Supply Chain Industrial Policy, Local Entry, and Stock Returns*

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January 2026

ABSTRACT

This paper examines Supply Chain Industrial Policy in China—a set of policies that aim to strengthen a focal industry by supporting firms in their supplier and customer industries—and their effects on local public firms. Using over three million government policy documents and firm registration records covering the universe of Chinese firms from 2007–2022, we construct firm-level exposure to supplier/customer policy support (CSIP) and local supplier/customer entry rates (CSER). We show that CSIP significantly increases subsequent CSER. Higher CSER is associated with improvements in real performance and predicts stock returns: a CSER-based long–short strategy earns a monthly alpha of 0.755% (t = 3.1). While industrial policies themselves are not directly associated with higher returns, they increase firm value by promoting CSER. The effects are highly localized and concentrated within administrative jurisdictions, consistent with a coordinating role of local governments. The effects are strongest in industrial sectors and supply-chain-intensive industries, but are ineffective in industries with excessive competition, suggesting that industrial policies would be effective when closely aligned with market conditions. Overall, our findings link industrial policy to firm valuation through localized supply-chain-based externalities.

JEL Classification: G12, G14, R11, M11

Keywords: Agglomeration Economics, Local Supply Chain, Return Predictability, China's Regional Economics

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* We thank the participants at the FMA Asia Conference 2024, Asia FA Annual Conference 2024, CICF 2024, CES China Annual Conference 2024, China Financial Frontier Academic Forum 2024. All errors are our own.

1. Introduction

Industrial policy, broadly defined as government actions aimed at shaping the development of targeted industries, has attracted renewed attention in recent years. However, its effectiveness remains highly contested (Juhász et al., 2024). On the negative side, the prevailing view among economists reflects a "skeptical consensus" toward industrial policy (e.g., Rodrik, 2014). Empirical evidence shows that industrial policy can harm targeted industries through overcapacity, failures in picking winners, and policy-induced social obligations (e.g., Lim et al., 2018; Branstetter et al., 2023; Li and Branstetter, 2024; Barwick et al., 2025). On the positive side, industrial policy is often viewed as a response to market failures motivated by externalities, coordination failures, and public goods provision (Juhász et al., 2024). Consistent with this view, industrial policy is widely regarded as a key contributor to the East Asian miracle, and recent studies document its positive effects on innovation, productivity, and supply-chain resilience (Tian and Xu, 2022; Choi and Levchenko, 2025; Chen et al., 2026).

This paper studies the success of industrial policy in China over the 2007–2022 period. We extend the current literature in several important ways. First, we have a unique focus on policies that benefit targeted industries by subsidizing firms in their supplier and customer industries, i.e., policies referred to as "产业链政策", which can be roughly translated as **Supply Chain Industrial Policy**. The general idea is that because of externalities and coordination failures, there may be underinvestment along a supply chain that can be alleviated with subsidies and political intervention.[1] Second, although these policies are primarily motivated by political objectives that go beyond the interests of corporate shareholders, we examine their effects on the financial performance and stock returns of public firms in targeted industries. In particular, we focus on subsequent local entry by customers and suppliers encouraged by these policies as the channel. Finally, we provide evidence that in addition to boosting entry, policymakers create value by facilitating coordination between firms and local customers and suppliers.

Our analysis examines two unique large datasets that we construct. The first is a full sample of Chinese firms reported in registration data from China's State Administration for

[1] This mechanism is formalized in Okuno-Fujiwara (1988) and discussed in Juhász et al. (2024).

Industry and Commerce (SAIC), which covers more than 58 million firms. The dataset provides details on each firms' registration information, industry and location, allowing us to construct monthly, city-industry level panels of firm entry and incumbency for each industry and municipality. We merge this data with financial and stock return data for all public firms in China's A share market. Our public firm data includes firms' industry affiliations as well as the customer and supplier industries identified using an input–output table. The second data set allows us to identify public firms in our data set that benefited directly or indirectly (through customers or suppliers) by industrial policy. To create this dataset, we initially process three million government documents obtained from the PKULAW database. By restricting our analysis to those documents that include "industry" in the document title, we reduce the number to 61,736 documents, which we evaluate using a fine-tuned DeepSeek LLM to generate 15,535 city-level industrial policies with clearly defined target industries and specific policy instruments. Specifically, for each city-industry-month observation, policy support takes a value of 1 if the industry is supported by the city during a given period and 0 otherwise.[2]

We first measure the extent to which supply chain industrial policies promote local entry by potential customers and suppliers for each public firm. To do this, we construct two measures: the customer-supplier entry rate (CSER) and the customer-supplier industrial policy (CSIP). CSER is calculated as the weighted average of the monthly entry rates[3] of each firms' customer and supplier industries as defined in IO table. CSIP is calculated as the weighted average of the policy support provided to each public firm's customer and supplier industries. As we show, higher policy support to an industry tends to be associated with greater entry in the industry. Specifically, our regressions indicate that a one-unit increase in CSIP[4] is associated with a 0.54 percentage-point increase in monthly CSER over the subsequent year. Economically, this effect corresponds to about 2.7 additional entrant firms and 7.02 (1) million RMB (USD) in investment per month in each customer/supplier industries located in the public firm's city,[5] and is large enough to move the firm from the second to the highest CSER quintile

[2] If the city government issues a market regulation policy on the targeting industry during the given period, then policy support takes 0 regardless of whether other policy tools are included or not.

[3] For each city–industry–month, the entry rate is defined as the number of new entrants scaled by the number of incumbent firms at the end of the month.

[4] This implies that all of a firm's customer and supplier industries are supported by industrial policy.

[5] As of December 31, 2022, the median number of incumbent firms in each city–industry is 500, and the average registered

cross-sectionally. In the regression, we control for proxies for local economic conditions (GDP and GDP growth) as well as measures of the industries' economic prospects within each city.[6]

We next examine whether entry into customer and supplier industries generate positive externalities for public firms. Specifically, we test whether the customer and supplier entry rate (CSER) is positively associated with the firms' subsequent stock returns. In each month, we sort the stocks of all public firms into quintiles based on CSER over the past 12 months and construct a long–short portfolio that buys stocks in the highest quintile and shorts those in the lowest. The value-weighted long-short portfolio earns significant excess returns, with a Fama–French five-factor alpha of 0.607% (t = 3.45) per month and a Liu–Stambaugh–Yuan four-factor alpha of 0.761% (t = 2.90) per month. These results are robust across alternative factor models and Fama–MacBeth regressions that control for firm characteristics, own-industry momentum (Jegadeesh and Titman, 1993), and a set of cross-stock momentum measures (Moskowitz and Grinblatt, 1999; Menzly and Ozbas, 2010; Parsons et al., 2020). Moreover, the returns of the CSER strategy do not exhibit subsequent reversals.

Similarly, we find that customer and supplier entry rates (CSER) is positively associated with improvements in firms' fundamental performance. We find that a one–percentage-point increase in CSER is significantly associated with 0.11, 0.47, and 0.07 percentage-point increases in subsequent quarterly sales-to-assets (SOA), return on assets (ROA), and the EP ratio, respectively, as well as 0.09 and 0.05 standard-deviation increases in year-over-year growth in net profit and EPS. We also show that CSER is positively associated with earnings surprises, measured as the difference between announced EPS and the analysts' consensus forecast. Overall, these results suggest that CSER generates positive externalities that improve firm performance. One interpretation of the CSER return predictability is that because these performance effects were ex ante uncertain in our sample period, stock prices did not respond

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capital per newly registered firm is 2.6 million RMB. A 0.54 percentage-point increase in CSER therefore implies that, for a representative listed firm, each of its customer or supplier industries within the same city experiences an average monthly increase of 2.7 entrant firms (0.54% × 500), corresponding to 7.02 million yuan in new investment. We assume an exchange rate of 7 RMB per U.S. dollar.

6 The measures are constructed in the spirit of Balassa (1965) and Fang et al. (2025) and include revealed comparative advantage (RCA) and an industrial cluster measure. RCA is defined as the share of firms in a given industry within a city relative to the city's total number of firms, normalized by the same share at the provincial or national level. A higher RCA indicates that the industry is more important in the city and more likely to serve as a pillar industry. The cluster measure is defined as the share of firms in a given industry–city pair relative to the national total. Higher values of these measures indicate stronger industry prospects within the city and thus greater attractiveness for customer and supplier entry.

until the accounting performance was actually realized.

One might think the above results imply that policies that promote entry in supplier and customer industries result in positive subsequent stock returns on average. However, we find that industrial policies targeting customer and supplier industries (CSIP) do not positively predict stock returns. This result holds both for short-window announcement returns, including (−1, 1) and (−5, 30) cumulative abnormal returns, and for long-horizon tests using CSIP measured over months t-12 to t (or t−24 to t−12) to predict stock returns in month t+1. These findings indicate that the overall effect of these policies on the performance of the affected public firms has negative as well as positive aspects. In addition to the positive effects that are likely to arise from entry by additional customers and suppliers, there are likely to additional policy objectives, such as increasing employment, that may have a negative effect of firm performance.

To better understand the causal relationship between changes in CSER, which is attributable to CSIP, and performance, we run a two-stage regression. As a first-step, each month we regress firm-level CSER averaged over the past 12 months (month t-12 to t) on CSIP measured over months t−24 to t−12, along with proxies for local economic conditions and measures of industry prospects as controls. Based on the estimated coefficients, we decompose CSER into three components: fitted components attributable to industrial policy, components unrelated to industry policy and a residual component.[7] Next, we find that the policy driven component of CSER continues to significantly predict returns in month t+1 even after controlling for all other components: a 1% increase in policy-driven CSER is associated with a 0.753% (t=3.16) higher return in the cross section. In other words, that component of policy that increases CSER does in fact predict future stock returns.

We next conduct two progressive tests to examine the role of local governments in generating positive externalities of industrial policies. First, we distinguish whether these externalities are intrinsically localized within a specific administrative region. To examine this, we construct both province-level measures ($CSER^P$) and national-level measures ($CSER^N$), in addition to the city-level measure (CSER) used in the previous analysis. We find that $CSER^N$

[7] We find that the policy-driven component accounts for 20%-80% of the cross-sectional variation in CSER depends on how the residual components is accounted for.

exhibits no return predictability, whereas the local measures (CSER and $CSER^P$), as well as the components of $CSER^P$ that are orthogonal to $CSER^N$ and the components of CSER that are orthogonal to both $CSER^N$ and $CSER^P$, display significant return predictability.[8] The results suggest that the benefits of local supply chain entry extend beyond national-level supply chain factors and are largely driven by localization, underscoring the importance of local implementation and coordination.

Local entry by customers and suppliers does not necessarily benefit focal firms if information frictions and coordination failures prevent entrants and incumbents from forming stable production relationships. Industrial policies can help resolve such failures, as their authority to allocate resources to promote coordination (Juhász et al., 2024). Indeed, 55.75% of the policies in our sample explicitly mention facilitating coordination.[9] We empirically examine the coordination effects by controlling for geographic distance and examining the impact of administrative boundaries. For each firm, we separately calculate CSER based on registered firms located within 100 km inside the same province and those within 100 km but outside the province. We find that intra-provincial CSER exhibits significant return predictability, whereas inter-provincial CSER does not. This evidence is consistent with the view that geographic proximity alone is insufficient to generate positive spillovers and that coordination within administrative jurisdictions—where local governments have greater capacity to implement and coordinate—are important for translating entry into value-relevant spillovers.

Last but not least, we examine when industry policy is more effective. We find that the effect of CSER is stronger in the industrial sector than in the agricultural and service sectors, and is stronger in industries that rely more heavily on the activities of their customer and supplier industries.[10] These findings are consistent with positive externalities operating

[8] For example, the components of CSER orthogonal to both $CSER^N$ and $CSER^P$ is calculated as the residual from a cross-sectional regression of CSER on $CSER^P$ and $CSER^N$.

[9] For example, according to the "4151" plan for building an advanced manufacturing industry issued by the Shaoxing Government, firms newly recognized as leaders of provincial-level industrial chains will receive a reward of 500 thousand yuan. Firms that organize provincial-level "Ten Chains, Hundred Events, Ten Thousand Enterprises" (In Chinese "十链百场万企", which is a large-scale industry matchmaking activity), with participation exceeding 100 enterprises, will receive a subsidy of 250 thousand yuan. For similar municipal-level activities, where participation exceeds 50 enterprises, the subsidy is 150 thousand yuan. See for details: https://www.sx.gov.cn/art/2025/2/24/art_1229265242_1908229.html.

[10] We use input–output tables to measure firms' reliance on their customer and supplier industries (Rasmussen, P. N., 1956). Specifically, for each focal firm, we quantify the dollar value of inputs sourced from supplier industries and the dollar value of outputs sold to customer industries per dollar of production. Larger values indicate greater dependence on upstream and

through input–output linkages, suggesting that industrial policy more closely aligned with market conditions may be more effective. Next, we show that industrial policy has less effect on firm performance in more competitive industries, as measured by a Herfindahl–Hirschman Index (HHI) below 500. Although additional entry attracted by local governments may have positive effects (e.g., expanded production capacity), the associated profit opportunities are likely to be competed away.

Our analysis relates to several strands of literature. First, we contribute to the literature on the implementation and effects of industrial policy. The most relevant paper is Fang et al. (2025), who provide a thoughtful summary on industrial policies in China, revealing their foundations, tools, impacts on firms, and potential downsides like overcapacity. We distinguish from their study mainly in two points. First, instead of focusing on industrial policies targeted at a specific industry, which also is a common setting in existing literature (e.g., Barwick et al., 2025; Choi and Levchenko, 2025), we are the first to study supply chain industrial policy and show that policies targeting customer and supplier industries, rather than a firm's own industry, generate spillover effects. Second, we go beyond traditional economic output metrics by linking the industrial policies to individual firm valuation, providing a micro foundation for better understanding on the effectiveness of industrial policy. Our results present the quantitative value created by industrial policy when production networks are explicitly incorporated and formalize and validate the implications of existing theoretical analyses (Okuno-Fujiwara, 1988; Pack, 2000; Liu, 2019). In addition, we contribute to the literature on place-based industrial policy by exploiting substantial within-country variation, rather than focusing on national-wide policies as in much of the existing literature (e.g., Juhász et al., 2022).

Second, we contribute to the literature that examines the effects of industrial policy on firm outcomes. The traditional literature on industrial policy focuses primarily on macro-level outcomes, such as industry development, structural transformation, and aggregate welfare (e.g., Okuno-Fujiwara, 1988; Pack, 2000; Wu and Zhu, 2019; Lashkaripour and Lugovskyy, 2023; Barwick et al., 2025), while more recent studies examine firm-level real effects, including productivity, innovation, and profitability (e.g., Lim et al., 2018; Tian and Xu, 2022; Branstetter

downstream industries.

et al., 2023; Li and Branstetter, 2024; Choi and Levchenko, 2025). We build on this growing body of work by focusing on stock returns, which provide the most direct, timely, and precise measure of changes in firm value, yet remain unexplored in the literature. What's more, some studies question whether industrial policy enhances firm value, given its political motivations rather than a focus on shareholder value (Lim et al., 2018; Fang et al., 2025). In contrast, we identify a novel externality-based channel through which industrial policy positively affects firm value, offering a complementary perspective on the economic consequences of industrial policy.

Our study also contributes to the literature on the geographic determinants of stock returns. Early studies document location-based return patterns and attribute them to investors' home bias, local information advantages, and correlated trading (Coval and Moskowitz, 1999, 2001; Pirinsky and Wang, 2006; Korniotis and Kumar, 2013). More recent work emphasizes firm-level real economic fundamentals, including shared investment opportunities (Dougal et al., 2015), region-specific cash flows (Smajlbegovic, 2019), underreaction to correlated fundamentals (Parsons et al., 2020), city-level productivity (Dougal et al., 2022), and high-skilled immigrant agglomeration (Jiang et al., 2025). Building on this literature, we document a new channel through which the agglomeration of local customers and suppliers affects stock returns via positive externalities that enhance firm profitability, and we are the first to introduce industrial policy as a mechanism through which local government behavior enters the geographic determinants of stock returns.

Our results may be subject to endogeneity concerns, as favorable industry prospects could simultaneously drive industrial policy, CSER, and firm performance. We mitigate this concern in several ways. First, we use stock returns as the outcome variable (Edmans, 2011, 2023). The underlying idea is that it is unlikely for entrants to possess superior information about firms' future prospects while financial markets remain uninformed (Pack and Saggi, 2006)[11]. A

[11] The key idea is that it is implausible for new entrants to possess superior information about an industry's future favorable prospects that is not already reflected in financial markets. As noted by Pack and Saggi (2006): "*However, such an argument defies credibility because it requires one to believe that firms that have not even begun production know more about their prospects than investors whose main objective is to find profitable uses for their excess capital and have previously analyzed and financed similar projects. And even if one grants the presence of asymmetric information, what prevents potential producers from conveying such information to likely investors? After all, entrepreneurs seeking funds for new businesses overcome this problem on a routine basis.*"

treatment-effect interpretation instead allows for delayed market recognition of positive externalities that are gradually revealed through realized earnings, creating a lag between CSER and stock returns. In addition, if our results merely reflect the selection of firms with strong future performance by industrial policy, stock returns should precede or coincide with policy announcements when such prospects information is broadly known. However, we find no significantly positive cumulative abnormal returns around policy announcements. Instead, returns materialize following policy-induced increases in CSER, consistent with delayed market reactions to the real effects of policy-induced entry. Finally, heterogeneity related to the treatment effects of CSER on firm performance provides additional support for our results. With all this said, we acknowledge that we cannot fully rule out selection concerns and do not claim that our estimates are unbiased. Rather, our objective is to provide descriptive evidence and to assess the extent to which the results reflect treatment effects.

2. Data and Methodology

We use two unique datasets for our analysis: the firm registration data that covers a full sample of Chinese public and private firms and structured industrial policy data that covers all industrial policies issued by subnational governments. We combine these two datasets with the Input-Output Table and a series of firm fundamental and trading data to perform our analysis.

2.1 Data Sources and Summary

2.1.1 Firm Registration Data

To capture entry dynamics among firms' customers and suppliers, we assemble a comprehensive sample of Chinese firms using firm registration data from China's State Administration for Industry and Commerce (SAIC)[12]. The dataset contains registration records for more than 58 million firms from 1978 to 2022, including both private and public firms. According to SAIC requirements, a firm's registration information must be disclosed within

[12] Although the original source of the data is SAIC and the individual firm information can be queried on its official website, the agency does not directly provide a complete historical panel covering the full sample period. Several data providers compile this information, and we obtain the data from CnOpenData. The same data are also available from other sources, such as Wind and the Qichacha website.

three working days after registration. As a result, this information is publicly available to the market in a timely manner.

