A Race to Lead: How Chinese Government Interventions Shape the U.S.-China Production Competition ☆

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Abstract

Integrating establishment-level data for public and private firms from U.S. and China, we study the dynamic interdependence in industrial activities between the two economies. Births of Chinese firms predict same-industry firm exits and lowered employment in the U.S., but the relation in the reverse is not significant. China's Five-Year Plans were not preceded by low production/employment in the same industries in the U.S., but were followed by shrinkage afterwards. The dynamics of stock returns, firm valuation, and desire to hire indicate that the market and companies did not expect deterioration of the targeted industries prior to, but made adjustments after the announcement of the Plans.

Keywords: Investment policy, employment, subsidies to firms in China

U.S. and China host the two largest economies in the world, with their GDP account for 23.6% and 15.5% of the world GDP in 2018 (at the nominal exchange rate). The two countries trade over $600 billion annually in 2018.[1] Behind these numbers were the astounding dynamic rebalancing of the economic prowess of the two countries. Back in 1980, China, being the fourteen-largest economy, boasted a GDP that was 5.2% of that of the U.S.[2] As China continued its relentless growth path, its trade frictions with the U.S. also escalated into trading wars, especially after 2010 when China displaced U.S. as the world's largest manufacturing nation.

To a large extent, the rise of China from a low base and its convergence to a developed economy is a successful case of classic economics. For example, the *comparative advantage* school suggests that, due to disparity of income and labor cost between the two countries, Chinese firms have a comparative advantage over U.S. firms in labor-intensive industries from textiles to electronic assembly. The birth and growth of firms in these industries in China benefited from the decline of those factories in the U.S. as the latter restructured its economy toward service and knowledge-intensive sectors. In the more recent period, however, Chinese firms started to flex muscles in industries that were in their prime with high value-added in the U.S., such as computers, telecommunication products, and alternative energy equipment. When China became a serious competitor in these sectors also prized by the U.S., clashes became more common, especially given the concern that China's rise in these new industries could have been helped significantly by the Chinese government[3] such that U.S. firms could be outcompeted by their rivalries aided by Chinese government's industrial policy.

[1]Source: https://www.statista.com/.

[2]Source: the World Bank.

[3]See, for example, "State Support Helped Fuel Huawei's Global Rise", Wall Street Journal, December 25, 2019.

This paper studies the dynamic interdependence in industrial activities between the U.S. and China in shaping the industrial relationships between the U.S. and China, with primary focus on the impact of Chinese government subsidies, especially in targeted industries China perceives as key for economic development and technology leadership. The study is based on U.S. and China establishment-level data (including non-public companies) covering 1,643,000 unique business establishments on the U.S. side and 1,100,000 firms on the Chinese side during 1998-2013. We establish three key results.

First, we show that there is a negative correlation between firm numbers and employment within the same industry between the two countries. More importantly, a panel VAR method shows that high birth rates of Chinese firms predict same-industry firm exits and lowered employment in the U.S. one and two years down the road. These results are particularly strong in the export-intensive industries in China and are driven by the birth of domestic private firms rather than the birth of foreign-owned or state-owned firms in China. When we consider the reverse relationship, we find that changes in employment (but not establishments) in the U.S. also predict changes in the opposite directions of the number of Chinese firms in a two-year horizon, albeit the relation is notably weaker. All these results are confirmed as Granger causality, suggesting a general competitive and substitutive relationship in production between the two countries.

Second, we leverage data on Chinese government subsidies to individual firms to shed light on how direct government support to enhance the country's global standing in certain industries may lead to such industries' relative decline in the U.S. On the one hand, the Chinese government could foresee deteriorating investment opportunities and disruptions of some industries globally but decides to shore up these industries in China. Alternatively, the similar empirical patterns could arise if subsidies represent strategic decisions to hone up or to create a competitive advantage of Chinese firms, possibly at the expense of the

U.S. firms in a turf war. Interestingly, we find that the Chinese government provides subsidies when an industry experiences growth in both countries, which is more consistent with the hypothesis that the ensuing decline of the same industries in the U.S. is due to a displacement effect.

Third, we accomplish a tighter inference for the impact of China expansion on U.S. production using China's Five-year Plans as shocks to China's industry growth. The Five-Year plans, originated from the former Soviet Union, serve as the highest level of the central government's industrial policies as they highlight the key sectors the governance plans to encourage and to support. The particular Plans we study are the Tenth to the Thirteenth Five-Year Plans, announced in 2001, 2006, 2011, and 2016, from which we obtain identities of industries that the government "encouraged" following the definition used by Chen, Li and Xin (2017). We find that after the shock, the treated industries in China expanded significantly more than the control group. In contrast, firms in corresponding industries in U.S. experience slower growth in the number of establishments and employment than firms in other industries.

