	+		+	+	+
Increased eligibility for govt arbitration		+	+		+	+		+	+	+	+	+			+	+	+	+	+	+	+
Govt dispute resolution guidance	+	+		+	O	O		O	O	O	O	O	O			O	+		+		+
IP rights assistance system		+		+	+	+		+	+	+	+	+	+	+	+	+	+		+		+
Other institutional support																					
Patent transfer system	+	+	+	+	+	+	+	+	+	O	+	+	+	+	+	+	+	+	+	+	+
Trading platform guidance	+	+	+	+	+	+	+	O	O	+	+	O	+	+	+	+	+	+	+	+	+
Patent brokerage guidance	+		+			+		+	+	+	+	O	+	+	+		+	+	+	+	+
University-enterprise cooperation	+	+		+		+	+	+	+	+	+	+	+	+	+	+	+		+	+	+
Increased training for patent officers		+		+	+	+	+	+	+	+	+		+	+	+	+	+	+	+	+	
Provision of ICT support		+			+	+		+	+		+			+	+	+	+		+		
IP education campaign	+	+	+	+	+	+	+	+	O	+	O	O	O	+	+	+	O	+	+	+	+
Patent grants as indicator of govt performance		+				+		+	+		+					+		+	+	+	

Notes: The policy documents are available through the website of China's State Intellectual Property Office (CNIPA) at http://pss-system.cnipa.gov.cn (under "Policies and Regulations"). "+": newly added content; "O": existing content.

Online Appendix

O1 A model of innovation and marketing

In this section, we present a theoretical model to formalize our discussion of the interplay between innovation and marketing. As R&D investment and marketing decisions are endogenous choice variables of firms, our focus is on analyzing the effects of an exogenous policy shock on firm behavior. By studying the policy effects, we aim to shed light on the interdependent relationship between innovation and marketing.

Our model emphasizes the differences between two types of marketing activities: advertising that delivers new product information, and other sales effort that expands a firm's existing business. To parsimoniously capture the interaction between innovation and marketing decisions and the dynamic decision-making process, we build a two-period model of firm investment under budget constraints. While we intentionally keep the model simple and tractable to deliver new insights and testable hypotheses, our model is general in many aspects and can be modified in a number of ways without affecting the main results.

O1.1 Model setup

Suppose there are two time periods. In each period, a firm can spend to promote sales in its existing market. Such marketing expenditures are denoted as m_1 and m_2 for the two periods, respectively. In Period 1, the firm can invest in R&D—denoted as r_1—which leads to product quality improvement and thus has an immediate positive effect on its revenue. Firm revenue for Period 1 is given by $s_1(m_1, r_1)$, which depends on both r_1 and its marketing expenditure, m_1. We assume that the revenue function, $s_1(m_1, r_1)$, is non-separable in its arguments to allow for interactions between r_1 and m_1, with $\frac{ds_1}{dm_1} > 0$ and $\frac{ds_1}{dr_1} > 0$. Notably, we do not make specific assumptions about its functional form or the sign of the cross partial derivative, $\frac{\partial^2 s_1}{\partial m_1 \partial r_1}$, which reveals how marginal return to one expenditure depends on the other. The cross partial derivative captures the substitutability/complementarity between the two decisions, and it is negative when they are substitutes and positive when they are complements (Milgrom and Roberts 1990).

In Period 2, first, past R&D is reflected in the revenue increase of a firm's existing business. Second, R&D might result in new product development in this period. The probability is given by $F(r_1)$, where F is a cumulative distribution function with a density f. We assume that any new product information can only be known to the market through advertising, following the informative advertising literature pioneered by Nelson (1974).[19] The advertising coverage function is $g(a_2)$ with $g' \equiv \frac{dg}{da_2} > 0$. Given the advertising technology, the firm's (expected) revenue from new product development is $F(r_1)g(a_2)v$ in Period 2, where v is the potential revenue from market sales and we assume is a constant. We model R&D incentives as a reward proportional to the firm's R&D expenditure, αr_1, which we assume occurs in Period 2. One can think of α as either an *ad-valorem* subsidy or additional return on R&D because of institutional factors, such as enhanced intellectual property protection. Lastly, in both periods, the firm faces some budget constraints—denoted as b_1 and b_2—which are exogenously given.