The registration data report each firm's registration date, operating industry, headquarters location, and other descriptive information. Industry classification follows the two-digit standard industry codes (Industrial Classification for National Economic Activities) defined by the National Bureau of Statistics of China, covering 97 industries. Firms' headquarters locations can be identified at the prefecture-level city, which is the primary geographic unit of analysis in our study.[13] China has 337 prefecture-level cities and centrally administered municipalities, consisting of four municipalities (Beijing, Shanghai, Tianjin, and Chongqing) and 333 prefecture-level cities. In China, a city is an administrative unit below the provincial level and above the county level. It encompasses not only the urban core but also surrounding areas under the same local government's jurisdiction. As a result, Chinese cities closely approximate functional economic areas and are more comparable to U.S. Metropolitan Statistical Areas (MSAs) than to narrowly defined cities.

We aggregate firm-level observations to the month–city–industry level to obtain, for each cell, the number of newly entering firms and the stock of incumbent firms. Although the data also contain information on registered capital, our analysis focuses on firm counts. This measure is commonly used in the literature (Bruno, Bytchkova, and Estrin, 2013; Gourio, Messer, and Siemer, 2016) and provides a cleaner proxy than registered capital in our dataset[14].

2.1.2 Industrial Policy Data

To examine whether a focal firm's customer and supplier industries are supported by

[13] We focus on supply chains within a firm's headquarters city for several reasons. First, cities constitute the basic units of regional economic activity and serve as the core drivers of regional growth in China. Second, analyzing local customer-supplier chains at the city level allows for a more precise identification of geographic linkages than studies conducted at broader administrative levels, such as states or provinces (e.g., Smajlbegovic, 2019). For comparison, we also construct alternative definitions of local customer-supplier chains at the provincial and national levels, as well as based on fixed geographic distances. As discussed later, city-level supply chain dynamics contain distinct information and exhibit return predictive power beyond that of broader geographic definitions.

[14] Because for our dataset, (1) The registered capital available is the latest registered capital up to 2022, rather than the registered capital at the time of registration. Then asset pricing tests based on registered capital have the problem of look-ahead bias. Although we tried to adjust the registered capital back to the time of registration according to the announcement text of registered capital change, there are still some inevitable biases due to the announcement irregularities and losses of non-listed firms in earlier years. (2) Chinese enterprises are registered under the subscribed capital system, rather than the paid-in capital system, so the registered capital in the data is not the actual capital of the firm. We find consistent empirical results based on firm registered capital.

industrial policy, we construct a novel policy dataset based on working documents issued by China's provincial and municipal governments. Our primary data source is the PKULAW database, one of the most authoritative legal repositories in China. We begin with three million policy documents issued by prefecture-level city governments in China between 2006 and 2022. We remove duplicates, documents issued by sub-municipal governments (i.e., counties and towns) and documents with missing metadata, such as title, policy text, issuing institution, and issuing date. The vast majority of these documents are routine administrative materials rather than industrial policy documents. We first filter documents whose titles explicitly contain the keyword "industry." This screening strategy is motivated by official naming conventions for government documents in China, which require titles to clearly specify the targeted objects and primary content of the policy. For example, the Shanghai municipal government issued an industrial policy in 2009 titled "Policy Provisions on Promoting the Development of the New Energy Vehicle Industry in Shanghai" (Chinese title:《关于促进上海新能源汽车产业发展的若干政策规定》). After this screening step, we retain a total of 61,736 industry-related documents issued by city- and provincial-level governments.

Not all "industry-related" policies constitute industrial policies in the strict sense. We therefore adopt and extend the definition proposed by Juhász et al. (2022). While Juhász et al. (2022) restrict industrial policy to actions at the national level, we relax this restriction and extend the definition to include policies implemented by local governments, consistent with China's decentralized policy implementation practice. Specifically, the industrial policies in our study are required to satisfy the following five criteria:

(1) The policy must be promulgated by a local government.

(2) The policy must explicitly target specific industries.

(3) The policy must have a clear objective of influencing the growth and development of the targeted industries and, through this channel, reshaping the regional economic structure by altering the relative position of these industries.

(4) The policy must specify concrete government-implemented policy instruments, falling into one of five categories: subsidies, tax incentives, government investment, supply chain coordination, and market regulation.

(5) The policy must not be a routine work report, an implementation progress update, or

an inspection document.

We use a fine-tuned large language model (DeepSeek-V2) to analyze these "industry-related" documents on a document-by-document basis.[15] First, the LLM determines whether each document qualifies as an industrial policy under our definition. Second, it extracts the industries targeted by each industrial policy and maps them to the 97 standard two-digit industry codes. Third, the LLM identifies the specific policy instruments employed and classifies the policy stance toward the targeted industries as either supportive or regulatory.

The final dataset contains 15,535 prefecture-level city documents identified as industrial policy document. Table 1 reports descriptive statistics for these policy documents. On average, each policy document targets 2.17 industries. Each city issues 4.32 industrial policy documents per year, covering 6.68 distinct industries. For each industry, an average of 14.62 cities issue industrial policy document per year, corresponding to 20.19 policy documents.

[Table 1]

In terms of policy instruments, subsidies are the most frequently used tool, appearing in 74.58% of industrial policy documents. The second most common instrument is supply chain coordination, highlighting governments' tendency to use industrial policy to support entire industrial chains rather than individual industries. In addition, 10.9% of policies impose regulatory measures on the targeted industries, typically to curb overcapacity, phase out outdated production, or meet environmental requirements (e.g., in the coal industry).

[Figure 1]

Figure 1 summarizes the distribution of industrial policies. Starting in 2006, the number of policies rises steadily, indicating the growing prominence of industrial policy in China's economic development (Panel A). Most local industrial policies are issued by People's Governments (59.46%), followed by specialized government departments (9.96%) and bureaus of industry and information technology (7.63%) (Panel B). Geographically, Guangdong, Henan, Jiangsu, Shandong, and Anhui issue the largest number of municipal-level industrial policies,

[15] The model is calibrated with the temperature parameter being 1 to prioritize accuracy and consistency in classification. According to the official documentation by DeepSeek, Temperature = 1 is mainly suitable for data extraction and analysis functions. We try to analyze the same file several times under this Temperature, and the analysis results were consistent across 10 attempts.

while Shenzhen, Chongqing, Zhengzhou, Shanghai, and Guangzhou are the most active cities (Panel C). Regions with higher marketization also issue more industrial policies: the number of policies is strongly correlated with a city's provincial marketization index, with a correlation coefficient of 0.7, consistent with a dynamic form of state–market coordination. Across industries (Panel D), local governments place the greatest emphasis on agriculture, which accounts for 17.37% of all policies[16]. The remaining most-supported industries are primarily in the secondary sector, including electronics manufacturing, pharmaceuticals, electrical equipment, special equipment, and automobile manufacturing.

2.1.3 Customer and Supplier Industries

For each industry, we identify its customer and supplier industries based on the input–output tables (Fan and Lang, 2000; Matsusaka, 1993; Menzly and Ozbas, 2010) compiled by the National Bureau of Statistics of China. These tables describe input–output linkages among 97 two-digit standard industries under the Industrial Classification for National Economic Activities. Specifically, for each industry, the input–output table reports the share of inputs sourced from its own industry and from each of the other 96 industries, as well as the corresponding distribution of its outputs across industries.

Broadly speaking, all other industries can be viewed as simultaneously serving as both customer and supplier industries of a focal industry, although the strength of these linkages varies substantially, with many input or output shares close to zero. We define the input–output weight between a customer or supplier industry B and a focal industry A as the average of B's share in A's inputs and the share of A's output sold to B. For example, if 30% of A's inputs are sourced from B and 40% of A's output is sold to B, then the weight of B on A is (30% + 40%) / 2 = 35%.

The National Bureau of Statistics of China has released six vintages of input–output tables constructed based on 97 two-digit industries since 2007. These tables correspond to benchmark years 2002, 2007, 2012, 2017, 2018, and 2020, and were released in 2007, 2008, 2015, 2020, 2021, and 2023, respectively. To avoid look-ahead bias, each vintage is used only after its

[16] The Chinese central government regards agriculture as a top priority for national security. Each year, the central government's No. 1 Document focuses on safeguarding agricultural security and promoting agricultural development.

official release. Accordingly, our analysis begins in January 2007.

2.1.4 Public Firms

Stock trading and accounting data are obtained from the China Stock Market and Accounting Research (CSMAR) database. Annual accounting data are merged with monthly trading data following standard practice in the literature (e.g., Fama and French, 2015), such that accounting information from the end of fiscal year t−1 is matched to trading data from July of year t to June of year t+1. Analyst forecast data are also sourced from CSMAR. Our initial sample includes all normally traded A-share stocks listed on the SHSE and SZSE. The sample period is from January 2007 to December 2022.

To mitigate the influence of penny stocks, we exclude stocks with prices below 5 yuan from the sample. In addition, following Liu et al. (2019), we exclude firms that (i) have been listed for less than six months, or (ii) have fewer than 120 trading days in the past year or fewer than 15 trading days in the past month. The latter restriction is intended to prevent our results from being driven by returns following prolonged trading suspensions. In robustness checks, we further exclude firms in the bottom 30% of the size distribution to mitigate the influence of shell value.

2.2 Key Variable Construction and Summary Statistics

2.2.1 Customer-Supplier Entry Rate (CSER)

For each public firm, the customer–supplier entry rate (CSER) measures the weighted average of local firm entry rates into its customer and supplier industries. In our baseline results, “local” refers to CSER computed at the prefecture-level city. In subsequent analyses, we extend the scope of CSER to provincial and national levels.

In each month t, for each public firm i headquartered in city c and operating in industry k, CSER is calculated as follows:

$$CSER_{i,t} = \sum_{d=1}^{96} w_{k,d} IER_{c,d,t}\ , \tag{1}$$

Where $IER_{c,d,t}$ is the monthly new firm entry rate in industry d and city c, defined as the number of new firms entering during month t scaled by the number of existing firms at the end of the month. Industry d is a customer or supplier industry of the focal firm's own industry k. $w_{k,d}$ is the input–output weight, defined as the average of industry d's share in industry k's total inputs and the share of industry k's output sold to industry d. By construction, $\sum_{d=1}^{96} w_{k,d} = 1$.

Using the same approach, we separately construct a firm's customer entry rate (CER) and supplier entry rate (SER) by replacing the input-output weights with output weights (the share of industry k's output sold to industry d) and input weights (industry d's share in industry k's total inputs), respectively. Because the input-output weight is defined as the average of the input and output weights, CSER is mechanically the simple average of CER and SER.

Figure 5 illustrates the construction of CSER using Contemporary Amperex Technology Co., Limited (CATL) as an example.

[Figure 2]

In addition, we construct a firm's own-industry entry rate, referred to as the industry entry rate (IER), which is defined as the number of new firms entering the public firm's own industry in its headquarters city, scaled by the total number of firms in that city–industry at the end of each month.

[Table 2]

Table 2 reports the summary statistics for CSER and firm characteristics of portfolios sorted on CSER. In panel A, we do summary statistics for CSER in each cross-section (month) and then take time-series averaged of all these statistics. As shown, CSER has a mean of 1.2%, or 14.4% annually, consistent with the rapid growth of China' s economy.[17] The mean values of CER, SER, and IER are 1.30%, 1.10%, and 1.04%, respectively. Our analysis focuses on cross-sectional variation in CSER across stocks. On average, each cross section contains 1,594 stocks, and CSER increases by 0.67 percentage points from the 20th to the 80th percentile (i.e., from the lowest to the highest quintile). In addition, we report descriptive statistics for CSER

[17] For example, according to a recent report by China's central government, there were about 7.06 million new entrants with 52 million incumbents nationwide from January to September 2023, indicating an average growth rate of about 1.51% per month, or 18.1% annually.

constructed at the provincial and national levels, as well as for the orthogonal components of city-level CSER with respect to provincial- and national-level CSER.

Panel B reports firm characteristics across CSER quintile portfolios. Firms with higher CSER are more likely to be manufacturing firms, less likely to be located in first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen), and more likely to be the only public firm in their city. These high-CSER firms are smaller relative to the overall market and their industries, yet larger within their own cities. This pattern reflects a feature of China's local economy: locally dominant public firms often serve as "flagships" or hubs of regional customer-supplier chains, either through natural agglomeration forces or because local governments have incentives to coordinate entry around them, which is associated with greater customer and supplier entry. We find no significant differences in book-to-market ratios, industry concentration (HHI), or stock prices across high- and low-CSER quintiles.

[Figure 3]

To further illustrate the properties of CSER, we also present its aggregate time-series variation (as shown in Figure 3). We find that the time-series pattern of CSER comoves with the Macroeconomic Prosperity Index, an indicator published by the National Bureau of Statistics to reflect overall economic conditions. In addition, CSER exhibits pronounced intra-year seasonality: it declines sharply around the Spring Festival and National Day holidays[18], and firm entry peaks in the second quarter. To mitigate the influence of seasonality, we use a 12-month moving average of CSER in our main analyses.

2.2.2 Customer-Supplier Industrial Policy (CSIP)

For each public firm, we construct a Customer–Supplier Industrial Policy (CSIP) index to quantify the intensity of industrial policy support for its local customer and supplier industries. CSIP is defined as the weighted average of dummy variables indicating whether each of the 96 customer and supplier industries is supported by industrial policies issued by the municipal government of the firm's headquarters city during a given past period. Specifically, CSIP is

[18] In China, the Spring Festival typically occurs around February, while the National Day holiday runs from October 1 to October 7.

calculated as follows:

$$CSIP_{i,[t-h,t]} = \sum_{d=1}^{96} w_{k,d} IP_{c,d,[t-h,t]}\,, \tag{2}$$

Where firm i is headquartered in city c and operates in industry k, and d indexes one of k's customer or supplier industries. During the sample period, 22,998 different city-industry-year policy data are extracted from 15,000 policy documents. $IP_{c,d,[t-h,t]}$ is a dummy variable equal to one if the municipal government of city c issued at least one supportive industrial policy targeting industry d during the past h months. If city c's policies targeting industry d during the past h months include market regulation, then $IP_{c,d,[t-h,t]}$ takes 0 regardless of whether other policy tools are included or not. $w_{k,d}$ is given by the input–output weights defined in the input–output table. For example, CSIP equals 0.8 if industrial policies support two customer or supplier industries accounting for 50% and 30% of the average input and output shares of the firm's own industry, respectively.

[Table 3]

Table 3 reports the summary statistics of CSIP at the firm level. When industrial policies are tracked over the past 3, 6, and 12 months, they support, on average, customer and supplier industries accounting for 9.4%, 12.9%, and 17.3% of a focal firm's total input–output volume, respectively. The most commonly used instrument is direct subsidies, followed by supply chain coordination and government investment. About 14.5%, 11%, and 10.1% of customers and suppliers of a firm are supported by government subsidies, supply chain coordination and government investment during past 12 months, respectively. The firm-level summary statistics align with the industrial policy document level summary statistics.

3. Main Results

3.1 Supply Chain Industrial Policy (CSIP) and Local Customer-Supplier Entry Rate (CSER)

In this section, we examine how industrial policies targeting customer and supplier industries (CSIP) promote firm entry into local customer–supplier chains (CSER). Specifically, we study the extent to which CSIP drives cross-sectional variation in CSER by estimating the following regressions cross-sectionally each month, and averaging the estimated coefficients over time.

$$CSER_{i,[t,t+m]} = \alpha + \beta_1 CSIP_{i,[t-h,t]} + \beta_2 IP_{i,[t-h,t]} + \beta_3 ln(GDP)_{i,t} + \beta_4 \Delta GDP_{i,t} + \beta_5 RCA^N_{i,t} + \beta_6 RCA^P_{i,t} + \beta_7 Cluster_{i,t} + \varepsilon_{i,t} \quad (3)$$

The dependent variable, $CSER_{i,[t,t+m]}$, is the average monthly CSER over the subsequent 3, 6, or 12 months (with the CSER window m = 3, 6, 12). The explanatory variables include policy-related ones and policy-unrelated ones. Policy-unrelated variables include CSIP, which measures the intensity of local government support for firm i's customer and supplier industries over the past h months, as well as IP, an indicator for whether the firm's own industry is supported. Policy-unrelated variables capture city-level and industry-level economic conditions, including the most recent annual GDP and GDP growth rate (ΔGDP), as well as revealed comparative advantage (RCA) and industry clustering. RCA^P and RCA^N measure the relative importance of the firm's industry in its headquarters city compared with its importance at the provincial and national levels, following the spirit of Balassa (1965) and Fang et al. (2025). Industry importance is defined as the number of registered firms in an industry divided by the total number of registered firms in the corresponding city, province, or nation. Cluster is defined as the share of registered firms in the firm's own industry that are located in the headquarters city relative to all firms in the same industry nationwide. All variables are measured at the end of month t.

Controlling for economic conditions, RCA, and clustering is necessary because these factors may confound the estimated effect of CSIP on CSER. Economically stronger regions have greater capacity to implement industrial policies (as shown in Section 2.1.2), and governments tend to support industries in which the city has a comparative advantage (Fang et al., 2025). As a result, firms with higher RCA and Cluster are also more likely to be exposed to higher CSIP. At the same time, higher GDP and stronger local industry advantages make a city more attractive to potential entrants, independently increasing CSER. By examining the coefficient on CSIP after controlling for these factors, we assess whether industrial policies generate additional entry beyond what favorable economic and industry prospects would predict, rather than merely supporting industries that are already attractive to customer and supplier entrants.

[Table 4]

Table 4 presents the regression results. When both the policy window and the CSER window are set to 12 months (column (9)), the estimated coefficient on CSIP is 0.546 (t-statistic = 4.94). This estimate implies that, in the cross section, firms whose customer and supplier industries are fully supported by industrial policies experience a 0.546 percentage point increase in monthly CSER over the subsequent year relative to unsupported firms. This effect is economically meaningful, corresponding to a shift from the second to the highest CSER quintile. The effect of CSIP is even stronger for shorter policy windows. Holding the CSER window fixed at 12 months, the estimated coefficients on CSIP are 1.119 (t-statistic = 4.16) and 0.732 (t-statistic = 5.14) for the 3-month and 6-month policy windows, respectively (columns (7) and (8)). Both estimates are significant at the 1% level and exceed the magnitude reported in column (9). Overall, these results indicate that supply chain industrial policies significantly promote firm entry into local customer and supplier industries, even after controlling for favorable local economic and industry conditions.

3.2 Local Customer-Supplier Entry Rate (CSER) and Stock Returns

3.2.1 Single Sort

Given the evidence that local industrial policy targeting the customer and supplier industries of a firm promotes entry into those industries, we next examine whether such entry generates positive externalities for incumbent public firms. Specifically, we test whether CSER is positively associated with firms' subsequent stock returns.

At the beginning of each month, we sort all stocks into quintile portfolios based on the past 12 months moving average CSER and generate a long-short portfolio by longing the stocks in the highest group and shorting those in the lowest. All stocks are value-weighted in each portfolio. The resulting portfolios are held for one month. To separately examine the roles of suppliers, customers, and same-industry entrants, we conduct single sorts based on the supplier entry rate (SER), customer entry rate (CER), and industry entry rate (IER). The sorting procedure and the construction of long–short portfolios follow the same methodology used for CSER.