We perform several heterogeneity tests to shed further light on the effects of Plans on U.S. firms. Consistent with the VAR results, we find that the effect from the Five-Year Plans is significantly more pronounced for the export-intensive industries. We then study the role of China business presence for U.S. firms. U.S. firms with facilities in China or joint ventures with local partners benefit from the extra public goods as a result of government policies promoting the specific industries. Moreover, most of the government preferential policies (e.g., tax rebates, research grants, and talent recruiting) are applicable to all firms residing in China, including foreign-owned and joint ventures. Indeed, we find U.S. firms that set up production establishments in China are able to, on average, completely offset the competitive effects from China's industrial policies.

Finally, we explore the heterogeneous effect of China's government support on U.S. industries with high and low labor productivity, and separately for the Five-Year Plans in the early period (i.e., 10th and 11th Plans) and the more recent period (i.e., 12th and 13th Plans). We find that during the earlier part of our sample, Five-Year Plans targeted industries that were of low labor productivity, or high labor intensity. In contrast, during the later part of our sample, Five-Year Plans primarily targeted higher labor productivity, or less labor-intensive industries, suggesting that the focus of the industrial policies embedded in the Five-Year Plans shifted from low labor productivity to high labor productivity industries.

Needless to say, to give the estimated effect a causal interpretation requires the assumption of a parallel trend, i.e., the treated and control industries would have evolved in parallel in the absence of the Five-Year Plan. We first demonstrate the premise based on the lack of preexisting trends in outcome variables such as number of establishments and employment. While a parallel trend post-shock in the counterfactual state is inherently untestable, we resort to two measures that incorporate forward-looking information: Stock market valuation and firms' desire to hire. Neither the stock market, in terms of firm valuation and stock returns, nor firm job postings (as tracked by Burning Glass), was anticipating the relative weakening of the industries in the U.S. that were soon to be targeted by China's Five-Year Plans. Therefore, an attribution of the effect to purely successful selection by the Chinese government into industries that, in its absence, will experience deterioration in the U.S. amounts to assuming that the Chinese government can process information to predict and anticipate evolutions in economic activities in the U.S. better than the aggregate wisdom of the securities market and the foresight of U.S. firm decision makers. Such an assumption is not supported by the vast economics literature; in fact, the ability to allocate resources based on forward-looking information represents a fundamental advantage of a market-driven economy over alternatives. The most likely explanation for our findings is, therefore, that China's government policies had a real impact on the Sino-U.S. race to lead in the targeted industries.

It is worth noting that performing the analyses at the business establishment level, as opposed to firm- or industry-level using standard databases such as Compustat, is crucial for our study. A key finding that the China production shocks predict decrease in the number of U.S. factories could not have been uncovered in the absence of such granular data; in fact, the number of Compustat firms remains more or less stable post shock. Relatedly, the standard databases covering mainly public firms fail to capture the impact on private firms which account for about 85% of the establishments and about 70% of employment by manufacturing sector in U.S.[4] Finally, an analysis at the industry level would not be able to inform whether the downsizing of U.S. production occurs at the extensive or intensive margin. While scaling back production by existing units and closing establishments could lead to observationally similar outcomes at the industry level, the latter changes often exert more profound impact on the community and local economies.

Our paper is primarily related to the literature that studies the relationship between Chinese and U.S. economies, with a particular emphasis on the effects of the "Made in China" on U.S. manufacturing firms and labor markets. Autor, Dorn and Hanson (2013) study the consequences of rising competition from Chinese imports for U.S. labor markets. The authors find that Chinese imports lead to adverse effects on U.S. labor markets that are exposed to import-competing manufacturing industries. These effects include higher unemployment, lower labor force participation, and reduced wages. Pierce and Schott (2016) and Acemoglu, Autor, Dorn, Hanson and Price (2016) show that import competition from China has contributed to reductions in U.S. employment. Whereas the analysis in

[4]Data source: U.S Bureau of Labor Statistics and U.S. Census Bureau.

Pierce and Schott (2016) employ industry-level empirical strategy, Acemoglu et al. (2016) zoom into the level of commuting zones and study reallocation and aggregate demand consequences of import competition from China.[5]

Another strand of the literature our paper is related to is the literature that studies the consequences of China's government support (such as subsidies) on Chinese firms. For instance, Chen et al. (2017) use China's Five-Year Plans to study the relationship between government subsidies and firm growth. Similarly, Liu and Mao (2017) use China's 2004 tax reform that introduced permanent tax credit for firms' investment in fixed assets and show that firms that enjoyed an effective tax reduction experienced increases in investment and productivity. Brandt et al. (2017) document positive consequences of WTO accession for productivity of manufacturing firms in China. Chen et al. (2020) study the impact of the 4 trillion yuan stimulus package on shadow banking and corporate bond markets in China. A concurrent paper by Cai et al. (2020) analyzes the impact on import competition resulting from credit provided by China Development Bank using loan-transaction level data.