Without loss of generality, assuming the discount factor is one, the firm's optimization problem

19. We often informally refer to new product advertising simply as "advertising," while, in principle, advertising can also be non-informative or persuasive (for instance, see Bagwell 2007). Here in our theoretical model, we treat non-informative advertising as other market-expanding sales efforts, called "non-ad marketing" in this paper.

is

$$\max_{m_1,r_1,m_2,a_2} \pi = s_1(m_1, r_1) - m_1 - r_1 + s_2(m_2, r_1) + F(r_1)g(a_2)v + \alpha r_1 - m_2 - a_2$$
$$\text{subject to} \quad m_1 + r_1 \le b_1, \quad m_2 + a_2 \le b_2. \tag{A.1}$$

O1.2 Main results

To derive comparative statics results, we mainly focus on the case when the budget constraints are non-binding. It follows that at the optimum, the marginal return to R&D or any type of marketing is exactly equal to one unit of currency.

More specifically, the first-order conditions (FOCs) are

$$\frac{\partial \pi}{\partial m_1} = \frac{\partial s_1}{\partial m_1} - 1 = 0, \quad \frac{\partial \pi}{\partial r_1} = \frac{\partial s_1}{\partial r_1} + \frac{\partial s_2}{\partial r_1} + fg(a_2)v + \alpha - 1 = 0,$$
$$\frac{\partial \pi}{\partial m_2} = \frac{\partial s_2}{\partial m_2} - 1 = 0, \quad \frac{\partial \pi}{\partial a_2} = F(r_1)g'v - 1 = 0.$$

We assume the second-order conditions (SOCs) are also satisfied; in particular, $\pi_{rr} < 0$, $\pi_{m_1m_1} < 0$, $\pi_{m_2m_2} < 0$, and $\pi_{aa} < 0$, where π_{aa}, π_{rr}, $\pi_{m_1m_1}$, and $\pi_{m_2m_2}$ denote the second partial derivatives.

To study the effects of the policy-induced innovation incentives (represented by α), we apply the implicit function theorem to the above FOCs and use the Cramer's Rule to obtain:

$$\frac{dr_1^*}{d\alpha} = -\frac{\pi_{m_1m_1}\pi_{m_2m_2}\pi_{aa}}{\mathrm{D}_4} > 0,$$
$$\frac{dm_1^*}{d\alpha} = \frac{\pi_{m_1r}\pi_{m_2m_2}\pi_{aa}}{\mathrm{D}_4},$$
$$\frac{dm_2^*}{d\alpha} = \frac{\pi_{m_2r}\pi_{m_2m_2}\pi_{aa}}{\mathrm{D}_4},$$
$$\frac{da_2^*}{d\alpha} = \frac{\pi_{ar}\pi_{m_1m_1}\pi_{m_2m_2}}{\mathrm{D}_4} > 0;$$

where $\mathrm{D}_4 = \pi_{m_1m_1}\pi_{rr}\pi_{m_2m_2}\pi_{aa} - (\pi_{m_1r})^2\pi_{m_2m_2}\pi_{aa} - (\pi_{m_2r})^2\pi_{m_1m_1}\pi_{aa} - (\pi_{ar})^2\pi_{m_1m_1}\pi_{m_2m_2} > 0$ by the associated second-order conditions.

The first result immediately implies $\frac{dF(r_1^*)}{d\alpha} > 0$ (i.e., the R&D promotion policy increases future innovation output). For the last three expressions, each of their signs depends on the sign of π_{m_1r}, π_{m_2r}, and π_{ar}, respectively. In other words, with non-binding budget constraints, how the R&D promotion policy would affect a marketing variable entirely depends on their strategic relationship; the policy impact is positive (negative) if and only if the marketing variable complements (substitutes) R&D investments. In particular, given $\pi_{ar} = fg'v > 0$, we have $\frac{da_2^*}{d\alpha} > 0$ in this model.