[Table 5]

Table 5 reports monthly value-weighted excess returns and factor-model alphas for the resulting portfolios. Panel A presents results based on CSER, while Panel B reports results based on SER, CER, and IER. We find a strong and monotonic relation between CSER rankings and future stock returns. The CSER long–short portfolio generates highly significant average excess returns of 0.736% per month (t-statistic = 4.50), equivalent to 8.832% annually, and a Fama–French five-factor alpha of 0.633% per month (7.596% annually). The return spread is driven by both the long and short legs of the portfolio. Overall, these results indicate that firms with higher CSER outperform those with lower CSER, consistent with positive externalities from customer–supplier entry enhancing the value of local public firms. Our findings also stand for Fama-French (2018) six-factor model and Liu-Stambaugh-Yuan (2019) CH-3 and CH-4 factor models. Figure 4 illustrates the time-series performance of the CSER strategy returns.

[Figure 4]

In Panel B, we similarly sort stocks based on SER, CER, and IER. For brevity, we report only the excess returns and alphas for the highest (High) and lowest (Low) portfolios, as well as the long–short portfolio (H–L). The results indicate that the effects of CSER arise from both the customer and supplier sides. The long–short portfolios formed on SER and CER earn Fama–French five-factor alphas of 0.716% per month (t-statistic = 3.69) and 0.643% per month (t-statistic = 3.31), respectively. Other factor models yield qualitatively similar results .

In contrast, we find no significant return predictability for IER. For example, the long–short portfolio based on IER yields an average excess return of 0.35% per month (t-statistic = 1.59). This result can be explained by the fact that new entrants within the same industry and region generate both scale economies and competitive pressures for incumbent firms, and the positive and negative effects offset each other. Importantly, this finding has implications for the motivation of supply chain industrial policy: policies that encourage entry into a focal firm's customer and supplier industries generate positive externalities, whereas policies that merely promote clustering within the same industry do not.

3.2.2 Fama-Macbeth Regression

In this section, we estimate Fama-MacBeth (1973) regressions of stock returns in month t+1 on the local customer-supplier chain entry rate (CSER) of the stock in month t, where CSER is calculated as a 12-month lagged moving average. We control for a set of return predictors documented in the previous literature (all defined in Appendix A). (1) Firm characteristics, including firm size (Ln(Size)), book-to-market ratio (BM), industry concentration (HHI), and market beta (Beta), all calculated at the end of month t. (2) The stock's own momentum, including its return in the month t (RET1), cumulative returns over the past 1 to 12 months (RET1to12), and cumulative returns over the past 13 to 36 months (RET13to36). (3) Related stock returns in the month t, including returns from stocks in the same industry (INDRET), same city (GEORET), customer industries (CUSRET), and supplier industries (SUPRET). (4) Liquidity measures including the monthly illiquidity ratio (Illiquid) and turnover (Turnover).

[Table 6]

The results of reported in Table 6 are consistent with that in Table 5. In the baseline specification in column (1), the estimated coefficient of CSER is 0.621 (t-statistic = 8.09), indicating that a 1% increase in CSER is associated with a 62 bases point increase in stock returns next month. The estimated coefficients of CSER are all positive and statistically significant at the 1% level when we include control variables in columns (2) - (4). These results suggest that CSER has a significant return predictability that is not absorbed by the documented return predictors, confirming that the entry into local customer and supplier industries has unique effects on firms' future performance, rather than being merely an extension or replication of the return predictors related to momentum (Jegadeesh and Titman, 1993), customer-supplier link (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), industry (Moskowitz and Grinblatt, 1999; Hou, 2007), or geographic location (Parsons et al., 2020).

3.3 CSER and Real Performance

To investigate whether the entry into local customer-supplier chain is associated with improved fundamental performance, we examine the relationship between CSER and firms' future performance measures. Specifically, we run the panel regressions:

$$\pi_{i,q+1} = \alpha + \beta_1 CSER_{i,q} + \gamma Controls_{i,q} + \mu_i + \delta_q + \varepsilon_{i,q} \quad (4)$$

The dependent variables $\pi_{i,q+1}$ are quarterly return on asset (ROA), sales on asset (SOA), earnings price ratio (E/P), profit growth ($\Delta Profit$), and EPS growth (ΔEPS), calculated at the end of quarter q+1. The independent variable of interest is the 12-month lagged moving average CSER, calculated at the end of quarter q. The regressions control for firm size (Ln(Size)), book-to-market ratio (BM), industry concentration (HHI), and market beta (Beta), all calculated at the end of quarter q, as well as quarterly returns of the focal stock (RET1) and related stocks in the same industry (INDRET), same city (GEORET), customer industries (CUSRET), and supplier industries (SUPRET) in quarter q. All variables are defined in detail in Appendix A. The firm and year-quarter fixed effects are also included.

[Table 7]

The results reported in Table 7 show that CSER in a quarter is positively related to the firm's real performance and performance growth in both the current and next quarter. As column (1) shows, when regressing ROA on CSER, the estimated coefficient of CSER is 0.494 (t-statistic = 2.88), significant at the 1% level. It indicates that a 1% increase in the average monthly CSER over the past year is associated with a 0.494% increase in ROA in the current quarter, which is 50% (= 0.494% / 0.988%) increase relative to the sample mean. As column

(2) and (3) show, when regressing SOA and E/P on CSER, the estimated coefficients of CSER are 0.106 (t-statistic = 3.05) and 0.064 (t-statistic = 2.07), respectively. It indicates that a 1% increase in the average monthly CSER over the past year is associated with a 0.106% increase in SOA and a 0.064% increase in E/P in the current quarter. When regressing $\Delta Profit$ on CSER in column (4), the estimated coefficient of CSER is 9.581 (t-statistic = 2.79), significant at the 1% level. The economic magnitude is also sizable. It indicates that a 1% increase in CSER is associated with an average increase in the profit growth of approximately 9.581%. And a 1% increase in CSER is associated with an average increase in the EPS growth of approximately 5.135%, as shown in column (5). The above results show that the entry into local customer-supplier chain is positively and significantly associated with improvements in firms' fundamental performance, indicating that the return predictability of CSER is associated with improved fundamental performance.

3.4 CSER and Analyst Earnings Surprise

The above results indicate that the entry into local customer-supplier chain is beneficial to firm value, but not immediately capitalized by the stock market. To provide direct evidence on this channel, we examine how CSER is associated with firms' analyst earnings surprise. Using a similar methodology to the prior literature (e.g., Core et al., 2006; Edmans, 2011), we run the following panel regression:

$$SUE_{i,t\,(t+1)} = \alpha + \beta_1 CSER_{i,t} + \gamma X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \qquad (5)$$

We consider the earnings surprise in both the current year t and the next year t+1. The dependent variable $SUE_{i,t\,(t+1)}$ is the actual earnings per share for the fiscal year ending in year t (t+1) minus the median analyst forecast over the past 12 months, deflated by the stock price at fiscal year-end. The analyst forecast data is from CSMAR. We only keep the latest forecast provided by each analyst each year. The independent variable of interest is the average monthly CSER over year t. The regressions include the same control variables as that in Equation (4), but calculated at the annual level, along with the log of analyst forecast dispersion (Dispersion), measured by the standard deviation of all forecasts for the firm in year t. We include industry, firm, and year-quarter fixed effects in different specifications.

[Table 8]

Results in Table 8 show that CSER is positively associated with earnings surprises in both the current and next year. Column (1) shows that regressing current-year earnings surprises on CSER yields an estimated coefficient of 0.214 (t-statistic = 4.42). This estimate implies that a 1% increase in CSER is associated with current-year earnings announcements that exceed analysts' expectations by approximately 0.214% of the stock price. Column (4) shows that CSER also predicts next-year earnings surprises: the estimated coefficient is 0.222 (t-statistic = 6.76), indicating that a 1% increase in CSER is associated with earnings announcements in the following year that exceed analysts' expectations by about 0.222% of the stock price. The results are robust after we include industry and firm fixed effects. Together with the improvements in fundamental performance, these findings suggest that entry into the local customer-supplier chain generates positive externalities that enhance firm value. These effects are not incorporated into prices in a timely manner, leading the market to underreact to earnings until actual EPS are disclosed, at which point the information is revealed as earnings surprises.

3.5 Supply Chain Industrial Policy and Stock Returns

Based on the above findings that industrial policies improve focal firms' performance by promoting entry into their local customer-supplier chains, we consider whether industrial policies are directly linked to focal stock returns. Specifically, we examine both short-term and long-term return reactions to industrial policies targeting the firm's customer and supplier industries issued by the government of its headquartered city.

We examine the short-term return reaction to industrial policies using an event study approach. The announcement date of the local industrial policies targeting the focal firm's customer and supplier industries is set as the event date (t = 0). We compute the cumulative total return (CTR) and cumulative abnormal return (CAR) as $CTR_i = \sum_{t=t_1}^{t_2} R_{i,t}$ and $CAR_i = \sum_{t=t_1}^{t_2} AR_{i,t}$, where the event window are [-1, 1] and [-5, 30], respectively. $R_{i,t}$ and $AR_{i,t}$ are the realized return and abnormal return of stock i on day t. $AR_{i,t}$ is calculated as $R_{i,t}$

minus the expected return based on several factor models, including CAPM, Fama-French three-factor model, Fama-French five-factor model, and Liu-Stambaugh-Yuan four-factor model, with stock-specific factor loadings estimated using daily data for a one-year period (252 trading days) ending 30 trading days prior to the event date. We require firms to have at least 120 days of return data during the parameter estimation period.

We then examine the long-term return reaction to industrial policies using Fama-Macbeth regressions.

$$Ret_{i,t+1} = \alpha + \beta_1 CSIP_{i,[t-12,t]}(CSIP_{i,[t-24,t-12]}) + \gamma X_{i,t} + \varepsilon_{i,t} \quad (6)$$

The dependent variable is stock returns in month t+1, and the independent variable of interest is CSIP, constructed from industrial policies targeting each firm's customer and supplier industries issued over the periods t−12 to t and t−24 to t−12, respectively. Other empirical settings and control variables are the same as those in Table 6.

[Table 9]

The results are reported in Table 9. Panel A shows that the CARs around the announcement dates are economically small and statistically insignificant. For the [-1, +1] window, the mean CARs are nearly zero (ranging from -0.03% to 0.01%) and insignificant across all four factor models. For the longer [-5, +30] window, the mean CARs range from -0.27% to 0.05%, which are also nearly zero or slightly negative with little statistical significance. These findings show that the market does not view the announcement of local policies targeting customer and supplier industries as good news for the focal firm's value.

The results of Fama-Macbeth regressions in Panel B provide complementary evidence to the event study. As column (1) shows, the estimated coefficient of recent policy exposure ($CSIP_{i,[t-12,t]}$) is -0.005 (t-statistic = -1.08), which is economically and statistically insignificant. All the coefficients of CSIP show no or little significance when we control for relevant firm characteristics in column (2), focus on one-year lagged policy exposure ($CSIP_{i,[t-24,t-12]}$) in columns (3) and (4), or include both recent and one-year lagged CSIP in columns (5) and (6). It shows that firms with more local industrial policies targeting their customer and supplier industries do not overperform, or even slightly underperform in a longer horizon.

Overall, the direct effect of customer-supplier industrial policies on focal stock returns is insignificant, if anything, is slightly negative. It is reasonable since the primary motivation of industrial policies is to achieve political objectives such as industrial development, regional economic growth, and social welfare, rather than focusing explicitly on firm profitability. Consequently, these policies may include factors detrimental to firm operations, such as requiring firms to absorb more employment (Lim et al., 2018), undertake larger investments (Bai and Lian, 2013; Zhou and Zhao, 2022), or increase research expenditures, which may not directly translate into profits and may negatively affect stock returns. Therefore, it's necessary to isolate the policy-induced part of CSER and examine whether this part benefits the focal firm.

3.6 The Return Predictability of Policy-induced CSER

The above results support that supply chain industrial policy generates positive externalities for public firms' performance by promoting customer and supplier entry, the mechanism through which may be attenuated by additional non-shareholder objectives. To test this mechanism, we conduct a two-step analysis: first isolate the policy-induced part of CSER and then examine how this part is associated with future stock returns.

In the first step, we isolate the effect of CSIP on CSER to identify the additional entry induced by industrial policy. Specifically, in each month t, we recursively estimate the following Fama–MacBeth regression using an expanding window of historical firm–month panel data:

$$\begin{aligned} CSER_{i,\tau} = \alpha + \beta_1 CSIP_{i,[\tau-24,\tau-12]} + \beta_2 IP_{i,[\tau-24,\tau-12]} + \beta_3 ln\left(GDP_{i,\tau}\right) + \beta_4 \Delta GDP_{i,\tau} \\ + \beta_5 RCA^{N}_{i,\tau} + \beta_6 RCA^{P}_{i,\tau} + \beta_7 Cluster_{i,\tau} + \varepsilon_{i,\tau}, \qquad \tau \leq t \end{aligned} \tag{7}$$

The dependent variable is the firm's customer-supplier entry rate averaged over months τ−12 to τ ($CSER_{i,\tau}$). The independent variables include policy-related ones and policy-unrelated ones. Policy measures include the customer–supplier industrial policy index measured over months τ−24 to τ−12 ($CSIP_{i,[\tau-24,\tau-12]}$), and a dummy variable indicating whether the firm's own industry is supported by industrial policy during the same period ($IP_{i,[\tau-24,\tau-12]}$). [19] Policy-unrelated measures are local economic conditions and industry prospects, including the most recent annual GDP ($GDP_{i,\tau}$), and the GDP growth rate ($\Delta GDP_{i,\tau}$), as well as revealed comparative advantage ($RCA^{N}_{i,\tau}$ and $RCA^{P}_{i,\tau}$) and the clustering measure ($Cluster_{i,\tau}$). The definitions of all variables follow those in Table 4.

Based on the estimated coefficients in each month t, we decompose CSER averaged over months t−12 to t into three components: the fitted values attributable to policy measures ($\widehat{CSER_{Policy}}$), the fitted values unrelated to policies, including local economic conditions ($\widehat{CSER_{GDP}}$) and local industry prospects ($\widehat{CSER_{RCA}}$), as well as a residual component ($\widehat{CSER_{r}}$). Specifically, the decomposition is given as follows:

$$CSER_{i,t} = \hat{\alpha} + \underbrace{\widehat{\beta_1} CSIP_{i,[t-24,t-12]} + \widehat{\beta_2} IP_{i,[t-24,t-12]}}_{\widehat{CSER_{Policy}}} + \underbrace{\widehat{\beta_3} ln\left(GDP_{i,t}\right) + \widehat{\beta_4} \Delta GDP_{i,t}}_{\widehat{CSER_{GDP}}}$$
$$+ \underbrace{\widehat{\beta_5} RCA^{N}_{i,t} + \widehat{\beta_6} RCA^{P}_{i,t} + \widehat{\beta_7} Cluster_{i,t}}_{\widehat{CSER_{RCA}}} + \underbrace{\widehat{\varepsilon_{i,t}}}_{\widehat{CSER_{r}}}. \quad (8)$$

$$\widehat{CSER} = \hat{\alpha} + \widehat{CSER_{Policy}} + \widehat{CSER_{GDP}} + \widehat{CSER_{RCA}}, \quad (9)$$

where $\hat{\alpha}$ is a constant that takes the same value for all stocks within each cross section.

In this decomposition, we interpret the fitted value attributable to policy measures, $\widehat{CSER}_{Policy}$, as policy-induced CSER. We then examine the extent to which this component drives cross-sectional variation in total CSER. Specifically, we conduct a variance decomposition by computing the ratio of the variance of $\widehat{CSER}_{Policy}$ to the sum of variances across all CSER components. The results of the variance decomposition are reported in Figure 5.

[Figure 5]

Because we cannot precisely attribute the source of the residual variance, we consider three benchmark cases. Lower bound: we assume that the residual component is entirely unrelated to policy, in which case policy-related components explain approximately 20% of the cross-

[19] We find consistent results if we exclude IP and only use CSIP as the policy measure in the regression.

sectional variation in CSER. Middle bound: we ignore the variance of the residual component, in which case policy-related components explain between 40% and 90% of the total variation in CSER. Upper bound: we attribute the entire residual variance to policy-related factors, in which case policy-related components explain nearly all of the variation in CSER. Across all cases, supply chain industrial policy explains a significant share of the variation.

At the second step, we examine how policy-induced CSER is associated with future stock returns. We run the Fama-MacBeth (1973) regressions of the stock returns in month t+1 on the fitted value and components of CSER in month t. In this regression, we include the same control variables as in Table 6.

[Table 10]

Table 10 reports the results. We first examine the overall fitted CSER in columns (1) and (2). As column (1) shows, the coefficient of the overall fitted CSER ($\widehat{CSER}$) is 1.578 (t-statistic = 4.75), which is statistically significant at the 1% level. This result indicates that, on average, a one-unit increase in the fitted value of customer-supplier entry rates is associated with a 1.578% increase in a firm's stock return next month in the cross section. The coefficient of the overall fitted CSER remains statistically and economically significant after controlling for an extensive set of known return predictors in column (2). This confirms that CSER, especially the components explained by fundamental economic and policy factors, contains valuable information for predicting future stock returns. More importantly, as shown in column (3), the coefficient of the policy-induced component of CSER is 0.753 (t-statistic = 3.16) and is also statistically significant at the 1% level. This estimate has a clear interpretation under our identification strategy: it captures the association between the portion of CSER driven specifically by the supply chain industrial policy (CSIP) and future stock returns. A one-unit increase in the policy-driven entry of a firm's local customers and suppliers leads to a 0.753% increase in the firm's stock return next month. The results are significant when we include a series of control variables in column (4), where a 1% increase in policy-driven component of CSER is associated with a 0.537% (t-statistic = 2.70) higher return next month. Overall, these results are consistent with the mechanism that supply chain industrial policy benefits firms through promoting entry of their local customers and suppliers.

4 The Role of Local Government

Our finding that supply chain industrial policies generate positive externalities raises a pivotal question: what is the role of local government in this implementation? In this section, we conduct two progressive tests to explore this question. First, we distinguish whether these externalities stem from a broad, national supply-chain factor or are intrinsically localized within the focal firm's own province or city. However, even localized entry may fail to yield benefits due to inherent market frictions like information barriers (Boudreau et al., 2017)[20] and coordination failures (Juhász et al., 2024)[21]. This concern motivates our second test: we examine whether the positive effects are bounded by administrative jurisdictions, rather than by mere geographic distance. Together, these tests are designed to investigate whether local governments act as essential external forces that actively overcome coordination challenges within their jurisdictional purview, transforming industrial policy into firm-level value.