Our paper contributes to these strands of the literature by showing that Chinese government support plays a significant role in enhancing the competitive standing of Chinese firms. Ours is the first study that directly connects China and U.S. data at the business establishment level, and uncovers the impact of government support from the micro-level data. The key findings support the concern that U.S. firms are displaced by China's manufacturing prowess, not just in sunset industries from which the U.S. was happy to retreat, but also in industries that both countries are eager to lead, in a race that

[5]Several studies address the effect of Chinese imports on European countries. Utar (2014) exploits the dismantling of quotas on Chinese products combined with employer-employee matched data from Denmark and finds significant changes in the workforce composition in Denmark, including decreases in employment and intangible assets. Bloom et al. (2015) study consequences of Chinese import competition on twelve European countries. They show that the increased competition led to technical changes within firms and reallocation of employment towards more technologically advanced firms.

has been significantly shaped by the Chinese government.

1. Data and Overview

1.1. Data sources

This study builds on various data bases from both the U.S. and China that could be integrated at the establishment- or industry-year (or month) level, which combined covering the period from 1998 to 2019. The construction of our main sample requires a merge of U.S. and China nationwide data at the industrial establishment level, which has not been done before in the literature. We are able to merge the China Industrial Enterprises Database and U.S. Census LBD data using 4-digit International Standard Industrial Classification (ISIC) for the sample period of 1998 to 2013.

The Longitudinal Business Database (LBD) at U.S. Census Bureau is a census of business in the U.S. that covers 23 million business establishments affiliated with public and private companies in all industries and all states from 1975-2015. The LBD tracks the longitudinal change in economic activities such as establishment birth/death, payroll, and employment at the establishment level. It also contains establishment characteristics such as industry classification and location. To match the U.S. industries with the corresponding industries in China, we transform the 6-digit NAICS industry classification in the LBD to 4-digit ISIC using the concordances provided by U.S. Census Bureau.

Similarly, the China Industrial Enterprises Database (CIED) tracks the longitudinal evolution in operating and financial variables of a large sample of private and public firms from 1998-2013. The Database builds on annual surveys of firms with revenue above 20 million RMB (before 2009, above 5 million RMB)[6] conducted by the National Bureau of Statistics of China. The key variables from the Database include employment, sales, export,

[6] During our sample period the official exchange rate is about RMB 7.6 per U.S. dollar.

government subsidy, total assets, total liabilities, among others. Earlier studies that built on the database include Hsieh and Klenow (2009) and Song et al. (2011).[7] We transform the 6-digit CIC (China Industry Classification) codes in the Database to 4-digit ISIC based on an industry matching table from the National Bureau of Statistics of China.

It is worth noting that both databases build on mandatory and comprehensive government surveys, and are longitudinal; they cover business entities affiliated with public and private corporations. The unit of an "establishment" on the U.S. side is slightly more disaggregated than a "firm" on the China side, but the two are close in tracking activities at the business unit level. While an establishment is a production site equivalent to a factory, a "firm" in CIED is equivalent to a branch of a corporation sorted by regions or product lines. For example, the company Huawei Technology Co. has 20 firm-level entries in our database; and there are seven recorded "firms" affiliated with P&G Great China.

A critical data input from CIED regarding government subsidy warrants additional elaboration. Public and private firms in China are required to list direct government subsidies/grants in their income statements, and such information is covered by the database. The subsidy income, either from the central or local government, takes various forms, including tax rebates, financial subsidies, incentives for new product and technological innovation including R&D grants.[8] It does not include indirect government support in the form of terms of transactions that are more favorable than the market, such as low interest loans from state-owned banks or land acquired at below-market prices. Given the difficulty quantifying the indirect support, we acknowledge that recorded subsidy is an incomplete measure for government support; instead, we make the assumption that

[7]Nie et al. (2012) raised various criticisms regarding the quality of CIED data. In Online Appendix Appendix A, we described how we mitigate the major issues they raised that are relevant to our study.

[8]In China, a quarter of firms' R&D expenditures come from government subsidies according to Fang et al. (2018).

subsidies are an informative proxy of the overall support firms receive from the government, especially at the industry level.