Our modeling of advertising is in line with the extensive literature on informative advertising that has built on Nelson (1974) and Butters (1977). Given the generic form of advertising technology, R&D and informative advertising naturally complement each other in our framework. Meanwhile, other business-expanding marketing efforts might or might not complement R&D, as we do not make any specific functional form assumption. Notably, if $s_2(m_2, r_1)$ is additively separable in m_2 and r_1, then R&D and marketing decisions become independent choices with $\frac{\partial^2 s_2}{\partial m_2 \partial r_1} = 0$. In this case, the R&D promotion have no impact on non-ad marketing expenditure in both periods.

O1.3 Other considerations

Binding budget constraints. Since Schumpeter (1934), a large literature has focused on the importance of financial constraint on innovation (see, for instance, Hall and Lerner (2010) for a literature review). This motivates us to also consider the case with binding budget constraints; i.e., $m_1^* + r_1^* = b_1$ and $m_2^* + a_2^* = b_2$. It follows that at the optimum, the marginal return to R&D or any type of marketing always exceeds one unit of currency. The firm's maximization problem can then be rewritten as

$$\max_{r_1, a_2} \quad \pi = s_1(b_1 - r_1, r_1) - b_1 + s_2(b_2 - a_2, r_1) + F(r_1)g(a_2)v + \alpha r_1 - b_2. \tag{A.2}$$

The first-order conditions (FOCs) are

$$\begin{aligned} \frac{\partial \pi}{\partial r_1} &= -\frac{\partial s_1}{\partial m_1} + \frac{\partial s_1}{\partial r_1} + \frac{\partial s_2}{\partial r_1} + fg(a_2)v + \alpha = 0, \\ \frac{\partial \pi}{\partial a_2} &= -\frac{\partial s_2}{\partial m_2} + F(r_1)g'v = 0; \end{aligned}$$

That is, at the optimum, r_1^* equates the marginal return on R&D to the marginal return on Period 1's non-ad marketing, and a_2^* equates the marginal return on Period 2's advertising to the marginal return on Period 2's non-ad marketing.

We assume the second-order conditions (SOCs) are also satisfied; in particular, $\pi_{rr} < 0$, $\pi_{aa} < 0$, and $\mathrm{D}_2 \equiv \pi_{rr}\pi_{aa} - (\pi_{ar})^2 > 0$.

By applying the implicit function theorem and using the Cramer's Rule, we obtain

$$\frac{dr_1^*}{d\alpha} = -\frac{\pi_{aa}}{\mathrm{D}_2} > 0, \quad \text{and} \quad \frac{da_2^*}{d\alpha} = \frac{\pi_{ar}}{\mathrm{D}_2}.$$

The first result immediately implies $\frac{dm_1^*}{d\alpha} < 0$ due to the binding budgets, and $\frac{dF(r_1^*)}{d\alpha} > 0$. For the second result, $\pi_{ar} = fg'v - \frac{\partial^2 s_2}{\partial m_2 \partial r_1}$, where $fg'v > 0$, and the sign of $\frac{\partial^2 s_2}{\partial m_2 \partial r_1}$ depends on the substitutibility/complementarity between R&D and other non-ad marketing. Indeed, as long as m_2 does not complement r_1 *more strongly* than a_2 does, or $fg'v > \frac{\partial^2 s_2}{\partial m_2 \partial r_1}$, the innovation incentives raise advertising spending (i.e., $\frac{da_2^*}{d\alpha} > 0$) and reduce other marketing expenditure in the second period (i.e., $\frac{dm_2^*}{d\alpha} < 0$).

In summary, considering binding budget constraints brings two changes that reinforce our main results. Specifically, the negative effect of the R&D incentives on Period 1's non-ad marketing is no longer hinged on the substitutability between R&D and non-ad marketing expenditure, due to a crowding-out effect inside the budget constraint. In other words, regardless of their strategic relationship, a policy-led increase in R&D expenditure reduces non-ad marketing expenditure in the same period.