4.1 The Scope of Externality of Local Customer-Supplier Chains

In this subsection, we examine the scopes of customer-supplier chains by constructing CSER at multiple levels. In addition to the city-level measure (CSER), we construct province-level ($CSER^P$) and nation-level ($CSER^N$) measures to represent and customer-supplier chain entry rates within the province and across the entire nation. To isolate local effects, we further construct a province-level measure orthogonal to the nation level (CSERP $^{P\perp N}$), which is the residual of cross-sectional regression of $CSER^P$ on $CSER^N$, and a city-level measure orthogonal to both the province and nation levels ($CSER^{\perp P\&N}$), which is the residual of cross-sectional regression of CSER on $CSER^P$ and $CSER^N$.

[Table 11]

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[20] Boudreau et al. (2017) demonstrate that significant matching frictions exist even among geographically proximate scientists within the same institution, and that randomly structured information-sharing sessions can increase the probability of collaboration by 75%. Similarly, deliberate efforts may be required to facilitate coordination among firms.

[21] Firm-level cooperation is not guaranteed, especially when both firms earn profits only if they engage in complementary production activities simultaneously, while either firm would incur losses if it undertakes the activity alone. In such settings, a bad equilibrium can arise in which both firms choose not to engage in the activity. Government coordination is therefore necessary as an authoritative mechanism, particularly when the government has the power to allocate resources, which makes such coordination and commitments more credible.

We test the return predictability of these CSER measures in Table 11. In the cross-sectional regressions, the dependent variable is the stock return next month and the key independent variables are CSER across different regional levels. As shown in column (1), the coefficient of $CSER^{N}$ is -0.507 (t-statistic = -1.06), which insignificantly predicts stock returns next month. In contrast, as shown in columns (2) and (3), the coefficients of $CSER^{P}$ and CSER are 0.357 (t-statistic = 3.15) and 0.362 (t-statistic = 4.95), both of which significantly predict stock returns next month. It indicates that the entry into customer-supplier chains within the same province or the same city benefit focal firms, while that within the nation does not make much difference. Furthermore, in columns (4) and (5), the coefficient of $CSER^{P\perp N}$ and $CSER^{\perp N\&P}$ are 0.618 (t-statistic = 6.26) and 0.534 (t-statistic = 6.21), both of which significantly predicting future stock returns. This indicates that the $CSER^{P}$ provides unique effects beyond the $CSER^{N}$, and the CSER provides additional unique effects beyond both $CSER^{N}$ and $CSER^{P}$. This finding also justifies our use of CSER in the main analysis.

4.2 More than Geographical Proximity

The above results show that different regional levels matter in the benefits of customer-supplier chains. This subsection further examines whether this difference is due to simple geographical proximity or the significant role of administrative jurisdiction. We control for geographic distance and use administrative boundaries to identify jurisdictions. If the externalities of customer-supplier chains are only spillover effects caused by geographical proximity, the return predictability of CSER within a fixed geographical distance would be similar. However, if jurisdiction matters for facilitating coordination, since the industrial policies of each government is relatively independent (Gao, 2004; Wu et al., 2019), there would be a tighter connection among firms within the same administrative boundaries, thus CSER within the same administrative boundaries would have stronger return predictability, even after controlling for a fixed geographic distance.

[Figure 6]

To test these predictions, for each firm, we separately calculate the customer-supplier chain entry rates (1) within the headquartered city, (2) within 100 km, (3) within 100 km outside the headquartered city, (4) within 100 km inside the same province, (5) within 100 km inside the same province and outside the headquartered city, (6) within 100 km outside the province. Figure 6 gives an example of the process of distinguishing (4) and (6). Consider a listed firm headquartered in Xuzhou City, Jiangsu Province, which has four neighboring cities within a 100-kilometer radius. Suqian City is located within the same province (Jiangsu Province), while the other three neighboring cities are in different provinces. In this example, for a public firm headquartered in Xuzhou City, its customer-supplier chain entry rates within 100 km inside the province consider the entry in Suqian city, while those within 100 km outside the province consider the entry in the other three cities.

[Table 12]

Table 12 shows the return predictabilities of the entry into customer-supplier chains within different areas. As shown in columns (1) and (2), the coefficients of CSER are 0.362 (t-statistic = 4.95) and 0.357 (t-statistic = 2.66), both significant at the 1% level, indicating that a firm's customer-supplier chain entry in its headquartered city or that within a 100 km radius has strong return predictability. In column (3), the coefficient of CSER is 0.241 (t-statistic = 1.99), which is significant at the 5% significance level and slightly lower than that in columns (1) and (2), indicating that the entry into customer-supplier chains outside the city has weaker predictability, even within a 100 km radius. In columns (4), the coefficient of CSER is 0.375 (t-statistic = 3.18), indicating that the entry into customer-supplier chains within a 100 km radius within the same province has strong return predictability. The effect slightly weakens, but remains significant if we exclude the headquartered city within a 100 km radius in the same province in column (5). In contrast, in column (6), the coefficient of CSER is only 0.172 (t-statistic = 1.35), insignificantly predicting stock returns, indicating that the entry into local customer-supplier chains outside the province, even within a 100 km radius, fails to predict future returns. In summary, the externalities of the entry into local customer-supplier chains depend on conditions that facilitate coordination, highlighting the significant role of local governments.

5. The Effectiveness of Industrial Policy

The above results show that industrial policy benefits firms by promoting the entry into their local customer-supplier chains. In this section, we further examine under what conditions the industry policy is more effective.

5.1 Industrial Sector and Inter-industry Dependence

First, we examine whether the effect of CSER on returns is heterogeneous across industrial sectors and inter-industry linkages. On one hand, firms in the primary, secondary, and tertiary sectors differ in their production and sales processes. On the other hand, different industries may have different levels of dependence on their customers and suppliers. How firms benefit from their local customer-supplier chains may vary with these factors. We discuss these heterogeneities by conducting Fama-MacBeth regressions of stock returns on CSER interacted with industry indicators.

$$Ret_{i,t+1} = \alpha + \beta_1 CSER_{i,t} + \beta_2 CSER_{i,t} \times Industry\ Indicator_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t} \quad (10)$$

The dependent variable is the stock returns in month t+1 and the key independent variables are interactions between CSER and industry indicators, including High Reliance and Industrial Sector in month t. In each month, the stocks on each cross-section are divided into three terciles based on their dependence on supplier and customer industries[22]. High Reliance equals to one if the stock is in the second or third tercile, and zero otherwise. Industrial Sector equals to one if the stock's industry belongs to the secondary sector (industry code from 06 to 50), and zero otherwise[23]. The control variables are the same as that in Table 6.

[Table 13]

The results are reported in Table 13. As column (1) shows, the coefficient of

[22] The dependence is measured using the Backward Coefficient and the Forward Coefficient calculated from the Input-Output Table (e.g., Jones, 1976; Rodríguez-Clare, 1996; Ojaleye and Narayanan Gopalakrishnan, 2021).

[23] According to the classification provided by the National Bureau of Statistics of China, all 97 industries of the national economy are classified into the primary, secondary, and tertiary sectors. The primary sector includes agriculture, forestry, animal husbandry, fishing, and agricultural service industry (industry code from 01 to 05). The secondary sector consists of processing, manufacturing, and construction companies (industry code from 06 to 50). The tertiary sector includes all services industries (industry code from 51 to 97).

$CSER \times High\,Reliance$ is 0.756 (t-statistic = 3.62), which is significant at 1% level. It indicates that compared with firms that have a lower reliance on customer-supplier chains, firms with a higher reliance benefit more from CSER. A 1% increase in CSER leads to a 0.756% greater increase in next-month stock returns of firm with a higher reliance compared to those with a lower reliance. As shown in column (3), the coefficient of $CSER \times Industrial\,Sector$ is 0.763% (t-statistic = 3.39), which is significant at 1% level, indicating that a 1% increase in CSER leads to a 0.763% greater increase in next-month stock returns of firm in the secondary sector compared to those in the primary or tertiary sectors. The results are robust after all control variables are included in columns (2) and (4). Overall, the evidence suggests that the benefits of CSER are more pronounced in industries that are more deeply embedded in customer-supplier chains, implying that industrial policy focusing on sectors where spillovers are greater is likely to be more effective.

5.2 Industry Competition

Next, we examine how industry competition shape the effect of CSER on returns. The motivation stems from the concern of industrial competition, an unintended consequence of aggressive and regional industrial policies. When local governments incentivize local entry in pursuit of strategic development goals, they risk triggering a wave of fierce competition in these targeted industries. Therefore, how firms benefit from the entry into their local customer-supplier chains may also depend on industry competition. To test this problem, we conduct Fama-MacBeth regressions of stock returns on CSER interacted with an industry competition indicator.

$$Ret_{i,t+1} = \alpha + \beta_1 CSER_{i,t} + \beta_2 CSER_{i,t} \times High\,HHI_{i,t} + \gamma Controls_{i,t} + \varepsilon_{i,t} \qquad (11)$$

The dependent variable is the stock returns in month t+1 and the key independent variable is the interaction between CSER and High HHI in month t. High HHI equals one if the Herfindahl-Hirschman Index (HHI) of the stock's industry exceeds 500, and zero otherwise[24].

[24] HHI=500 indicates that each firm in the market only accounts for 5% of the market share and there is no absolute leader, which is a conservative estimate of the degree of intense competition. In addition, the cut-off value of 500 is about half of the observations in terms of sample size. Therefore, using the HHI value 500 as the dividing line is also reasonable considering the balance of subsample observations in interacted regressions.

HHI measures market concentration as the sum of the squared sales shares of all firms in the industry, which is calculated annually considering its time variation. The control variables are the same as that in Table 6.

[Table 14]

The results are reported in Table 14. In the baseline specification in column (1), the coefficient of CSER × High HHI is 0.771 (t-statistic = 3.28), which is positively significant at the 1% level. It indicates that a 1% increase in CSER leads to a 0.771% less increase in next-month stock returns of firm in intensely competitive industries compared to firms in less competitive industries. The result remains consistent when control variables are included in column (2). After including High HHI and CSER × High HHI in the regressions, the estimated coefficient of CSER is no longer significant, which is 0.046 (t-statistic = 0.27) in baseline regression and 0.049 (t-statistic = 0.35) after including all control variables. It indicates that firms in less competitive industries benefit a lot from the entry into their local supply chains, while for firms in intensely competitive industries, these benefits almost vanish.

This variation in policy effectiveness underscores a nuanced reality. In industries that are not excessively competitive, firms appear to have more space for growth and differentiation. Here, industrial policies aimed at fostering entry into local customer-supplier chains are likely to yield more sustainable and efficient outcomes, as they support development without immediately triggering fierce competition. Firms can integrate into local networks to capture synergies without being forced into a fight for survival. Conversely, in industries already facing intense competition, the marginal benefits of further encouraging entry into local customer-supplier chains become ambiguous. Therefore, our analysis delivers that the impacts of entry into local customer-supplier chains are not uniform. Industrial policies would be better to adopt a differentiated, industry-specific approach. Strategic support should be carefully calibrated and preferably directed towards sectors with healthy growth potential and less competition. For industries already exhibiting signs of fierce competition, the policy priority should shift from stimulating further entry and localized duplication to facilitating consolidation, upgrading, innovation, and exit mechanisms. This tailored approach is essential to ensure that industrial policy cultivates competitive advantage rather than deepening fierce competition.

6. Robustness Check

In this section, we provide robustness checks for the results linking CSER to stock returns. This relationship is central to our analysis, as it forms the foundation for assessing whether supply chain industrial policies that aim to promote CSER are effective in enhancing stock returns.

First, we exclude firms that may interfere with our results. Specifically, Liu, Stambaugh, and Yuan (2019) argue that the smallest 30% of firms in China are often valued for their potential use as shells in reverse mergers that circumvent stringent IPO constraints. To mitigate the influence of shell firms, we exclude these stocks from our sample. In addition, following the literature, we exclude financial firms when examining stock returns, as their returns are less closely related to operating fundamentals (e.g., Fama and French, 1992).

In Table 15, we re-conduct the single-sort analysis based on CSER, following the same procedure as in Table 5, after excluding these firms. We find that CSER continues to exhibit significant return predictability when either the smallest 30% of firms or financial firms are excluded, and the economic magnitudes are very close to those reported in Table 5.

[Table 15]

Second, we examine CSER measured over alternative horizons. In our baseline analysis, we construct CSER as a 12-month moving average of the monthly entry rates into local customer and supplier industries for each firm. This choice is motivated by three considerations. First, our objective is to capture the positive externalities generated by local entrants that affect public firms' real performance and, ultimately, firm value. Such real effects take time to materialize, as newly registered firms may not begin production immediately. Averaging CSER over the past 12 months allows us to incorporate externalities that emerge with a lag. Second, we aim to capture medium-term developments in local supply chains. Very short-horizon measures, such as one-month CSER, may primarily reflect transitory shocks (e.g., lockdown policies during the COVID-19 period) rather than persistent supply chain dynamics. Third, as shown in Figure 3, firm registrations exhibit pronounced seasonality. For example, registration activity declines sharply in months containing the Chinese Spring Festival or other major holidays. Although such seasonality affects all firms in a given cross section, it renders monthly CSER less informative and introduces additional noise into the analysis.

Table 16 examines the return predictability of CSER constructed using moving averages over alternative horizons. Panel A presents single-sort portfolio results. We find that one-month CSER does not predict stock returns, whereas CSER averaged over the past three and six months exhibits strong return predictability. The corresponding long–short portfolios generate Fama–French five-factor alphas of 0.65% (t-statistic = 3.16) and 0.616% (t-statistic = 2.68) per month, respectively.

In Panel B, we further examine the predictive power of CSER measured over the intervals [t−3, t], [t−6, t−3], and [t−12, t−6] for stock returns in month t+1. In Columns (2)–(4), we include each horizon-specific CSER measure separately and find that all exhibit statistically significant predictive power, with economic magnitudes that decline monotonically as the lag length increases. In Column (5), we include all three measures simultaneously to assess their incremental explanatory power. We find that CSER measured within the past six months remains significant, whereas the effect of CSER from months t−12 to t−6 is fully absorbed. These results suggest that the positive externalities generated by CSER are largely incorporated into stock prices within approximately six months.

[Table 16]

Based on these results, we use CSER averaged over the past 12 months in our main analysis to incorporate potential lagged effects as fully as possible, yielding a relatively conservative estimate.

7. Conclusion

This paper examines the effects of customer-supplier chain industrial policy (CSIP) in China from 2007 to 2022, focusing on its ability to promote entry into local customers and suppliers (CSER) and its subsequent impact on the stock returns and fundamental performance of listed firms. We construct novel datasets combining comprehensive firm registration data, structured local industrial policy data extracted using LLM, and firm financial data to examine the influence from policy to entry, and from entry to firm value.

Our analysis yields several key findings. First, local industrial policies targeting a firm's customer and supplier industries significantly increase the entry into those industries. Second, this entry generates positive externalities for focal firms, leading to improvements in their profitability and stock returns. A trading strategy based on past CSER earns significant risk-adjusted returns. However, we find that policies themselves do not directly predict higher returns, suggesting that the non-shareholder objectives embedded in industrial policy may confuse potential benefits. Third, we identify the policy-induced entry and find that the component of CSER driven by CSIP positively predicts future returns, even after controlling for other factors. This indicates that the policy's effectiveness operates specifically through promoting entry into local supply chains.

We provide further analysis that results indeed to related the crucial role of local government. The return predictability of CSER is pronounced at the city and province level, but weakens at the nation level. We further examine the coordination effects by controlling for geographic distance and examining administrative boundaries. Results show that intra-provincial CSER exhibits significant return predictability, whereas inter-provincial CSER does not, although both of them are within 100 km. This evidence supports that geographic proximity alone is insufficient to generate positive spillovers while the coordination within administrative jurisdictions matters. To study under what conditions the industrial policy is more effective, we examine the variation in the benefits of CSER on returns and find that they are stronger in the industrial sector, in industries with higher reliance on their customers and suppliers, and in industries that are less competitive, suggesting that industrial policy more closely aligned with market conditions is likely to be more effective.

In sum, this study provides evidence that industrial policy can create firm value by promoting entry into their local customer-supplier chains and facilitating coordination to foster agglomeration externalities. We acknowledge two primary limitations. First, while our analysis identifies that local supply chain industrial policies enhance the valuation of local public firms, this focused scope does not assess broader welfare implications, such as potential cross-region crowding-out effects or the aggregate national economic impact. It leaves an open question of whether localized gains come at the cost of efficiency in other jurisdictions or for the nation.

Second, while we employ multiple strategies to address endogeneity, we cannot fully rule out all selection concerns. However, exploring these questions is beyond the scope of this study, which we leave for future research.

References

Bai, Jun, and Lishuai Lian. 2013. “Why Do State-Owned Enterprises over-Invest? Government Intervention or Managerial Entrenchment.” *China Journal of Accounting Studies* 1(3–4):236–59.

Balassa, Bela. 1965. “Trade Liberalisatfaion and “Revealed” Comparative Advantage.” The Manchester School 33 (2):99–123.

Barwick, Panle Jia, Myrto Kalouptsidi, and Nahim Bin Zahur. 2025. “Industrial Policy Implementation: Empirical Evidence from China’s Shipbuilding Industry.” *Review of Economic Studies* rdaf011.

Boudreau, Kevin J., Tom Brady, Ina Ganguli, Patrick Gaule, Eva Guinan, Anthony Hollenberg, and Karim R. Lakhani. 2017. “A Field Experiment on Search Costs and the Formation of Scientific Collaborations.” *Review of Economics and Statistics* 99(4):565–76.

Branstetter, Lee G., Guangwei Li, and Mengjia Ren. 2023. “Picking Winners? Government Subsidies and Firm Productivity in China.” *Journal of Comparative Economics* 51(4):1186–99.

Bruno, Randolph Luca, Maria Bytchkova, and Saul Estrin. 2013. “Institutional Determinants of New Firm Entry in Russia: A Cross-Regional Analysis.” *Review of Economics and Statistics* 95(5):1740–49.

Chen, Y. Joy, Robin Kaiji Gong, and Jinlin Li. 2026. “Industrial Policy in a New Era: Government Venture Capital in the US–China Trade War.” *Journal of Development Economics* 178:103599.

Choi, Jaedo, and Andrei A. Levchenko. 2025. “The Long-Term Effects of Industrial Policy.” *Journal of Monetary Economics* 152:103779.

Cohen, Lauren, and Andrea Frazzini. 2008. “Economic Links and Predictable Returns.” *Journal of Finance* 63(4):1977–2011.

Core, John E., Wayne R. Guay, and Tjomme O. Rusticus, 2006, Does weak governance cause weak stock returns? An examination of firm operating performance and investors' expectations, *Journal of Finance* 61(2), 655–687.

Coval, Joshua D., and Tobias J. Moskowitz. 1999. “Home Bias at Home: Local Equity Preference in Domestic Portfolios.” *Journal of Finance* 54(6):2045–73.