In addition to the establishment-level data, two additional information sources contribute to our analyses. The first piece is the policy shocks induced by the Five-Year Plans by the Chinese government aimed at promoting industries deemed of key importance to national economy or security. The data on Five Year Plans is manually retrieved from the official documents provided by the State Council of China. The Plans of particular interest to us are the 10th, 11th, 12th, and 13th Five-Year Plan that came into effect in 2001, 2006, 2011, and 2016, respectively. We follow Chen et al. (2017) in defining the government-supported industries, which we term "encouraged industries." To further tighten the classification of industries that are treated by government support, we require the industries to be both encouraged in the plan and receiving increased government subsidies post Plan. More specifically, the treatment requires that the magnitude of subsidy increases during the five years after the shock over the benchmark level during the pre-shock period is above the median among all industries. The control group is those not explicitly encouraged in the plan.[9]

The second external data input come from Burning Glass, which is currently the leading data vendor in job postings in the U.S. The postings are scraped from more than 40,000 digital and non-digital sources, including web sites, news letters, and agency reports, and cover the period of 2007, and then 2010-2019. Acemoglu et al. (2020) show that Burning Glass data covers 60-80% of all U.S. job vacancies. The data reports employer names, as well as the sector, job title, skill requirements, and sometimes the offered salary range. The number of all job postings (unique employers) increase from 13.6 million (26,522) in 2007

[9] The control group thus includes industries that received high subsidy but are not in the plan. This is meant to be conservative because excluding these firms from the control will only make the difference larger between the treated and control firms.

to 35.5 million (1.28 million) in 2019.[10] Similarly, we transfer the 6-digit NAICS industry classification in Burning Glass into 4-digit ISIC using the concordances provided by U.S. Census Bureau. For the industries covered by LBD and CIED, the numbers are 372,659 (2,262) in 2007 to 691,888 (1,677) in 2019. The value of job-posting data is that they capture firms' desire to hire, which isolates labor demand by the firm from the outcome of employment that is jointly determined by labor demand and supply. Our analyses based on Burning Glass data will be at the industry-month level, and we separate skilled from unskilled, as well as first posting (a cleaner measure for a desire to hire) from repeat posting (which might also reflect a failure to fill the position). We define repeat posting as the postings with the same job title, employer, county, job hours, but different hiring date within a year.

1.2. Sample overview and summary statistics

The merge of LBD and CIED yields 2,100 observations at the industry-year (4-digit ISIC) level from 1998-2013, covering 1,643,000 unique business establishments on the U.S. side and 1,100,000 unique firms on the Chinese side. The variables concerning U.S. economic activities are constructed by aggregating all U.S. establishments in the LBD in a given industry-year. On the China side, CIED restricts its coverage to the firms with at least RMB 20 million (about $2.9 million) of revenue as of 2011,[11] the industry aggregation on the China side is thus a sum over all Chinese firms with revenue above the threshold. Moreover, the filter implicitly requires that each industry-year observation includes at least one Chinese firm with revenue over the RMB 20 million threshold, but this requirement is hardly binding except in a handful of industries in the early years of the sample period in

[10]The increase in the number of employers is partly driven by the improved data collection of employer names over time.

[11]The calculation builds on the average exchange rate between U.S. dollar and Chinese yuan from 1998 to 2013, which is about 7.58 RMB/USD.

China.

The summary statistics are reported in Table 2,[12] following Table 1 which defines all variables. On average, each industry includes 5,210 U.S. establishments and 1,208 Chinese firms, employing 124,000 and 496,100 people, respectively. The average number of employees is therefore 23.8 (410.7) in the U.S. (China). It is not surprising that China firms are overall more labor intensive. The summary statistics of U.S. establishments are comparable to those reported in the earlier studies (e.g., Giroud and Rauh (2019), Kim and Ouimet (2014)). For instance, the wage per employee for the U.S. establishments is around \$55,460 in our sample and is between \$40,520 and \$51,890 for Kim and Ouimet (2014). In a given month, an average industry in the U.S. has 334 job postings, out of which 68.0% are for skilled worker, and 76.8% for first-time posts.

[Insert Table 1 here.] [Insert Table 2 here.]

The average leverage, as measured by the fraction of long-term liability in the total assets for the Chinese establishments, is 12%, slightly lower than the leverage level of public firms alone in China (Gul et al., 2010). The export intensity, defined as the proportion of outputs that are export-bound, was higher for the average Chinese industry (17.83%) than the U.S. average (10.05%). Given the bilateral trade surplus to China's favor, such a gap is not surprising. Finally, the direct help firms receive from the Chinese government is visible: for an average industry, 12.4% of the firms receive some type of subsidies, and the average industry-level subsidies in a given year amount to RMB 490 million (\$64.6 million) or about 0.26% of the annual sales of the industry. Government subsidies are not unique

[12] Due to the clearance requirement of U.S. Census Bureau, we report pseudo percentiles of each variable (i.e., 25th, 50th (median), and 75th percentiles) as an estimation for the corresponding percentiles. For example, the pseudo 25th percentile is defined as the mean value for the subsample between 24th and 26th percentiles.

in China, but are common in most major economies.[13] However, the subsidy on the U.S. side is not recorded in the Census database, and is not a focus of our study.