Alternative model of innovation incentives. In the main model, the innovation policies are treated as an R&D subsidy proportional to the amount of R&D expenses. Alternatively, we may model such incentives as interacting directly with advertising; for instance, the potential revenue from new product sales, v, can be a function of α with $v' \equiv \frac{dv(\alpha)}{d\alpha} > 0$, so that the firm's expected revenue from new product development is $F(r_1)g(a_2)v(\alpha)$. In this case, the innovation incentives directly raise the marginal return to advertising; i.e., $\frac{\partial}{\partial \alpha}\frac{\partial \pi}{\partial a_2} = F(r_1)g(a_2)v' > 0$. Nonetheless, it is convenient to show that our main qualitative results continue to hold. Intuitively, the policy incentives have a direct impact on advertising exactly because of the multiplicative form of

$F(r_1)g(a_2)v(\alpha)$; instead, if r_1 and a_2 are strategically unrelated, given that $v(\alpha)$ is attached to the innovation outcome function $F(r_1)$, it follows automatically that $\frac{\partial}{\partial \alpha}\frac{\partial \pi}{\partial a_2} = 0$. In summary, how firm's advertising response to the innovation incentives can still tell us about the innovation–advertising interaction.

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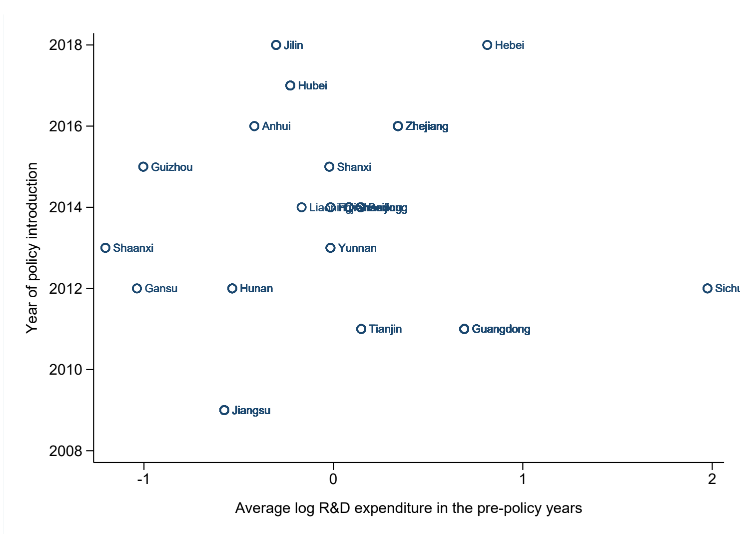
O2 Additional Figures and Tables

Table O.1: Correlation of the policy timing with local economic variables

explanatory variable	dependent variable: *Year of policy introduction*		
$LnGDP$	0.757		
	(0.780)		
$LnPerCapitaGDP$	-1.151		
	(1.039)		
$Manufacturing$		-10.145	
		(11.777)	
$Services$		-4.994	
		(9.627)	
$LnExports$			-0.242
			(0.945)
$LnImports$			0.225
			(0.852)

Notes: Each column in this table reports the regression coefficients of the year of policy introduction on different provincial economic variables in 2009 and a constant. $Manufacturing$ and $Services$ are the shares of manufacturing and services value added of GDP, respectively. $LnExports$ and $LnImports$ are the log of the total value of exports and imports of a province/municipality. Standard errors are heteroskedasticity-robust. $N = 21$.

Figure O.1: The policy timing and pre-reform R&D level



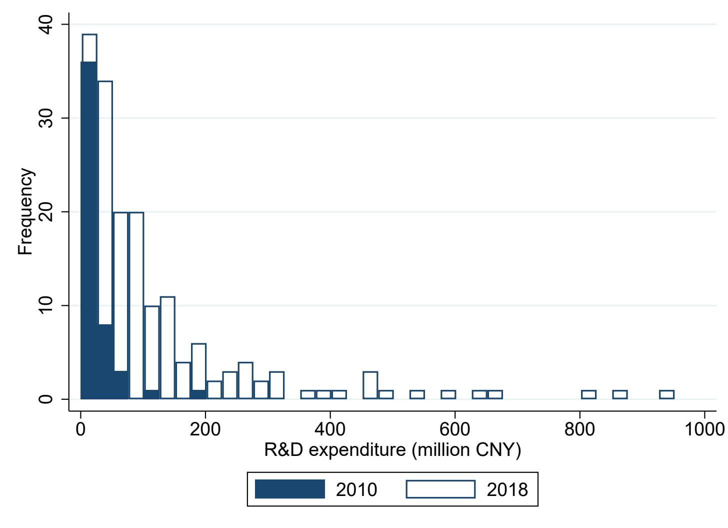
Notes: This graph plots the average provincial R&D investment by pharmaceutical firms in the pre-policy years and the year of the policy introduction. In a regression of the policy year on the average R&D before the policy introduction, the coefficient and *p-value* for the correlation are 0.015 and 0.96, respectively.