Coval, Joshua D., and Tobias J. Moskowitz. 2001. “The Geography of Investment: Informed Trading and Asset Prices.” *Journal of Political Economy* 109(4):811–41.

Dougal, Casey, Christopher A. Parsons, and Sheridan Titman. 2015. “Urban Vibrancy and Corporate Growth.” *Journal of Finance* 70(1):163–210.

Dougal, Casey, Christopher A. Parsons, and Sheridan Titman. 2022. “The Geography of Value Creation.” *Review of Financial Studies* 35(9):4201–48.

Edmans, Alex. 2011. “Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices.” *Journal of Financial Economics* 101(3):621–40.

Edmans, Alex, Darcy Pu, Chendi Zhang, and Lucius Li. 2023. “Employee Satisfaction, Labor Market Flexibility, and Stock Returns Around the World.” *Management Science*.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of*

Political Economy 81(3), 607–636.
Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47(2), 427–465.
Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116(1), 1–22.
Fama, Eugene F., and Kenneth R. French, 2018, Choosing factors, *Journal of Financial Economics* 128(2), 234–252.
Fan, Joseph PH, and Larry HP Lang, 2000, The measurement of relatedness: An application to corporate diversification, *Journal of Business* 73(4), 629–660.
Gao, Ting. (2004). Regional industrial growth: evidence from chinese industries. *Regional Science and Urban Economics*, 34(1), 101-124.
Gourio, François, Todd Messer, and Michael Siemer. 2016. "Firm Entry and Macroeconomic Dynamics: A State-Level Analysis." *American Economic Review* 106(5):214–18.
Hou, Kewei. 2007. "Industry Information Diffusion and the Lead-Lag Effect in Stock Returns." *Review of Financial Studies* 20(4):1113–38.
Jegadeesh, Narasimhan, and Sheridan Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48(1):65–91.
Jiang, Hao, Chris Parsons, Lin Sun, and Sheridan Titman. 2025. "Skilled Foreign Labor, Urban Agglomeration, and Value Creation."
Jones, Leroy P., 1976, The measurement of Hirschmanian linkages, *Quarterly Journal of Economics* 90, 323–333.
Juhász, Réka, Nathan Lane, Emily Oehlsen, and Verónica C. Pérez. 2022. "The Who, What, When, and How of Industrial Policy: A Text-Based Approach."
Juhász, Réka, Nathan Lane, and Dani Rodrik. 2024. "The New Economics of Industrial Policy." *Annual Review of Economics* 16(Volume 16, 2024):213–42.
Korniotis, George M., and Alok Kumar. 2013. "State-Level Business Cycles and Local Return Predictability." *Journal of Finance* 68(3):1037–96.
Lashkaripour, Ahmad, and Volodymyr Lugovskyy. 2023. "Profits, Scale Economies, and the Gains from Trade and Industrial Policy." *American Economic Review* 113(10):2759–2808.
Li, Guangwei, and Lee G. Branstetter. 2024. "Does 'Made in China 2025' Work for China? Evidence from Chinese Listed Firms." *Research Policy* 53(6):105009.
Lim, Chu Yeong, Jiwei Wang, and Cheng (Colin) Zeng. 2018. "China's 'Mercantilist' Government Subsidies, the Cost of Debt and Firm Performance." *Journal of Banking & Finance* 86:37–52.
Liu, Ernest. 2019. "Industrial Policies in Production Networks." *Quarterly Journal of Economics* 134(4):1883–1948.
Liu, Jianan, Robert F. Stambaugh, and Yu Yuan. 2019. "Size and Value in China." *Journal of Financial Economics* 134(1):48–69.
Matsusaka, John G., 1993, Takeover motives during the conglomerate merger wave, *RAND Journal of Economics*, 357–379.
Menzly, Lior, and Oguzhan Ozbas. 2010. "Market Segmentation and Cross-predictability of Returns." *Journal of Finance* 65(4):1555–80..
Moskowitz, Tobias J., and Mark Grinblatt. 1999. "Do Industries Explain Momentum?" *Journal of Finance* 54(4):1249–90.
Ojaleye, Dayo, and Badri Narayanan Gopalakrishnan, 2021, Identification of key sectors in a lower middle-

income country - Evidence of backward and forward linkages from input-output analysis, SSRN Scholarly Paper.

Okuno-Fujiwara, Masahiro. 1988. “Interdependence of Industries, Coordination Failure and Strategic Promotion of an Industry.” *Journal of International Economics* 25(1):25–43.

Pack, Howard. 2000. “Industrial Policy: Growth Elixir or Poison?” *The World Bank Research Observer* 15(1):47–67.

Pack, Howard, and Kamal Saggi. 2006. “Is There a Case for Industrial Policy? A Critical Survey.” *The World Bank Research Observer* 21(2):267–97.

Parsons, Christopher A., Riccardo Sabbatucci, and Sheridan Titman. 2020. “Geographic Lead-Lag Effects.” *Review of Financial Studies* 33(10):4721–70.

Pirinsky, Christo, and Qinghai Wang. 2006. “Does Corporate Headquarters Location Matter for Stock Returns?” *Journal of Finance* 61(4):1991–2015.

Rodríguez-Clare, A. (1996). Multinationals, Linkages, and Economic Development. *American Economic Review*, 86(4), 852–873.

Rodrik, Dani., 2014, An African Growth Strategy. Brookings Institution, Africa Growth Initiative.

Smajlbegovic, Esad. 2019. “Regional Economic Activity and Stock Returns.” *Journal of Financial and Quantitative Analysis* 54(3):1051–82.

Tian, Xuan, and Jiajie Xu. 2022. “Do Place-Based Policies Promote Local Innovation and Entrepreneurship?” *Review of Finance* 26(3):595–635.

Wu, Yiyun, Xiwei Zhu, and Nicolaas Groenewold. 2019. “The Determinants and Effectiveness of Industrial Policy in China: A Study Based on Five-Year Plans.” *China Economic Review* 53:225–42.

Zhou, Bole, and Shouguo Zhao. 2022. “Industrial Policy and Corporate Investment Efficiency.” *Journal of Asian Economics* 78:101406.

Figures and Tables

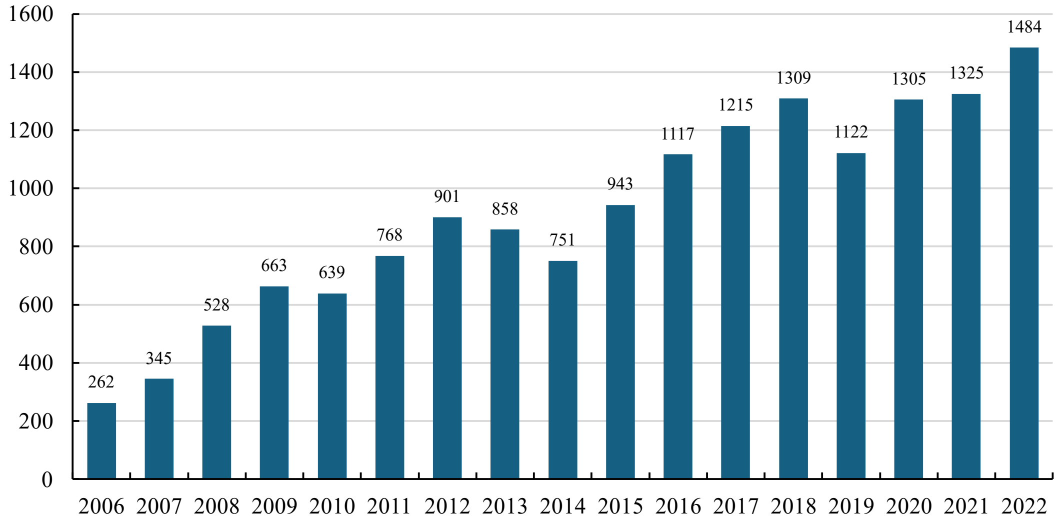


Figure 1. Panel A. Number of Industrial Policies per Year

This figure presents the annual distribution of industrial policies issued by prefecture-level city governments, including the four centrally administered municipalities.

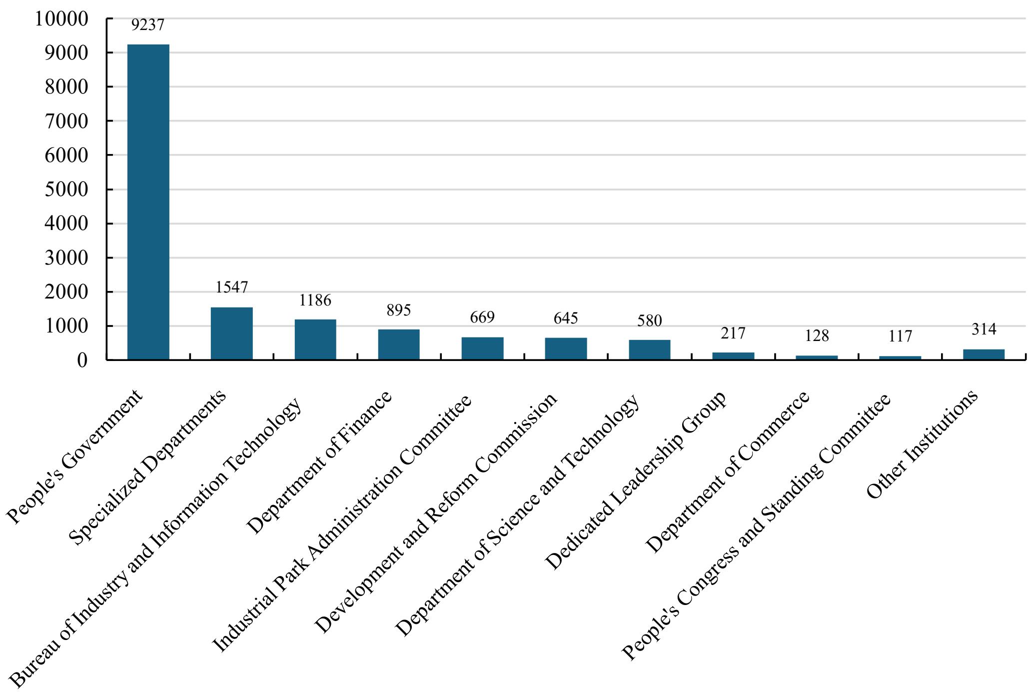
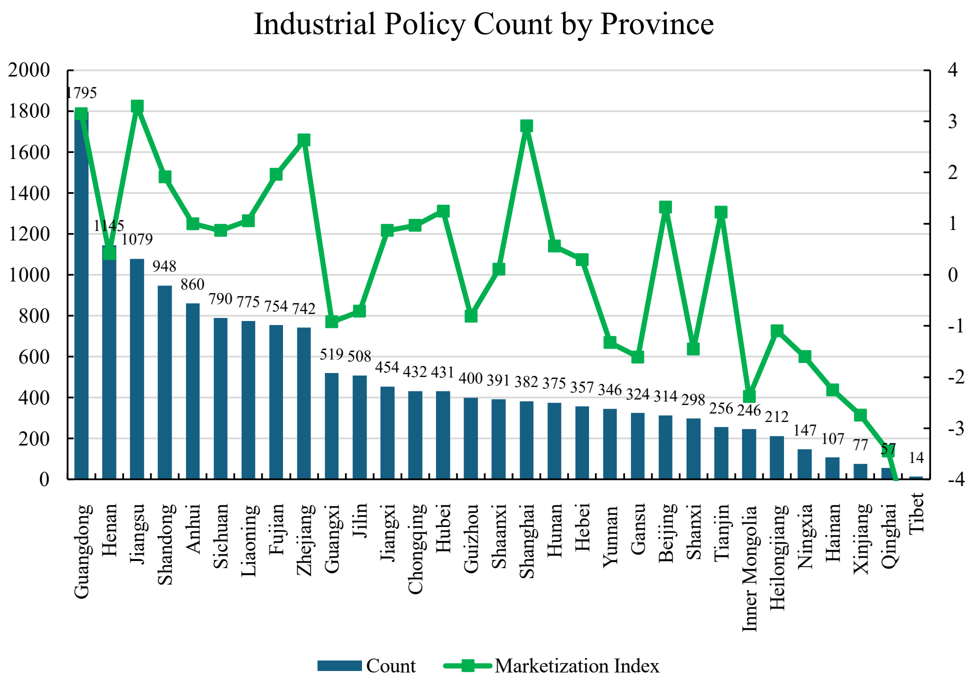


Figure 1. Panel B. Number of Industrial Policies by Type of Government Department

This figure shows the distribution of industrial policies issued by different types of government departments at the prefecture-level city, including the four centrally administered municipalities.



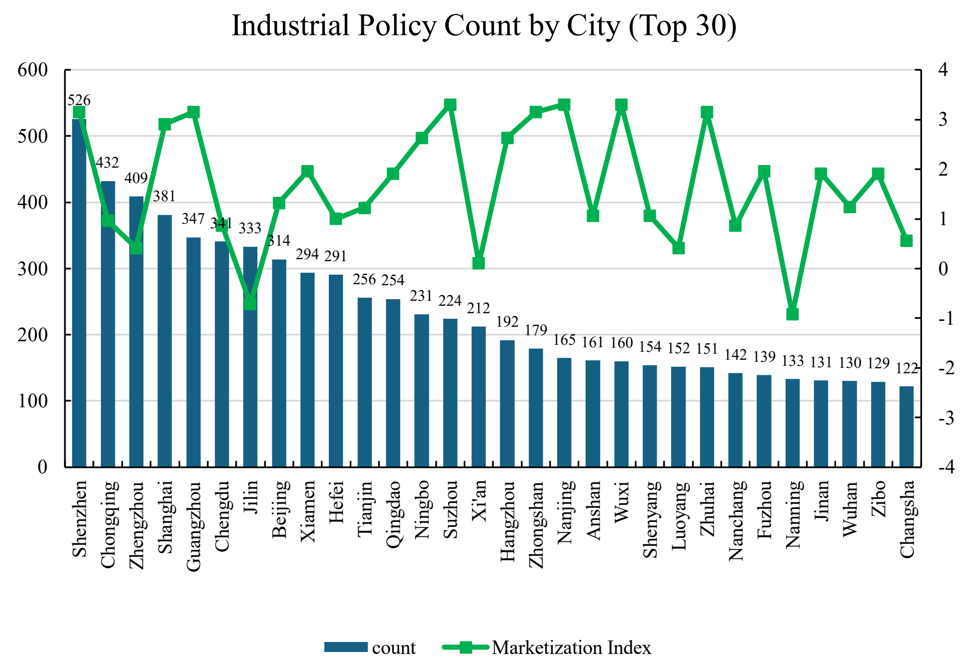


Figure 1. Panel C. Geographic Distribution of Industrial Policies

This figure shows the distribution of industrial policies issued by local governments at the prefecture level across different provinces and cities. The blue bars represent the number of policies, while the green line depicts the marketization index from the China Market Index Database. The index is demeaned: values above zero indicate that a province or city has a marketization level above the national average.

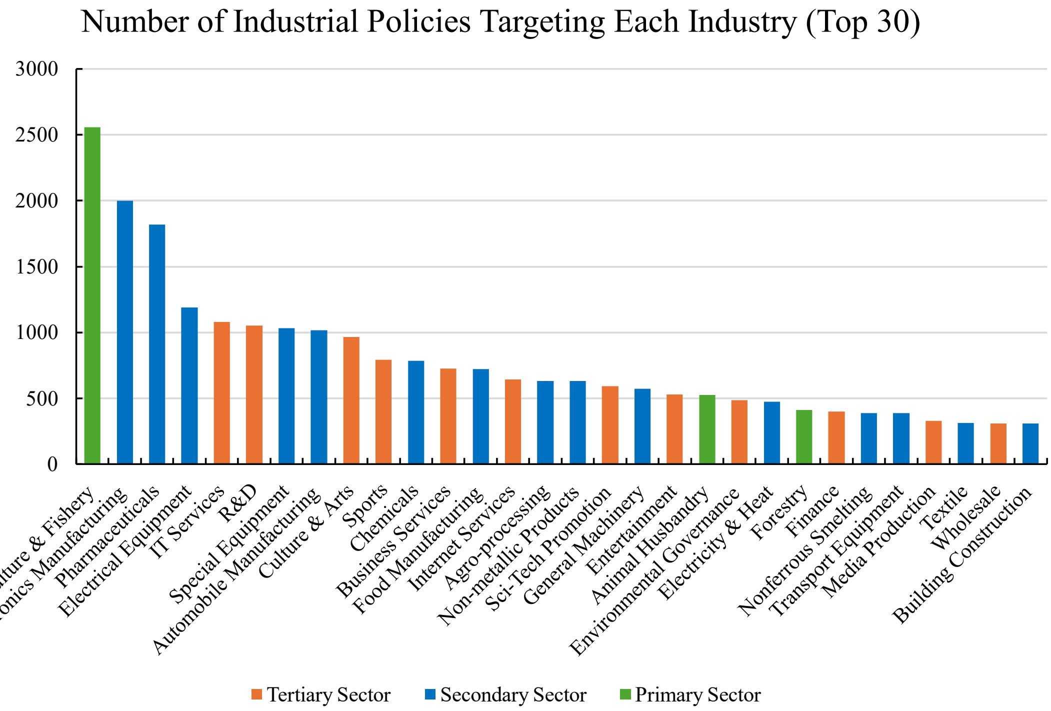


Figure 1. Panel D. Number of Industrial Policies Targeting Each Industry (Top 30)

This figure shows the top 30 industries most frequently targeted by industrial policies. Each bar represents the total number of policies that explicitly support the corresponding industry. Industries are grouped into the primary (green), secondary (blue), and tertiary (orange) sectors. The sample includes all industrial policies issued by local governments at the prefecture level (including the four centrally administered municipalities) over the period 2006 to 2022.