Building our study based on comprehensive and mandatory national surveys of business establishments in both countries is crucial to mitigate the data limitation associated with the conventional data sources covering only publicly traded firms. In 1998 (2015), public-listed U.S. firms accounted for about 15.6% (11.2%) of the establishments in the U.S. manufacturing sector, and 34.3% (28.8%) of employment. On China's side, public firms account for a much smaller share of business activities. According to CEIC and China's National Bureau of Statistics in 2015, the employment of all public domestic firms in China accounts for 2.4% of total employment in China, while the same shares in earlier years were even more negligible.

2. The interdependent relations between U.S. and China productions

Given that the U.S. and China are the two largest economies and constitute the largest trading partner pair in the world, it is expected that industrial activities in one country have a ripple effect over industrial activities in the other, especially in the same industry. We begin the analysis with the panel vector autoregression model (VAR) methodology to characterize the potentially two-way lead-lag relations between the measures of economic activities in the United States and China, using the generalized method of moments (GMM) framework (Sims, 1980; Hansen, 1982; Holtz-Eakin et al., 1988). This technique combines the traditional VAR approach with the panel data structure, which allows for unobserved individual heterogeneity at the country-industry level.

The model assumes a simultaneous equation system for industrial outputs at industry

[13]See a recent report (https://www.cfr.org/backgrounder/industrial-policy-making-comeback) by the Council of Foreign Relations in 2021.

(j)-year (t) level for country $c \in \{US, CN\}$ (China and the U.S.). Let $\boldsymbol{y}_t = \begin{bmatrix} y_{US,j,t} \\ y_{CN,j,t} \end{bmatrix}$ be a vector of the endogenous variable, which follows the following structural process:

$$A\boldsymbol{y}_t = B_1\boldsymbol{y}_{t-1} + ... + B_k\boldsymbol{y}_{t-k} + \boldsymbol{\alpha} + C\boldsymbol{u}_t^*, \tag{1}$$

where $\boldsymbol{\alpha} = \begin{bmatrix} \alpha_{US,j} \\ \alpha_{CN,j} \end{bmatrix}$ a vector of country-specific industry fixed effects, and $\boldsymbol{u}_t$ a vector of error disturbances. A, B, and C are all 2×2 matrices. To incorporate the country-specific time fixed effects, we use variables that are demeaned annually within own country. Following the common practice, we use the first difference to eliminate $\boldsymbol{\alpha}$:

$$A\boldsymbol{y}_t = B_1\Delta\boldsymbol{y}_{t-1} + ... + B_k\Delta\boldsymbol{y}_{t-k} + C\boldsymbol{u}_t, \tag{2}$$

where $\boldsymbol{u}_t = \Delta\boldsymbol{u}_t^*$. We impose the condition $E(\boldsymbol{u}_t\boldsymbol{u}_t') = I$ and $E(\boldsymbol{u}_t\boldsymbol{u}_{t'}') = 0, \forall t \neq t'$, without loss of generality.

In Equation (2), we express output variables ($\boldsymbol{y}_t$) in logarithm terms so that their differenced version ($\boldsymbol{y}_t$), log-growth rate, is stationary. Equation (2) allows each endogenous variable, output growth in either the U.S. or China, to be a function of the lagged endogenous variables. Moreover, when $A \neq I$, the system also incorporates contemporaneous relationship among the two endogenous variables. The error disturbances $\boldsymbol{\varepsilon}_t = C\boldsymbol{u}_t$ may also be contemporaneously correlated because each of them is a linear combination of the fundamental structural shocks $\boldsymbol{u}_t$, which are constructed to be mutually orthogonal.

The literature has developed standard methods to identify (1) by imposing necessary constraints on the matrices. The most common method of identification is to set $A = I$, and require C to be triangular. Or equivalently, require A to be triangular while setting $C = I$. Under the first set of conditions, there is a unique triangular C to be recovered from $CC' = \Sigma = E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t')$ using the Cholesky decomposition. If C is lower triangular, then the innovation in the U.S. output will impact Chinese output concurrently, but the innovation in Chinese output will only impact the U.S. with a lag. If C is upper triangular, then the reverse order is true. To maintain a priori agnosticism, we estimate the model separately under the lower and upper triangularity conditions (which will result in different impulse-response functions). Finally, due to the relatively short time series in panel data, we restrict the maximal lag $k = 2$.

Table 3 reports the estimates of the coefficient matrix B. Panel A reports the dynamic interdependent relationship between the logarithm of establishments in a U.S. industry (the outcome variable in columns (1) and (2)) and the logarithm of firms in the corresponding industry in China (the outcome variable in columns (3) and (4)), at the industry-year (ISIC 4-digit) level. The independent variables include the lagged outcome variables in years $t-1$ and $t-2$ in both countries. $y_{c,j,t-1}$ and $y_{c,j,t-2}$ are instrumented by the third to sixth lags of $y_{c,j,t}$ ($c \in \{US, CN\}$) following the method adopted in Head et al. (2014) and Love and Zicchino (2006).[14] We incorporate country-specific industry fixed effects in all columns and country-specific year fixed effects in columns (2) and (4). Columns (1) and (3) are estimated as a system as specified in equation (2), and so are columns (2) and (4).