Table O.2: Comparison of the treatment and control firms in 2008

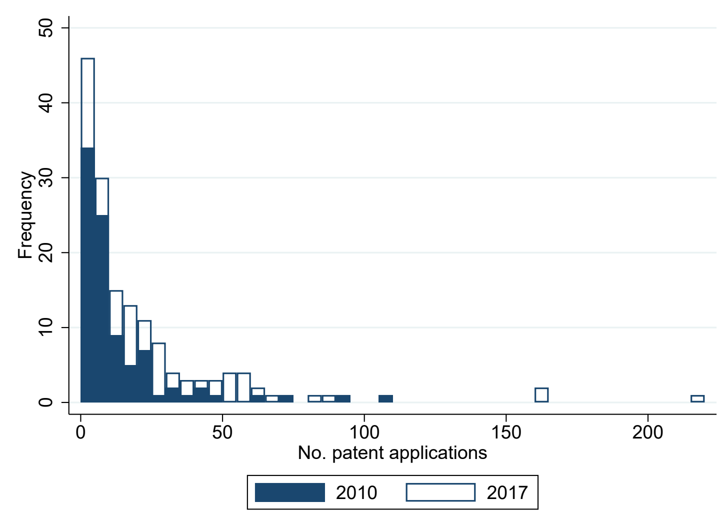
variable	control mean (1)	treatment mean (2)	diff (3)	p-value (4)
Covariates				
LnAssets	20.423	20.671	-0.248	0.365
LnEmployee	6.785	7.205	-0.419	0.112
PPEAssets	0.239	0.275	-0.036	0.291
CAPEXAssets	0.038	0.063	-0.025	0.109
TobinQ	2.170	1.903	0.267	0.567
LEV	0.377	1.087	-0.710	0.497
CashRatio	0.010	0.009	-0.001	0.879
Outcome variables				
R&D (million CNY)	20.564	21.689	-1.126	0.913
Patents	5.417	11.060	-5.643	0.280

Notes: This table reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding p-values in the pre-policy year 2008. As information on itemized marketing expenses does not exist prior to 2010, we do not include the marketing variables for comparison. All money values are in 2018 Chinese *yuan* (CNY).

Figure O.2: Distributions of R&D spending and patents of China's listed pharmaceutical firms in selected years



(a) R&D spending (million CNY)



(b) No. successful patent applications

Table O.3: Correlation between R&D and marketing variables

dependent variable	$LnTotalMkt$			$LnNonAdMkt$			$LnAd$		
	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS	(6) IV	(7) OLS	(8) OLS	(9) IV
$LnR\&D$	0.778***	0.387***	0.183	0.829***	0.409***	0.075	0.454*	0.412*	0.415
	(0.073)	(0.097)	(0.129)	(0.097)	(0.122)	(0.239)	(0.229)	(0.206)	(0.324)
Control variables	N	Y	Y	N	Y	Y	N	Y	Y
Year fixed-effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm fixed-effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1002	1002	919	979	979	904	733	733	667
Adjusted R^2	0.859	0.890	–	0.819	0.854	–	0.835	0.838	–

Notes: This table reports the regression results of $LnR\&D$ on three measures of firm marketing expenditure. The IV estimates are obtained by using lagged R&D as the instrument in a 2SLS regression. Significance at * 10%, ** 5%, and *** 1% levels.

Table O.4: Policy effects on external financing

dependent variable	$KZindex_t$	$LnLongtermDebt_t$	$NewDebt_t$	$NewEquity_t$
	(1)	(2)	(3)	(4)
$Policy$	0.068	-0.204	0.009	0.003
	(0.206)	(0.758)	(0.033)	(0.046)
Control variables	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y
Firm fixed-effects	Y	Y	Y	Y
N	978	1002	839	837
Adjusted R^2	0.643	0.495	0.130	0.088

Notes: This table reports the regression results of the policy effect on the variables related to external financing. Detailed information on variable construction is in Appendix A.1. Robust standard errors clustered by province are displayed in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.