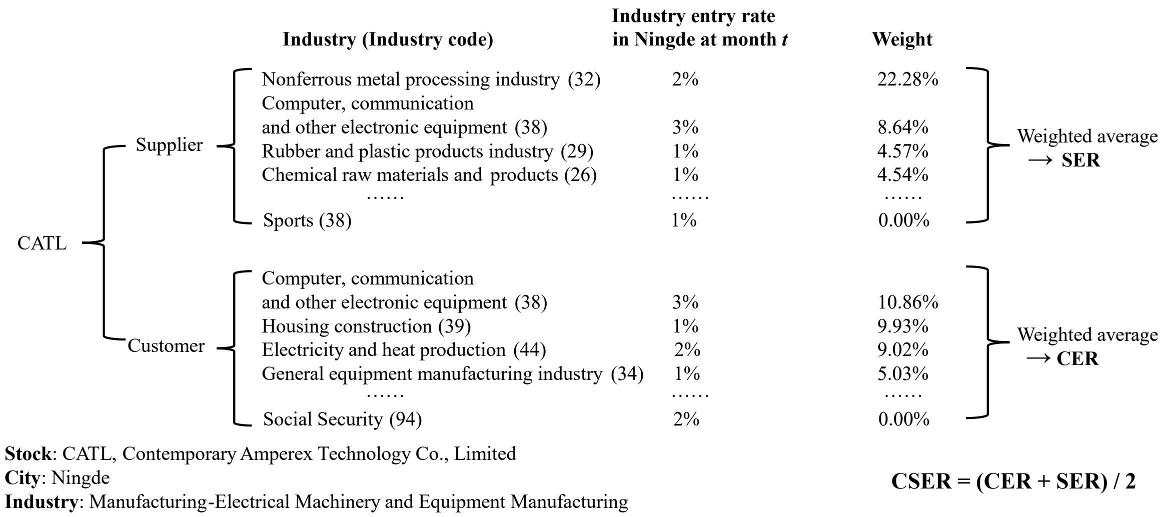


Figure 2. The Calculation of CSER

This figure shows the process of calculating the local customer-supplier chain entry rate (CSER), taking Contemporary Amperex Technology Co., Limited (CATL) as an example. At the beginning of each month, we first match all the supplier and customer industries of CATL following the National Economic Input-Output Table (IO-Table). We calculate the new-firm entry rate of each industry (IER) in Ningde (where the headquarter of CATL is located) as the number (capital) of newly registered firms within the month scaled by the total number (capital) of existing registered firms at the end of the month. Then we define the monthly supplier entry rate (SER) and customer entry rate (CER) of CATL as the weighted average new-firm entry rate of all its supplier and customer industries, with the weight being the inflow (outflow) volume of goods to (from) manufacturing-electrical machinery and equipment manufacturing (CATL's industry). CSER represents the simple average of SER and CER.

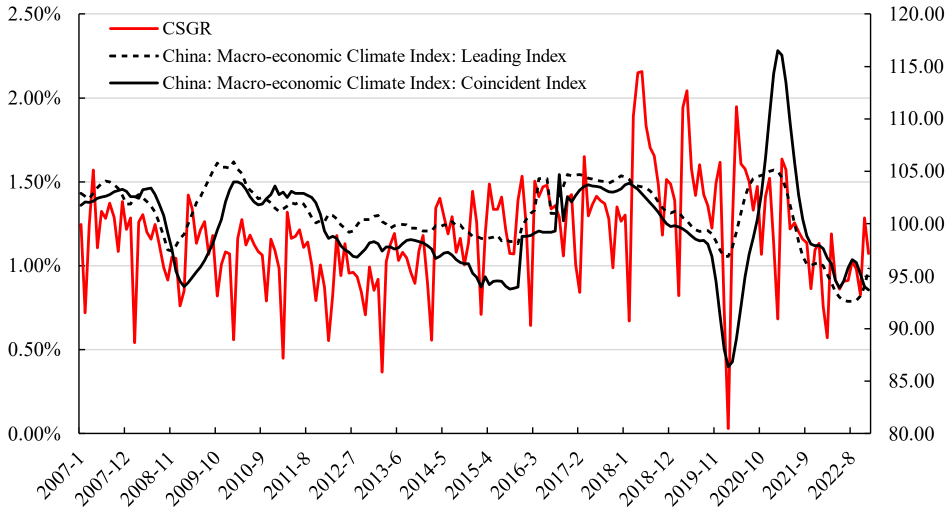


Figure 3. Time Series of CSER and China's Macro-economic Prosperity Index

This figure shows the time series of cross-sectional average of CSER (red line) and the China's Macro-economic Climate Index (black line). Each month, we calculate the cross-sectional average of CSER to obtain a time series of average CSER. Then, we merge the time series to the Macroeconomic Prosperity Index, a measure provided by the National Bureau of Statistics to reflect the degree of economic prosperity.

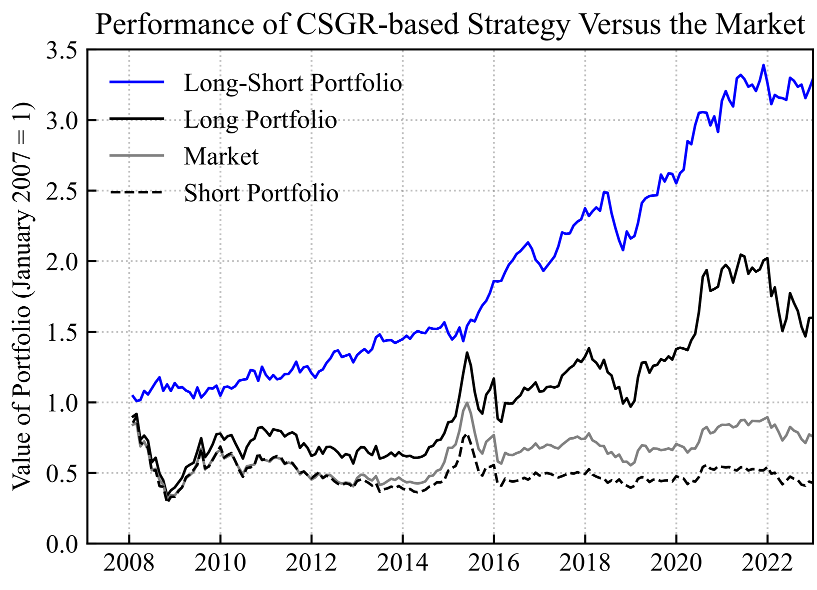


Figure 4. The Cumulative Performance of CSER Strategy

This figure shows the cumulative net value of the portfolios constructed based on CSER from January 2007 to December 2022. At the beginning of each month, we sort all stocks into quintile portfolios based on the average CSER over the past 12 months and form a long–short portfolio that is long stocks in the highest CSER quintile and short stocks in the lowest quintile. All stocks are equally (value) weighted within a given portfolio, and the portfolios are rebalanced every calendar month. At the beginning of the sample period (January 2007), the net value of the portfolios is one. This figure plots the evolution of the net value of the long portfolio, the short portfolio, the long-short portfolio, and the market portfolio over time.

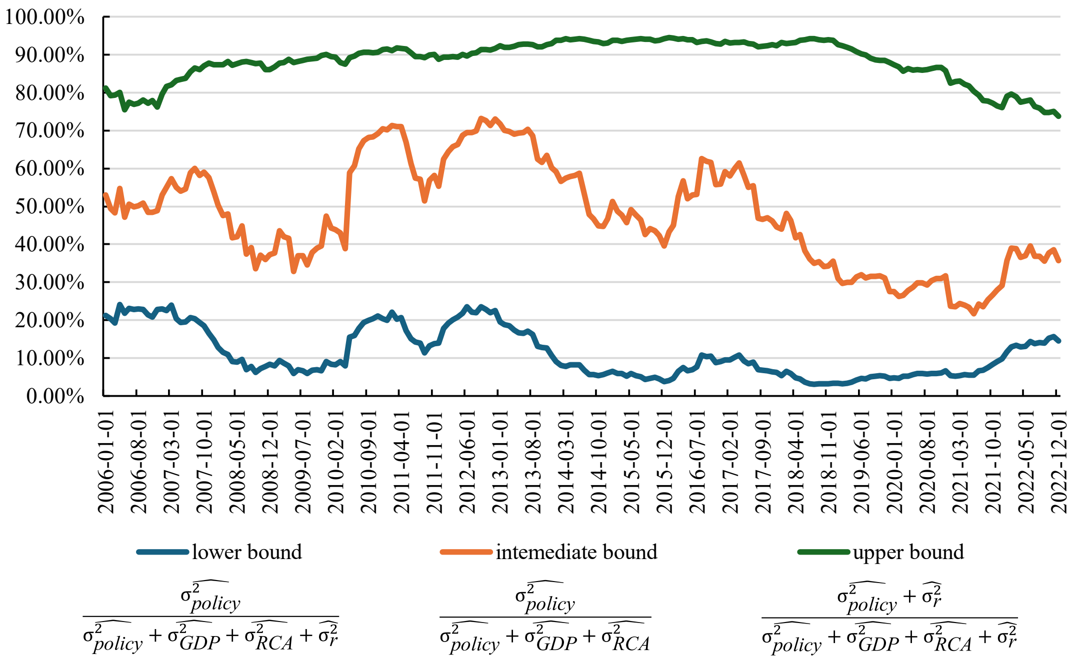


Figure 5. Variance Decomposition of CSER

This figure illustrates the cross-sectional variance decomposition of CSER. Specifically, we compute the cross-sectional variance of each CSER component and calculate the share explained by the policy-induced component. By attributing the variance of the residual component to different sources, we obtain lower, intermediate, and upper bounds for the proportion of variation explained by policy.

Figure 6. An Example of Neighboring Cities Spanning Provincial Boundaries

This figure illustrates an example of neighboring cities spanning provincial boundaries. Consider a public firm located in Xuzhou City, Jiangsu Province, has four neighboring cities within a 100-kilometer radius: Suqian City, Zaozhuang City, Huaibei City, and Suzhou City. Suqian City is located within the same province as Xuzhou City, while the other neighboring cities are situated in different province.

Table 1. Summary Statistics of Local Industrial Policies at the Prefecture-Level City

This table presents descriptive statistics of local industrial policies at the prefecture-level city. Panel A reports summary statistics for industrial policies. The statistics include the number of industries targeted per policy, number of policies issued per city-year, number of industries supported per city-year, number of policies issued per industry-year, number of cities supporting each industry per year, and number of policies issued per city-industry-year. Panel B reports the definitions, classifications, and usage frequencies of policy instruments, measured as the proportion of industrial policies in which each instrument is used. The sample includes 15,535 industrial policies, identified from a total 61,736 industry-related documents issued by prefecture-level city governments in China between 2006 and 2022. A document is classified as an industrial policy if it satisfies all of the following three criteria: (1) it targets a specific industry; (2) it states a clear policy objective aimed at altering the development trajectory of the industry; and (3) it specifies at least one concrete policy instrument. The sample covers 97 standardized industries as defined by the National Bureau of Statistics of China, and all 337 cities, including all prefecture-level cities and the four centrally administered municipalities (Beijing, Shanghai, Tianjin, and Chongqing).

Panel A. Summary Statistics for Industrial Policies

	N	Mean	SD	Min	P25	P50	P75	Max
# of industries targeted in each policy	15,535	2.17	5.22	1	1	1	2	97
# of policies issued per city-year	3,592	4.32	6.26	1	1	2	4	79
# of industries supported per city-year	3,443	6.68	11.12	1	2	3	8	97
# of policies issued per industry-year	1,573	20.19	29.07	1	4	9	24	273
# of cities supporting each industry per year	1,573	14.62	16.63	1	4	8	19	149
# of policies issued per city-industry-year	22,998	1.38	1.00	1	1	1	1	17

Panel B. Definitions of Industrial Policy Instruments

Instrument	Definition	Frequency
T1 - Subsidy	Direct financial support including product subsidies, performance-based awards, and R&D grants to reduce costs and stimulate firm activity.	74.58%
T2 - Tax Incentive	Tax relief via income tax, value-added tax, or business tax reductions, refunds, or extra deductions to ease firm burdens.	20.63%
T3 - Gov Investment	Public sector capital injection via direct investment, special funds, or investment vehicles to guide industrial upgrading.	42.22%
T4 - Supply Chain Coordination	Policy support to strengthen collaboration within industrial chains, enhance resource integration, and improve overall supply chain efficiency.	55.75%
T5 - Market Regulation	Administrative controls or standards to manage market access, structure, or competition for strategic or sustainable industry development.	10.9%

Table 2. Summary Statistics for Customer–Supplier Industry Entry Rate (CSER)

Panel A reports summary statistics for key variables. The new-firm entry rate of an industry in a city is the number of newly registered firms in each month scaled by the total number of existing firms at the end of the month. Then we define the monthly industry entry rate (IER), supplier entry rate (SER), and customer entry rate (CER) as the new-firm entry rate of a stock's own industry, the weighted average new-firm entry rate of its supplier and customer industries in its headquartered city. Supplier- and customer-industry weights are measured as the shares of inputs sourced from supplier industries and outputs sold to customer industries by the stock's own industry, respectively. The customer-supplier entry rate (CSER) is the simple average of SER and CER. We also consider the entry rate measured by newly registered capital (CSER_C). $CSER^{\perp N}$ is the residual of a cross-sectional regression with CSER as the dependent variable and the national-level customer-supplier entry rate as the independent variable. Panel B reports characteristics of portfolios sorted on CSER. At the beginning of each month, all stocks in the cross-section are divided into quintiles based on the moving average CSER over past 12 months. Within each portfolio, we report the percentage of stocks located in four first-tier cities (Beijing, Shanghai, Guangzhou, Shenzhen), stocks in manufacture industry, and stocks which are the only listed firms in a city. We also present the firm's characteristics: Size is the market capitalization (in Trillion yuan). Industry (city) adjusted size is the difference between the firm size and the average size of firms within the same industry (city). Other firm characteristics include total asset (in Trillion yuan), book-to-market ratio (BM), HHI (Hou and Robinson, 2006) and stock price at the end of the last month (Price). The sample includes all normally traded stocks listed on SSE and SZSE with available CSER measures and excludes stocks with prices lower than 5 yuan. Our Sample period is from January 2007 to December 2022.

Panel A. Summary Statistics for CSER

Variable	N	Mean	STD	Min	P20	P40	P50	P60	P80	Max
CSER	1595	1.20%	0.52%	0.24%	0.83%	1.02%	1.11%	1.20%	1.50%	5.42%
CSER_C	1595	1.02%	0.63%	0.10%	0.57%	0.79%	0.89%	1.01%	1.36%	7.00%
$CSER^{\perp N}$	1595	0.00%	0.45%	-1.40%	-0.31%	-0.14%	-0.06%	0.02%	0.27%	3.65%
CER	1595	1.30%	0.69%	0.05%	0.85%	1.08%	1.18%	1.29%	1.62%	8.33%
SER	1595	1.10%	0.51%	0.15%	0.73%	0.91%	1.01%	1.11%	1.41%	5.11%
IER	1595	1.04%	0.80%	0.00%	0.46%	0.72%	0.86%	1.02%	1.49%	8.09%

Panel B. Characteristics of Portfolios Sorted on CSER

Variable	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
CSER	0.650%	0.900%	1.120%	1.360%	2.030%
% Located in First-Tier Cities	55.850%	25.300%	18.400%	16.670%	21.500%
% in Manufacture Ind	61.790%	68.300%	70.180%	69.530%	75.130%
% of the Only Firm in a City	1.600%	2.300%	2.430%	3.670%	6.210%
Size	17.930	12.057	11.131	13.467	12.809
Industry-adjusted Size	4.492	-0.097	-0.509	0.389	0.082
City-adjusted Size	-2.240	0.327	0.686	2.154	1.871
Total Asset	69.001	61.625	31.680	38.302	29.691
BM	0.604	0.583	0.554	0.540	0.498
HHI	0.103	0.099	0.102	0.107	0.093
Price	17.820	17.110	16.319	17.728	18.841

Table 3. Measuring Industrial Policy Support to Local Customer-Supplier Chains

This table reports the summary statistics of the customer-supplier industrial policy support index (CSIP) at the firm level. For firm i, located in city c and operating in industry k, the index $CSIP_{i,[t-h,t]}$ measures the extent to which the local government of city c supported the customer and supplier industries of industry k through industrial policies issued during the period from month $t-h$ to month t, where $h \in \{3, 6, 12\}$. The index is calculated as $CSIP_{i,[t-h,t]} = \sum_{d\in[1,N]} w_{k,d} IP_{c,d,[t-h,t]}$, where $IP_{c,d,[t-h,t]}$ is a dummy variable equal to one if city c issued at least one industrial policy targeting industry d during the past h months. If city c issued a market regulation policy targeting industry d during this period, $IP_{c,d,[t-h,t]}$ is set to zero regardless of the presence of other policy types, reflecting the veto effect of regulatory interventions. The weight $w_{k,d}$is the average of the input share from industry d to industry k and the output share from industry k to industry d, as derived from the input–output table. We also compute five alternative versions of $CSIP_{i,[t-h,t]}$, each using only one specific policy category (T1 to T5), with a fixed window of $h = 12$. The summary statistics are based on firm-month level observations. The sample includes all normally traded stocks listed on SSE and SZSE with available CSIP measures and excludes stocks with prices lower than 5 yuan. Our Sample period is from January 2007 to December 2022.