[Insert Table 3 here.]

The coefficients on $log(Firm_{CN,t-1})$ and $log(Firm_{CN,t-2})$ in column (1) and $log(Firm_{CN,t-1})$ in column (2) are significantly negative at the 1% and 5% significant levels, respectively. The result suggests that the emergence of new firms in China predicts exits (or lower growth) by establishments in the corresponding industry in U.S. The insignificant estimates of the coefficients on $log(Establishment_{US})$ in columns (3) and (4) indicate that

[14]The identification comes from the orthogonality between the lagged regressors and the innovation in the current period in the first-difference model.

data do not support the prediction that entry and exit of U.S. establishments lead to changes in any direction among Chinese firms. Thus, we uncover an asymmetric dynamic relationship between firms in U.S. and China. Whereas the number of firms in China is a significant negative predictor of the number of establishments in the U.S., the corresponding reverse effect of U.S. establishments on the number of firms in China is largely absent empirically. In particular, a 1% increase in the numbers of Chinese firms predicts a 0.14% decrease in establishments in the corresponding industry in the U.S., based on the coefficient estimates in column (2).[15]

Panel B reports the interdependent relationship between the employment in a U.S. industry and the same industry in China. The outcome variable in columns (1)-(2)(columns (3)-(4)) is the logarithm of the number of employees in a U.S. (China's) industry in year t. The negative and significant coefficients on $log(Employment_{CN,t-1})$ in columns (1)-(2) indicate that the increased employment of Chinese firms predict the decline in employment in the corresponding U.S. industry. In particular, the coefficient on $log(Employment_{CN,t-1})$ suggests that a 1% employment expansion in Chinese firms predicts a 0.1% shrinkage in U.S. employment in the same industry. A similar relation also exists in the opposite direction, i.e., the negative coefficient on $log(Employment_{US,t-2})$ in column (3) indicates that growing employment on the U.S. side predicts reduction of Chinese employment in the same industries two years down the road. This relationship, however, is weaker, and also far from significance as shown in columns (3) and (4) of Panel B.

A natural way to trace out the dynamic impact of a chance from either side is through the impulse-response functions, taking into account the two potential possibilities attributing the original exogenous source of shock to be from either China or the U.S.,

[15]In terms of the diagonal blocks, coefficients are either significantly positive or insignificant. This is likely to be driven by a positive autocorrelation in the growth rate of establishments in the short run.

corresponding to the two forms of Cholesky decompositions of the covariance matrix of the error disturbances in 2. Results are plotted in Figure 1. In Subfigures (a) and (b) (Subfigures (c) and (d)), the impulse variable is $log(Establishment_{US})$ ($log(Firm_{CN})$), and the response variable is $log(Firm_{CN})$ ($log(Establishment_{US})$). Subfigures (a) and (c) (Subfigures (b) and (d)) build on the assumption attributing the original exogenous source of shock to be from China (the U.S.). All the significant effects are confirmed as Granger causality using the Granger (1969) test.

Subfigures (a) and (b) indicate that an initial increase in the number of firms in a Chinese industry leads to a lasting negative effect on U.S. establishments. The effect is significant for at least six years regardless of which of the two forms of Cholesky decomposition we adopt. In contrast, Subfigures (c) and (d) show that the effect of the U.S. establishments on the number of firms in the corresponding Chinese industries is insignificant. Overall, the relationship is robust that high birth rates of firms in China predict lower firm and employment growth (or exits) in the U.S., but the relations in the reverse direction from U.S. to China are much weaker and generally lack consistency and significance.

[Insert Figure 1 here.]

A large literature, summarized in Acemoglu et al. (2016), shows that the surge in import competition from China after 2000 has been a major force behind the reduction in U.S. manufacturing employment. To test this effect in our setting, we interact measures of Chinese economic activities in regression (1) with a measure of export intensity for industries in China. If imports from China outcompete U.S. producers, we expect the measures of economic activity from China to become a stronger negative predictor for consequent measures of economic activity in the U.S., especially for U.S. employment.

Table 4 reports the results. The outcome variables in columns (1)-(4) and (5)-(8) are the logarithm of establishments and the employment in a U.S. industry during year t, respectively. $Export_{CN,t}$ is the export intensity of an industry in China, which is measured by the average percentage of revenue that is attributed to export in the industry in a given year.[16] The significantly negative coefficients on $Firms_{CN,t-1} * Export_{CN,t-1}$ and $Firms_{CN,t-2} * Export_{CN,t-2}$ suggest that the adverse effect of growing number of firms in China on the economic activities in the U.S. is particularly pronounced when new firms in China emerge in export-intensive industries, highlighting the role of international trade in competition spill-over across the border. Moreover, the effect on employment is even stronger than that on business establishment, confirming the findings of Acemoglu et al. (2016) and Cai et al. (2020) at a more macro level.[17]

[Insert Table 4 here.]

Ownership is often a critical issue in research of Chinese firms, given the nation's historical transition from a state-dominated economy. We thus explore the role of firm ownership in China in the lead-lag relationship between economic activity in China and U.S. Specifically, we consider three types firms in China: state-owned firms, domestic private firms, foreign-owned firms. In our sample, the number of state-owned (domestically privately owned) firms decreased (increased) from 29.7% to 3.0% (52.4% to 86.2%) during 1998 - 2013. The employment shares changed from 58.2% to 6.7% (32.9% to 77.1%). Table 5 reports the results that sort on ownership types.

[16] We use the demeaned export intensity in the specification to make coefficients easier to interpret.

[17] We are agnostic about the impact of China shock on the employment of other industries related on the ones that are directly affected. Autor et al. (2016) show that employment gains in other industries were far from offsetting lost employment in the U.S. industries that were more exposed to import competition. Wang et al. (2018), on the other hand, find that the total impact of trading with China is a positive boost to U.S. employment because of the employment stimulation outside the manufacturing sector through the downstream channel.

We start with foreign-owned firms in China in order to learn whether the relation documented in Table 3 could have been driven by the reallocation of western firms (including those from the U.S.) to China. Panel A reports the dynamic interdependent relationship between the logarithm of establishments in a U.S. industry and the logarithm of foreign-owned firms in the corresponding industry in China, using the same specification in Table 3. The coefficients on $log(Firm_{CN,foreign,t-1})$ and $log(Firm_{CN,foreign,t-2})$ in columns (1) and (2) are insignificant, and so are the coefficients on $log(Establishments_{US,t-1})$ and $log(Establishments_{US,t-2})$ in columns (3) and (4). The result suggests that the birth of foreign-owned firms in China does not predict exits by establishments in the same industry in the U.S. In other words, the exit or low growth of U.S. factories are not due to U.S. multinationals setting up establishments in China that substitute their U.S. production. Instead, Chinese domestic firms more likely are the driving force in displacing U.S. firms.

[Insert Table 5 here.]

To further illustrate whether the two types of domestically owned Chinese firms play different roles, Panels B and C of Table 5 report the dynamic interdependent relationship between the establishments in a U.S. industry and the number of state-owned firms (panel B) and that of the domestic private firms (panel C) in China, respectively. The coefficients on $log(Firm_{CN,state,t-1})$ and $log(Firm_{CN,state,t-2})$ in columns (1) and (2) of panel B are insignificant, suggesting that state-owned firms in China do not drive the dynamic relationship either. In contrast, Panel C shows that the coefficients on $log(Firm_{CN,private,t-1})$ and $log(Firm_{CN,private,t-2})$ in column (1) are significantly negative at the 1% and 5% levels, respectively, and the coefficient on $log(Firm_{CN,private,t-2})$ in column (2) are significantly negative at the 5% significant level. The result suggests the birth of domestic private firms in China explain the subsequent decline in the U.S. establishments in the corresponding industry.

The combined results from the three panels in Table 5 highlight the fact that the relentless ascendance of private firms in China since the late 1970s have made them, as a whole, an archcompetitor of U.S. firms in the 21st Century. Such a composition is consistent with the model by Song et al. (2011) and Allen et al. (2005), which posits that private firms outshine state firms, despite the latter's preferential accesses to capital, in a globally competitive product market, by maintaining higher productivity thanks to adequate financing from savings, alternative financing channels and export surpluses. Our results also indicate that the Chinese firms end up substituting production by U.S. firms, instead of just driving them to China offshoring.

The lead-lag relation in the changes of economic activities in the same industries for U.S. and Chinese companies could be consistent with several potential economic mechanisms. On one side, firms in China—especially those in high export intensity industries—can be the fastest to respond to changes in global investment opportunities. If there is a first-mover advantage, there could be a negative effect on their industry peers in the U.S. Moreover, firms in China could be anticipating and accommodating U.S. firms' strategic choices to focus on certain industries (e.g., ones with high value added) while retreating from the production of others, especially labor-intensive products. Under such a scenario, the production substitution is not necessarily against the will of the U.S. manufacturers. However, the reverse could also be true. That is, similar observable patterns could be driven by U.S. firms losing ground in industries in which they actually desire to lead, but fail to do so due to the strengthened competition from Chinese players. If the latter obtain help from the government, the process could be accelerated. The coming section looks into the impact of government support.