	Mean	SD	Min	P25	P50	P75	Max
CSIP (h = 3)	0.094	0.178	0.000	0.000	0.010	0.090	1.000
CSIP (h = 6)	0.129	0.201	0.000	0.000	0.034	0.165	1.000
CSIP (h = 12)	0.173	0.223	0.000	0.007	0.073	0.263	1.000
CSIP (T1 - Subsidy)	0.145	0.213	0.000	0.001	0.041	0.203	0.807
CSIP (T2 - Tax Incentive)	0.037	0.112	0.000	0.000	0.000	0.013	0.676
CSIP (T3 - Gov Investment)	0.101	0.184	0.000	0.000	0.010	0.101	0.769
CSIP (T4 - Supply Chain Coordination)	0.110	0.187	0.000	0.000	0.019	0.121	0.788
CSIP (T5 - Market Regulation)	0.040	0.124	0.000	0.000	0.000	0.006	0.733

Table 4. Industrial Policy and CSER

This table reports Fama-MacBeth regressions that forecast individual stocks' CSER. The dependent variable is the average monthly CSER over the subsequent 3, 6, and 12 months. The dependent variable is the average monthly CSER over the subsequent 3, 6, and 12 months. Independent variables include the lagged local industrial policy measure (CSIP and IP), industry conditions (RCA and Cluster), and local economic conditions (GDP and ΔGDP). CSIP is the weighted sum of indicator variables for customer and supplier industries that are supported by industrial policy over the past 3, 6, or 12 months (the policy window). IP is an indicator variable equal to one if the firm's own industry is supported during the same policy window. RCA denotes the revealed comparative advantage of the stock's industry in its headquarters city, measured at the end of the previous month. $\mathrm{RCA}^{\mathrm{P}}$ and $\mathrm{RCA}^{\mathrm{N}}$ measure the relative importance of the stock's industry in its headquarters city compared with the importance of the same industry at the provincial and national levels, respectively. Industry importance is defined as the number of registered firms in an industry divided by the total number of registered firms in the corresponding city, province, or nation. Cluster is defined as the proportion of registered firms in the stock's own industry that are located in the headquarters city, relative to all firms in the same industry nationwide. GDP and $\Delta\mathrm{GDP}$ are the previous year's GDP and GDP annual growth rate. The cross-sectional regressions are conducted each month, and the estimated coefficients are averaged over time. The sample includes all normally traded stocks listed on SSE and SZSE with available CSER measures and excludes stocks with prices lower than 5 yuan. Our Sample period is from January 2007 to December 2022. We report Newey-West (1987) adjusted t-statistics in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

	CSER Window = 3 months			CSER Window = 6 months			CSER Window = 12 months		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Policy Window =	3 months	6 months	12 months	3 months	6 months	12 months	3 months	6 months	12 months
CSIP	**0.997*** **	**0.720*** **	**0.556*** **	**1.085*** **	**0.737*** **	**0.553*** **	**1.119*** **	**0.732*** **	**0.546*** **
	(4.64)	**(5.18)**	**(5.66)**	**(4.68)**	**(5.42)**	**(5.51)**	**(4.16)**	**(5.14)**	**(4.94)**
IP	0.027**	0.031**	0.027	0.026*	0.027**	0.028*	0.012	0.020	0.033**
	(2.10)	(2.44)	(1.54)	(1.82)	(2.01)	(1.81)	(0.55)	(1.31)	(2.33)
Ln(GDP)	-0.180***	-0.183***	-0.192***	-0.179***	-0.182***	-0.191***	-0.174***	-0.176***	-0.185***
	(-4.70)	(-4.75)	(-5.04)	(-4.69)	(-4.70)	(-4.98)	(-4.55)	(-4.52)	(-4.76)
ΔGDP	1.848**	1.864**	1.937**	1.746*	1.764*	1.839*	1.654*	1.637*	1.710*
	(2.01)	(2.06)	(2.07)	(1.86)	(1.91)	(1.91)	(1.72)	(1.74)	(1.73)
$\mathrm{RCA}^{\mathrm{N}}$	-0.001	-0.001	-0.000	0.000	0.000	0.001	0.003	0.003	0.004
	(-0.06)	(-0.05)	(-0.01)	(0.02)	(0.02)	(0.06)	(0.26)	(0.27)	(0.30)
$\mathrm{RCA}^{\mathrm{P}}$	-0.018	-0.016	-0.018	-0.015	-0.012	-0.016	-0.015	-0.013	-0.018
	(-0.64)	(-0.53)	(-0.56)	(-0.53)	(-0.41)	(-0.49)	(-0.52)	(-0.44)	(-0.56)
Cluster	2.248***	2.061***	2.275***	2.002***	1.845***	2.064***	1.704***	1.536***	1.748***
	(3.87)	(3.57)	(3.39)	(3.74)	(3.44)	(3.42)	(3.49)	(3.33)	(3.44)
Constant	2.104***	2.107***	2.135***	2.114***	2.114***	2.142***	2.096***	2.096***	2.125***
	(6.04)	(5.97)	(6.14)	(6.11)	(6.02)	(6.18)	(6.12)	(6.03)	(6.12)
Observations	306,721	306,721	306,721	306,721	306,721	306,721	306,721	306,721	306,721
R-squared	0.242	0.242	0.233	0.257	0.255	0.245	0.264	0.263	0.254
# of Months	192	192	192	192	192	192	192	192	192

Table 5. Single Sort Based on CSER

This table presents the results of single sort. Panel A reports the returns of sorted portfolios based on the local customer-supplier chain entry rate (CSER). Panel B reports the returns of sorted portfolios based on supplier entry rate (SER), customer entry rate (CER), and the industry entry rate (IER). At the beginning of each month, we sort all stocks into quintile portfolios based on the average CSER over the past 12 months and form a long–short portfolio that is long stocks in the highest CSER quintile and short stocks in the lowest quintile. All stocks are equally (value) weighted within a given portfolio, and the portfolios are rebalanced every calendar month. For brevity, Panel B reports only the highest quintile, the lowest quintile, and the long-short portfolio. The sample includes all normally traded stocks listed on SSE and SZSE with available CSER measures and excludes stocks with price lower than 5 yuan. Our Sample period is from January 2007 to December 2022. Returns and alphas are in percentage, Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

Panel A. Single Sort Based on CSER

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EXRET	CAPM	FF-3	FFC-4	FF-5	FF-6	CH-3	CH-4
Low	0.289	-0.282**	-0.37***	-0.378***	-0.326**	-0.32**	-0.27	-0.24
	(0.44)	(-2.42)	(-2.69)	(-2.73)	(-2.26)	(-2.12)	(-1.65)	(-1.4)
2	0.655	0.06	-0.031	-0.008	-0.009	0.008	-0.052	0.016
	(0.94)	(0.5)	(-0.28)	(-0.07)	(-0.08)	(0.07)	(-0.32)	(0.1)
3	0.648	0.054	-0.089	-0.123	-0.06	-0.08	0.038	-0.028
	(0.92)	(0.48)	(-0.78)	(-1.1)	(-0.51)	(-0.69)	(0.32)	(-0.23)
4	0.856	0.287*	0.157	0.164	0.216	0.222	0.225	0.25
	(1.26)	(1.74)	(0.87)	(0.98)	(1.16)	(1.23)	(0.85)	(1)
High	1.025	0.47***	0.334**	0.285*	0.307*	0.279*	0.47***	0.515***
	(1.61)	(2.9)	(2.06)	(1.94)	(1.92)	(1.83)	(2.65)	(2.9)
H - L	**0.736*** **	**0.752*** **	**0.705*** **	**0.663*** **	**0.633*** **	**0.599*** **	**0.74*** **	**0.755*** **
	(4.5)	**(4.6)**	**(4.43)**	**(3.92)**	**(3.57)**	**(3.31)**	**(2.89)**	**(3.1)**

Panel B. Single Sort Based on SER/CER/IER

	SER			CER			IER		
	Low	High	H - L	Low	High	H - L	Low	High	H - L
EXRET	0.319	1.048	0.728***	-0.206	0.601	0.807***	0.543	0.893	0.35
	(0.51)	(1.63)	(4.59)	(-0.33)	(0.98)	(3.95)	(0.86)	(1.25)	(1.59)
CAPM	-0.245**	0.503***	0.749***	-0.363***	0.442**	0.804***	-0.017	0.291*	0.308
	(-2.01)	(3.11)	(4.55)	(-3.33)	(2.17)	(3.89)	(-0.13)	(1.87)	(1.54)
FF-3	-0.363***	0.423***	0.786***	-0.354***	0.34*	0.693***	0.012	0.245*	0.233
	(-3.04)	(2.91)	(5.18)	(-2.86)	(1.71)	(3.55)	(0.1)	(1.66)	(1.15)
FFC-4	-0.344***	0.396***	0.74***	-0.36***	0.296*	0.656***	-0.004	0.243*	0.247
	(-2.65)	(2.82)	(4.3)	(-2.93)	(1.68)	(3.49)	(-0.03)	(1.7)	(1.15)
FF-5	-0.343***	0.373**	0.716***	-0.347***	0.296*	0.643***	0.043	0.241	0.197
	(-2.75)	(2.33)	(3.69)	(-2.78)	(1.87)	(3.31)	(0.36)	(1.61)	(0.98)
FF-6	-0.318**	0.364**	0.682***	-0.343***	0.281*	0.623***	0.041	0.237	0.197
	(-2.33)	(2.32)	(3.42)	(-2.7)	(1.81)	(3.23)	(0.31)	(1.64)	(0.95)
CH-3	-0.279	0.449***	0.728***	-0.413**	0.445*	0.858***	-0.158	0.373*	0.532*
	(-1.63)	(2.65)	(2.85)	(-2.24)	(1.83)	(2.68)	(-0.97)	(1.91)	(1.92)
CH-4	-0.265	0.468***	0.732***	-0.437**	0.436*	0.874***	-0.137	0.429**	0.566**
	(-1.62)	(2.68)	(2.9)	(-2.42)	(1.88)	(2.97)	(-0.83)	(2.35)	(2.16)

Table 6. Fama-MacBeth Regression

This table reports the results of Fama-MacBeth (1973) regressions of stock return in month t+1 on the local customer-supplier chain entry rate (CSER) for the stock in month t. The entry rates are calculated as a 12-month lagged moving average. The regressions include a set of control variables: (i) firm characteristics, including the natural logarithm of stock market value (Ln(Size)), book-to-market ratio (BM), industry concentration (HHI from Hou and Robinson, 2006), and CAPM Beta, all calculated at the end of month *t*; (ii) the stock's own return in the month *t* (RET1), cumulative returns over the past 1 to 12 months (RET1to12), and cumulative returns over the past 13 to 36 months (RET13to36); (iii) related stock returns in month *t*, including returns from stocks in the same industry (INDRET), same city (GEORET), customer industries (CUSRET), and supplier industries (SUPRET). (iv) the monthly Amihud (2002) illiquidity ratio and turnover. For cross-sectional regression, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). The sample includes all normally traded stocks listed on SSE and SZSE with available CSER measures and excludes stocks with price lower than 5 yuan. Our Sample period is from January 2007 to December 2022. When calculating average coefficients over time, we report Newey-West (1987) adjusted t-statistics in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

	(1) RET_{t+1}	(2) RET_{t+1}	(3) RET_{t+1}	(4) RET_{t+1}
CSER	**0.621***** **(8.09)**	**0.444***** **(9.04)**	**0.420***** **(6.29)**	**0.362***** **(4.95)**
RET1			-0.026*** (-2.73)	-0.034*** (-3.37)
RET2to12			0.004 (1.01)	0.004 (0.98)
RET13to36			-0.000 (-0.39)	-0.001 (-0.99)
INDRET				0.037* (1.73)
GEORET				0.022** (2.51)
CUSRET				0.066*** (2.73)
SUPRET				-0.007 (-0.08)
Ln (Size)		-0.005** (-2.00)	-0.004*** (-3.18)	-0.004*** (-2.75)
BM		-0.002 (-0.66)	-0.001 (-0.49)	0.000 (0.18)
HHI		-0.015*** (-2.70)	-0.011** (-2.05)	-0.003 (-0.51)
Beta		-0.001 (-0.34)	-0.001 (-0.28)	0.000 (0.17)
Illiquid		-0.010 (-0.38)	-0.011 (-0.24)	0.018 (0.38)
Turnover		-0.020*** (-6.22)	-0.022*** (-4.93)	-0.022*** (-5.27)
Constant	0.000 (0.05)	0.086** (2.18)	0.080*** (3.22)	0.064** (2.38)
Observations	306,217	303,193	206,196	198,494
R-squared	0.017	0.181	0.240	0.274
# of Months	192	192	192	192

Table 7. The Effects of CSER on Real Performances

The table reports results from panel regressions of individual firms' quarterly performance on their local customer–supplier entry rate (CSER). The dependent variables are next-quarter ROA, SOA, E/P, $\Delta Profit$ and ΔEPS. The key independent variable is CSER, measured as the average over the past 12 months and computed at the end of the current quarter. Return on Asset (ROA) is measured as net profits attributable to shareholders divided by one-quarter-lagged total assets. Sales on Asset (SOA) is measured as sales attributable to shareholders scaled by one-quarter-lagged total assets. Earnings Price ratio (E/P) is the quarterly earnings divided by the market price at the end of the quarter. $\Delta Profit$ and ΔEPS are calculated as the differences of their values over the past four quarters, standardized by the standard deviation of such differences over the past eight quarters. The regressions control for: (i) firm characteristics, including the natural logarithm of stock market value (Ln(Size)), book-to-market ratio (BM), industry concentration (HHI from Hou and Robinson, 2006), and CAPM Beta, all calculated at the end of quarter q; (ii) quarterly stock returns (RET1); (iii) quarterly returns of related stocks: same industry (INDRET), same city (GEORET), customer industries (CUSRET), and supplier industries (SUPRET). All specifications include both firm and year-quarter fixed effects. The sample includes all normally traded stocks listed on SSE and SZSE with available CSER measures and excludes stocks with price lower than 5 yuan. Our Sample period is from January 2007 to December 2022. T-values are reported in parentheses and standard errors are double clustered at the firm and year-quarter level. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

	(1) *ROA*	(2) *SOA*	(3) *E/P*	(4) $\Delta Profit$	(5) ΔEPS
CSER	**0.494*** **	**0.106*** **	**0.064** **	**9.581*** **	**5.135* **
	(2.88)	**(3.05)**	**(2.07)**	**(2.79)**	**(1.72)**
Ln (Size)	-0.001	0.003***	0.001**	-0.170***	-0.157***
	(-0.83)	(5.16)	(2.26)	(-6.11)	(-6.75)
BM	-0.028***	-0.007***	-0.003**	-0.621***	-0.465***
	(-8.73)	(-9.01)	(-2.65)	(-8.80)	(-7.42)
HHI	-0.019	0.005*	0.003	0.051	-0.018
	(-1.05)	(1.80)	(1.16)	(0.17)	(-0.07)
Beta	-0.001**	-0.000*	-0.000	-0.033	0.004
	(-2.50)	(-1.94)	(-1.18)	(-1.45)	(0.20)
RET1	0.013***	0.004***	-0.000	0.971***	0.809***
	(4.87)	(4.83)	(-0.06)	(9.03)	(9.60)
INDRET	0.006	0.002	0.001	0.245**	0.285**
	(1.13)	(1.43)	(0.68)	(2.04)	(2.50)
GEORET	0.004	0.001	0.001	0.138*	0.176**
	(1.08)	(0.96)	(1.30)	(1.79)	(2.08)
CUSRET	-0.009	-0.001	-0.004	-0.501	-0.571*
	(-0.44)	(-0.15)	(-0.95)	(-1.16)	(-1.75)
SUPRET	-0.003	-0.001	-0.001	-0.033	0.013
	(-0.55)	(-0.41)	(-0.72)	(-0.12)	(0.08)
Constant	0.193***	-0.033***	-0.009	3.320***	2.807***
	(6.39)	(-3.50)	(-1.16)	(7.06)	(7.15)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	121,500	121,500	121,500	121,500	121,500
R-squared	0.756	0.423	0.284	0.206	0.165

Table 8. CSER and Analyst Earnings Surprise

This table presents panel regressions of analyst earnings surprises on the local customer–supplier entry rate (CSER). The dependent variables are firms' current-year and next-year annual earnings surprises (SUE) relative to the analyst consensus forecast, defined as actual earnings per share for the fiscal year minus the median analyst forecast, scaled by the stock price at the fiscal year-end. The key independent variable is CSER, measured at the end of the current fiscal year as the average monthly value over the past 12 months. The regressions include the same control variables as in Table 6, computed at the annual level, as well as the logarithm of analyst forecast dispersion (Dispersion), measured as the standard deviation of all forecasts for each firm in the current year. The industry, year, and firm fixed effects are included in different columns. The sample includes all normally traded stocks listed on SSE and SZSE with available CSER measures and excludes stocks with price lower than 5 yuan. Our sample period is from January 2007 to December 2022. T-values reported in parentheses are calculated using standard errors double clustered at the firm and year level. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

	Current-Year SUE			One-Year-Ahead SUE		
	(1)	(2)	(3)	(4)	(5)	(6)
	SUE	*SUE*	*SUE*	*SUE*	*SUE*	*SUE*
CSER	**0.2136*****	**0.1399*****	**0.0539***	**0.2218*****	**0.1188*****	**0.1049****
	(4.42)	**(11.06)**	**(1.79)**	**(6.76)**	**(3.55)**	**(2.51)**
Ln (Size)	0.0009**	0.0012***	0.0022**	0.0010***	0.0012***	0.0010
	(2.91)	(5.36)	(2.32)	(3.57)	(5.87)	(1.33)
BM	-0.0003	-0.0003	-0.0010	-0.0002	-0.0001	-0.0004
	(-0.73)	(-0.68)	(-0.92)	(-0.59)	(-0.43)	(-0.66)
Beta	0.0006	0.0004	0.0017	-0.0001	-0.0046	-0.0025
	(0.43)	(0.05)	(0.22)	(-0.04)	(-1.53)	(-0.93)
RET1	0.0001	-0.0001	0.0002	-0.0000	-0.0002	0.0002
	(0.35)	(-0.81)	(0.54)	(-0.16)	(-0.70)	(0.61)
INDRET	0.0041***	0.0041***	0.0036***	0.0011**	0.0010**	0.0008
	(5.86)	(5.67)	(3.81)	(2.81)	(2.81)	(1.73)
GEORET	-0.0009	-0.0013	-0.0008	-0.0003	-0.0014	-0.0008
	(-0.73)	(-1.20)	(-0.82)	(-0.23)	(-1.25)	(-0.64)
CUSRET	0.0008	0.0007	0.0004	0.0004	0.0003	0.0002
	(0.96)	(0.80)	(0.39)	(0.53)	(0.58)	(0.47)
SUPRET	-0.0008	-0.0013	-0.0013	0.0032	0.0017	0.0023
	(-0.23)	(-0.42)	(-0.39)	(1.61)	(0.97)	(1.33)
Dispersion	0.0011	0.0003	-0.0010	-0.0001	-0.0007	-0.0013
	(0.16)	(0.06)	(-0.19)	(-0.02)	(-0.15)	(-0.35)
Constant	-0.0001	-0.0004	-0.0019	-0.0003	-0.0005	-0.0002
	(-0.14)	(-0.38)	(-1.21)	(-0.44)	(-0.71)	(-0.28)
Industry FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,555	11,553	11,062	11,555	11,553	11,062
R-squared	0.088	0.116	0.280	0.062	0.120	0.307

Table 9. The Return Predictability of CSIP

This table reports short-term and long-term return reactions to industrial policies issued by city-level governments and targeted at the customer and supplier industries of the focal stock. Panel A reports cumulative total returns (CTRs) and cumulative abnormal returns (CARs) around policy announcements. The event windows are from −1 day to +1 day and from −5 days to +30 days around the announcement date. Abnormal returns are adjusted using several factor models, with stock-specific factor loadings estimated from one year (252 trading days) of daily data ending 30 trading days prior to the event date. T-statistics are calculated based on standard errors clustered by the year-month of the policy announcement date. Panel B reports Fama–MacBeth regressions with individual stock returns in month t+1 as the dependent variable and customer–supplier industrial policy (CSIP) measured over months t−12 to t and t−24 to t−12 as the independent variables. CSIP is defined as the weighted average across all customer and supplier industries of dummy variables equal to one if the corresponding industry is supported by industrial policy issued during the relevant period (t−12 to t or t−24 to t−12), and zero otherwise, where the weights are taken from the Input–Output Table. The control variables are the same as that in Table 6. For cross-sectional regression, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). When calculating average coefficients over time, we report Newey-West (1987) adjusted t-statistics in parentheses. The sample includes all normally traded A-share stocks listed in SSE and SZSE with available CSER measure and the sample period is from January 2007 to December 2022. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

Panel A. CARs Around the Announcement of the Industrial Policies Targeted Customer and Supplier Industries.

Event Window	Mean CTR	AR Model	Mean CAR	t-stat
[-1,1]	0.20%	The Market Model	0.01%	0.17
[-1,1]		FF3 Model	-0.03%	-1.25
[-1,1]		FF5 Model	-0.03%	-1.47
[-1,1]		CH4 Model	-0.01%	-0.62
[-5,30]	2.03%	The Market Model	0.05%	0.12
[-5,30]		FF3 Model	-0.24%	-1.52
[-5,30]		FF5 Model	-0.27%	-1.79
[-5,30]		CH4 Model	-0.24%	-1.75

Panel B. The Return Predictability of CSIP

	(1)	(2)	(3)	(4)	(5)	(6)
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
CSIP[t-12, t]	-0.005	-0.006*			-0.004	-0.005*
	(-1.08)	(-1.68)			(-0.85)	(-1.95)
CSIP[t-24, t-12]			-0.002	-0.001	-0.002	-0.000
			(-0.71)	(-0.67)	(-0.56)	(-0.16)
Controls	No	Yes	No	Yes	No	Yes
Observations	306,217	198,494	306,217	198,494	306,217	198,494
R-squared	0.007	0.272	0.007	0.272	0.015	0.275
# of Months	192	192	192	192	192	192

Table 10. The Return Predictability of CSER Induced by Industrial Policy

This table reports Fama–MacBeth regressions in which the dependent variable is stock returns in month t+1, and the key independent variables are components of CSER measured in month t. The components of CSER are estimated from Fama–MacBeth regressions run at the end of month t using an expanding window of historical data. The dependent variable is the average CSER for each stock over months t−12 to t. The independent variables include local industrial policy measures (CSIP and IP), measured over months t−24 to t−12, as well as industry comparative advantage (RCA and Cluster) and local economic conditions (GDP and ΔGDP), both measured at the end of month t−12. Based on the estimated coefficients, we decompose total CSER into fitted components attributable to policy measures ($\widehat{CSER}_{Policy}$), comparative advantage ($\widehat{CSER}_{CA}$), and local economic conditions ($\widehat{CSER}_{GDP}$), along with a residual component ($\widehat{CSER}_{r}$). $\widehat{CSER}$ denotes total CSER excluding the residual component. The control variables are the same as in Table 6. For cross-sectional regressions, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). The sample includes all normally traded stocks listed on SSE and SZSE with available CSER measures and excludes stocks with prices lower than 5 yuan. Our Sample period is from January 2007 to December 2022. We report Newey-West (1987) adjusted t-statistics in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
$\widehat{CSER}$	1.578***	0.858**		
	(4.75)	(2.47)		
$\widehat{CSER}_{Policy}$			0.753***	0.537***
			(3.16)	(2.70)
$\widehat{CSER}_{GDP}$			2.514***	1.654***
			(4.89)	(3.79)
$\widehat{CSER}_{CA}$			3.912***	1.172
			(2.66)	(0.67)
$\widehat{CSER}_{r}$	0.605***	0.355***	0.544***	0.237***
	(5.44)	(5.41)	(4.15)	(3.55)
Controls	No	Yes	No	Yes
Observations	306,217	198,494	306,217	198,494
R-squared	0.030	0.278	0.055	0.287
# of Months	192	192	192	192

Table 11. Return Predictability of CSER Across Different Regional Levels: National, Provincial, and Municipal Perspectives

This table reports the results of Fama-MacBeth (1973) regressions of the stock return in month t+1 on the local customer-supplier chain entry rate (CSER) across different regional levels. In addition to the city-level measure (CSER), we construct province-level ($CSER^{P}$) and nation-level ($CSER^{N}$) measures to represent the customer-supplier chain entry rates within the province and across the entire nation. To isolate local effects, we construct a province-level measure orthogonal to the nation level ($CSER^{P\perp N}$) and a city-level measure orthogonal to both the province and nation levels ($CSER^{\perp P\&N}$). $CSERP^{\perp N}$ ($CSER^{\perp N\&P}$) is calculated as the residual of cross-sectional regression of $CSER^{P}$ on $CSER^{N}$ (CSER on $CSER^{P}$ and $CSER^{N}$). The entry rates are calculated as a 12-month lagged moving average, and the control variables are the same as that in Table 6. For cross-sectional regressions, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). When calculating average coefficients over time, we report Newey-West (1987) adjusted t-statistics in parentheses. The sample includes all normally traded A-share stocks listed in SSE and SZSE with available CSER measure and the sample period is from January 2007 to December 2022. ***, **, and * indicate 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)	(5)
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
$CSER^{N}$	-0.507				
	(-1.06)				
$CSER^{P}$		0.357***			
		(3.15)			
$CSER$			0.362***		
			(4.95)		
$CSER^{P\perp N}$				0.618***	
				(6.26)	
$CSER^{\perp N\&P}$					0.534***
					(6.21)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	198,494	198,494	198,494	198,494	198,494
R-squared	0.278	0.274	0.274	0.273	0.273
# of Months	192	192	192	192	192

Table 12. Return Predictability of the Customer-Supplier Chain Entry Rate within Specific Areas

This table presents the Fama-MacBeth regressions of stock returns on the customer-supplier chain entry rate within different areas. The customer-supplier chain entry rate (CSER) in this table is the weighted average monthly new-firm entry rate of a firm's supplier and customer industries within a specific area. For each firm, we calculate the customer-supplier chain entry rates (1) within the headquartered city, (2) within 100 km, (3) within 100 km outside the headquartered city, (4) within 100 km inside the same province, (5) within 100 km inside the same province and outside the headquartered city, (6) within 100 km outside the province. See Figure 5 for an example. The control variables are the same as that in Table 6. For cross-sectional regression, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). When calculating average coefficients over time, we report Newey-West (1987) adjusted t-statistics in parentheses. The sample includes all normally traded A-share stocks listed in SSE and SZSE with available CSER measure and the sample period is from January 2007 to December 2022. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
Within-City Firms	0.362***					
	(4.95)					
≤100 km Firms		0.357***				
		(2.66)				
≤100 km Firms, Outside City			0.241**			
			(1.99)			
≤100 km Firms, Within Province				0.375***		
				(3.18)		
≤100 km Firms, Within Province, Outside City					0.254**	
					(2.55)	
≤100 km Firms, Outside Province						0.172
						(1.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	198,494	198,494	178,367	198,494	135,911	64,526
R-squared	0.274	0.252	0.250	0.253	0.232	0.327
# of Months	192	192	192	192	192	192

Table 13. Heterogeneity Cross Industries

This table presents the Fama-MacBeth regressions of stock returns on CSER interacted with industry indicator variables. The dependent variable is the stock returns in month t+1 and the key independent variables are interactions between CSER in month t and industry indicator variables High Reliance and Industrial Sector. The stocks on each cross-section are divided into three terciles based on their dependence on supplier and customer industries. High Reliance equals to one if the stock is in the second or third tercile, and zero otherwise. Industrial Sector equals to one if the stock's industry belongs to the secondary sector (industry code from 06 to 50), and zero otherwise. The control variables are the same as in Table 6. For cross-sectional regression, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). When calculating average coefficients over time, we report Newey-West (1987) adjusted t-statistics in parentheses. The sample includes all normally traded A-share stocks listed in SSE and SZSE with available CSER measure and the sample period is from January 2007 to December 2022. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

	(1)	(2)	(3)	(4)
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
CSER	0.179	0.077	0.009	-0.278
	(1.28)	(0.63)	(0.06)	(-1.45)
CSER × High Reliance	0.756***	0.542***		
	(3.62)	(3.02)		
CSER × Industrial Sector			0.763***	0.804***
			(3.39)	(3.06)
High Reliance	-0.006**	-0.004*		
	(-2.31)	(-1.74)		
Industrial Sector			-0.006***	-0.006**
			(-2.79)	(-2.03)
Controls	No	Yes	No	Yes
Obs.	306,217	198,494	306,217	198,494
R2	0.056	0.288	0.069	0.290
# of Months	192	192	192	192

Table 14. Industry Competition and the Effects of CSER

This table presents Fama–MacBeth regressions of stock returns on CSER interacted with a High HHI indicator. The dependent variable is stock returns in month t+1, and the key independent variables are the interactions between CSER in month t and the High HHI indicator. High HHI equals one if the Herfindahl–Hirschman Index (HHI) of the stock's industry exceeds 500, and zero otherwise. HHI measures market concentration as the sum of the squared sales shares of all firms in the industry. The control variables are the same as in Table 6. For cross-sectional regression, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). When calculating average coefficients over time, we report Newey-West (1987) adjusted t-statistics in parentheses. The sample includes all normally traded A-share stocks listed in SSE and SZSE with available CSER measure and the sample period is from January 2007 to December 2022. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

	(1) RET_{t+1}	(2) RET_{t+1}
CSER	0.046	0.049
	(0.27)	(0.35)
CSER × High HHI (>500)	0.771***	0.535**
	(3.28)	(2.51)
High HHI (>500)	-0.011***	-0.007***
	(-3.17)	(-4.14)
Controls	No	Yes
Observations	306,217	198,494
R-squared	0.064	0.287
# of Months	192	192

Table 15. Excluding the Smallest 30% of Firms and Financial Firms

This table presents the results of single sort based on CSER. At the beginning of each month, we sort all stocks into quintile portfolios based on the average CSER over the past 12 months and form a long–short portfolio that is long stocks in the highest CSER quintile and short stocks in the lowest quintile. All stocks are equally (value) weighted within a given portfolio, and the portfolios are rebalanced every calendar month. The sample initially includes all normally traded stocks listed on the SSE and SZSE with available CSER measures and excludes stocks with prices below 5 yuan. In Panel A, we further exclude the smallest 30% of firms by market capitalization, which are more likely to be valued for their potential as shell firms in reverse mergers that circumvent stringent IPO constraints (Liu, Stambaugh, and Yuan, 2019). In Panel B, we instead exclude financial firms, whose returns are less closely related to operating fundamentals (Fama and French, 1992). Our Sample period is from January 2007 to December 2022. Returns and alphas are in percentage, Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

Panel A: Excluding the 30% Smallest Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EXRET	CAPM	FF-3	FF-4	FF-5	FF-6	CH-3	CH-4
Low	-0.169	-0.327***	-0.377***	-0.39***	-0.322**	-0.321**	-0.287*	-0.337**
	(-0.27)	(-2.89)	(-3.08)	(-3.11)	(-2.48)	(-2.28)	(-1.72)	(-2.07)
2	0.114	-0.054	-0.092	-0.08	-0.118	-0.11	-0.099	-0.1
	(0.17)	(-0.48)	(-0.86)	(-0.75)	(-1.08)	(-0.99)	(-0.64)	(-0.68)
3	0.136	-0.03	-0.219	-0.25*	-0.138	-0.165	-0.031	-0.052
	(0.21)	(-0.24)	(-1.65)	(-1.86)	(-0.92)	(-1.08)	(-0.27)	(-0.39)
4	0.377	0.217	0.158	0.175	0.193	0.208	0.209	0.197
	(0.58)	(1.31)	(0.94)	(1.09)	(1.18)	(1.27)	(0.82)	(0.79)
High	0.556	0.4**	0.364***	0.307**	0.285**	0.254**	0.47***	0.436**
	(0.92)	(2.44)	(2.65)	(2.56)	(2.25)	(2.03)	(2.59)	(2.32)
H - L	0.724***	0.727***	0.74***	0.697***	0.607***	0.575***	0.758***	0.773***
	(4)	(4.04)	(4.53)	(4.05)	(3.37)	(3.14)	(2.61)	(2.74)

Panel B: Excluding the Financial Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EXRET	CAPM	FF-3	FF-4	FF-5	FF-6	CH-3	CH-4
Low	-0.113	-0.273***	-0.355***	-0.364***	-0.308**	-0.308**	-0.172	-0.213
	(-0.18)	(-2.64)	(-3)	(-2.97)	(-2.52)	(-2.32)	(-1.23)	(-1.53)
2	0.208	0.033	-0.27*	-0.33***	-0.24*	-0.282**	0.153	0.109
	(0.3)	(0.2)	(-1.8)	(-2.65)	(-1.74)	(-2.26)	(1.07)	(0.67)
3	0.275	0.109	-0.208*	-0.238**	-0.121	-0.144	0.145	0.157
	(0.42)	(0.61)	(-1.66)	(-1.97)	(-0.76)	(-0.89)	(1.11)	(1.05)
4	0.514	0.349*	0.166	0.136	0.22	0.2	0.432	0.405
	(0.76)	(1.77)	(0.86)	(0.83)	(1.18)	(1.2)	(1.48)	(1.38)
High	0.594	0.442**	0.238	0.144	0.166	0.108	0.471*	0.434*
	(0.97)	(2.22)	(1.31)	(1)	(1.14)	(0.86)	(1.88)	(1.71)
H - L	0.707***	0.715***	0.592***	0.508***	0.474**	0.416**	0.643**	0.646**
	(3.34)	(3.47)	(3.2)	(2.69)	(2.52)	(2.22)	(2.01)	(2.12)

Table 16. Alternative CSER Horizons

This table presents the return predictability of CSER measured over different lagged horizons. Panel A reports single-sort portfolio results based on CSER measured over the lagged one-month period, as well as CSER constructed as moving averages over the past three and six months. At the beginning of each month, we sort all stocks into quintile portfolios based on CSER averaged over the past 1, 3, and 6 months, and construct a long–short portfolio that is long in the highest CSER quintile and short in the lowest CSER quintile. All stocks are equally (value) weighted within a given portfolio, and the portfolios are rebalanced every calendar month. Panel B reports Fama–MacBeth regressions with individual stock returns in month t+1 as the dependent variable. The independent variables include the average monthly customer–supplier entry rate (CSER) measured over months t−12 to t, t−3 to t, t−6 to t−3, and t−12 to t−6, respectively. The control variables are the same as in Table 6. For cross-sectional regression, we employ Weighted Least Squares (WLS) estimation with stock market value as weight to estimate coefficients following Hou, Xue, and Zhang (2010). When calculating average coefficients over time, we report Newey-West (1987) adjusted t-statistics in parentheses. The sample includes all normally traded A-share stocks listed in SSE and SZSE with available CSER measure and the sample period is from January 2007 to December 2022. ***, **, and * indicate 1%, 5%, and 10% statistical significance respectively.

Panel A: Single Sorts Based on CSER across Alternative Horizons

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		EXRET	CAPM	FF-3	FF-4	FF-5	FF-6	CH-3	CH-4
1 M	Low	0.375	-0.211*	-0.309**	-0.333***	-0.219*	-0.227*	-0.148	-0.096
		(0.54)	(-1.92)	(-2.44)	(-2.67)	(-1.79)	(-1.77)	(-0.99)	(-0.58)
	High	0.828	0.243	0.062	0.001	0.082	0.043	0.296	0.374
		(1.21)	(1.62)	(0.35)	(0)	(0.47)	(0.29)	(1.14)	(1.52)
	H - L	0.453**	0.454**	0.371**	0.333*	0.301	0.27	0.444	0.47
		(2.48)	(2.51)	(1.99)	(1.8)	(1.51)	(1.46)	(1.41)	(1.59)
3 M	Low	0.108	-0.383***	-0.466***	-0.507***	-0.423***	-0.444***	-0.311**	-0.267
		(0.17)	(-3.83)	(-3.55)	(-3.94)	(-3.33)	(-3.32)	(-1.98)	(-1.6)
	High	0.88	0.393**	0.241	0.186	0.226	0.19	0.426*	0.491**
		(1.38)	(2.56)	(1.5)	(1.37)	(1.32)	(1.29)	(1.77)	(2.11)
	H - L	0.771***	0.777***	0.707***	0.693***	0.65***	0.634***	0.736**	0.759***
		(4.33)	(4.36)	(4.1)	(3.93)	(3.16)	(3.18)	(2.52)	(2.81)
6 M	Low	0.009	-0.358***	-0.466***	-0.487***	-0.436***	-0.442***	-0.322*	-0.33*
		(0.02)	(-3.38)	(-3.07)	(-3.27)	(-2.87)	(-2.84)	(-1.84)	(-1.85)
	High	0.782	0.418**	0.258*	0.22	0.18	0.163	0.439**	0.445**
		(1.35)	(2.36)	(1.67)	(1.57)	(1.13)	(1.04)	(2.37)	(2.29)
	H - L	0.772***	0.776***	0.724***	0.707***	0.616***	0.605***	0.761***	0.776***
		(3.81)	(3.81)	(3.95)	(3.76)	(2.68)	(2.62)	(2.82)	(2.91)

Panel B: Fama-MacBeth Regression

	(1) RET_{t+1}	(2) RET_{t+1}	(3) RET_{t+1}	(4) RET_{t+1}	(5) RET_{t+1}
CSER[t-12, t]	0.362***				
	(4.95)				
CSER[t-3, t]		0.372***			0.250**
		(4.97)			(2.28)
CSER[t-6, t-3]			0.359***		0.303***
			(4.31)		(3.02)
CSER[t-12, t-6]				0.148**	-0.146*
				(2.04)	(-1.71)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	198,494	198,494	198,494	198,494	198,494
R-squared	0.274	0.274	0.274	0.273	0.280
# of Months	192	192	192	192	192

Appendix A. Variable Definitions

Variable	Definition
CSER	The weighted average of firm entry rates into a firm's customer and supplier industries in its headquartered city.
SER (CER)	The weighted average of firm entry rates into a firm's supplier (customer) industries in its headquartered city.
IER	The firm entry rate into a firm's industry in its headquartered city.
$CSER^P$ ($CSER^N$)	The weighted average of firm entry rates into a firm's customer and supplier industries in its province (nation).
CSIP	The intensity of industrial policy support for a firm's local customer and supplier industries in its headquartered city.
IP	An indicator for whether a firm's industry is supported by industrial policies in its headquartered city.
RCA^P (RCA^N)	The revealed comparative advantage of the firm's industry in its headquartered city compared with its importance at the provincial (national) levels.
Cluster	The share of registered firms in the firm's industry that are located in its headquarters city relative to all firms in the same industry nationwide.
Ln(Size)	The natural log of total market capitalization, calculated as market price multiplies the total number of shares outstanding (Trillion RMB).
BM	Book-to-market ratio, defined as book equity over market equity.
HHI	Industry concentration formed by averaging the sum of squared sales-based market shares of all firms in the industry over the past three years (Hou and Robinson, 2006).
Beta	The coefficient of the daily CAPM regression over the past twelve months.
RET1	The stock return in the current month t.
RET1to12	The cumulative stock returns from month t-12 to t-1.
RET13to36	The cumulative stock returns from month t-36 to t-13.
INDRET	Industry momentum (Moskowitz and Grinblatt, 1999; Hou, 2007), calculated as the value-weighted average return of all other stocks in the same industry.
GEORET	Geographic momentum (Parsons et al., 2020), calculated as the value-weighted average return of all other stocks in the same city.
CUSRET (SUPRET)	Customer (supplier) momentum (Menzly and Ozbas, 2010), calculated as the value-weighted average return of all stocks in the customer (supplier) industries.
Illiquid	Amihud (2002) illiquidity ratio, calculated as the monthly average ratio of absolute daily return over daily trading volume.
Turnover	The average monthly trading volume divided by the number of shares outstanding over the past twelve months.
Dispersion	The log of analyst forecast dispersion, measured by the standard deviation of all forecast for a firm in the current year.
Reliance	Dependence on supplier and customer industries, measured using the Backward and Forward Coefficients calculated from the Input-Output Table (Jones, 1976; Rodriguez-Clare, 1996; Ojaleye and Narayanan Gopalakrishnan, 2021).