3. Impact of Government Support

3.1. Subsidies and Five-Year Plans: Empirical Set-up

In this section we demonstrate how Chinese government's decisions to enhance the country's global standing in certain industries leads to such industries' relative decline in the U.S. To start with, we examine the pre-trend of the measures of aggregate economic activities in the affected industries. The reduction in industry aggregate output prior to subsidies would be consistent with the Chinese government responding to deteriorating investment opportunities and its attempt to mitigate the negative effects on Chinese firms (perhaps for considerations of employment). If the aggregate output remains constant or even grows prior to subsidies, the government is more likely to be motivated by strengthening global competitiveness of domestic firms.

Table 6 reports the results. Panel A and Panel B report how much the aggregate output of a Chinese industry and the corresponding U.S. industry predict the provision of subsidies. Since China's subsidy data is not available from 2008–2010, the analysis builds on a smaller sample than Table 4. The outcome variables are the logarithm of the subsidy a Chinese industry receives in millions RMB in a given year in columns (1)-(3), and the logarithm of the number of subsidized firms in an industry in columns (4)-(6). In panel A, the explanatory variables $log(Output_{CN,t-1})$ and $log(Output_{CN,t-2})$ are defined as the logarithm of the output of an ISIC-4-digit industry in China in a give year. In panel B, the explanatory variables $log(Output_{US,t-1})$ and $log(Output_{US,t-2})$ are defined as the logarithm of the output of an ISIC-4-digit industry in U.S. in a give year. Panel C incorporates the explanatory variables from both panel A and panel B.

[Insert Table 6 here]

The results in Panel A show that industry output growth in China is a positive and significant predictor of subsidies, regardless of whether we consider nominal subsidies or the number of firms in the given industries that receive subsidies. The results suggest that subsidies were mostly dispensed into growing, rather than declining industries in China. In contrast, Panel B shows that lagged output growth of U.S. industries is not in any way significantly related to subsidies provided to firms in China, suggesting that Chinese government does not subsidize industries based on their recent trends in the U.S. In particular, there is no evidence that the U.S. counterparts of the subsidized firms were losing ground prior to the subsidies. Panel C further confirms the findings from panels A and B in a more comprehensive specification. On the net, the empirical evidence lends more support to the hypothesis that the ensuing decline of the same industries in the U.S. is due to a displacement effect rather than to the hypothesis that Chinese government chased down industries that had already been declining in the U.S.

We next explore the impact of shocks of Chinese government support for certain industries. To this end, we resort to China's Five-Year Plans, a series of social and economic development initiatives issued since 1953. The Five-Year plans originated from the former Soviet Union and serve as the highest level of the central government's industrial policies as they highlight the key sectors the government plans to encourage and to support. China's Five-Year Plans epitomizes broader industrial policy, i.e., targeted government interventions to promote specific economic sectors with the aim of increasing their productivity and spreading positive externalities throughout the economy. Policies of such nature are not unique to China; in the last decade there has been a revival of interest among policy makers around the world (Warwick and Nolan, 2014; Stiglitz et al., 2013; Cherif and Hasanov, 2019).

More specifically, China's Five-Year Plans aim to provide guidelines to social and economic development, such as planning major government-sponsored projects, adjusting industrial structure, determining the allocation of government resources, among others. The encouraged industries represent about 15% of China's GDP at their announcements. The particular plans we study are the Tenth, Eleventh, and Twelfth Five-Year Plans, announced in 2001, 2006, and 2011, for analyses using the LBD data, and the Twelfth and Thirteenth (announced in 2016) Five-Year Plan for analyses using the Burning Glass data. The common Twelfth Plan in both analyses serve as a "bridge" for us to make consistent inferences over a longer sample period. Each plan covers the five years following the year of announcement. For example, the Tenth Five Year Plan covers 2001-2005. We obtain the identities of industries that the government "encouraged" in those Plans following the definition used by Chen et al. (2017).

The original data builds on "Index for Listed Firms Industry Classifications" published by the China Securities Regulatory Commission (CSRC) in 2001. To match the encouraged industries to our main sample, we first transfer the CSRC industry types to CIC industry code (2-digit to 4-digit) through the concordance provided by the CSRC. Then, we translate the CIC industries into a list of ISIC 4-digit industries and identify the ISIC industries encouraged by a Plan using the CIC-ISIC matching table from the National Bureau of Statistics of China. For example, ISIC industry class 3210 (manufacture of electronic valves and tubes and other electronic components) is matched with CIC industry classes 406, which is matched to the electronic components manufacturing industry (CSRC C5115) encouraged in the Tenth Five-Year Plan.

We then estimate the following regression:

$$y_{c,p,j,t} = \theta_1 Post_{p,t} \times \text{Treated}_{p,j} + \alpha_{c,p,j} + \alpha_{c,t} + \varepsilon_{c,p,j,t}, \tag{3}$$

The regression builds on the stacked panel data that covers the relevant industries for each of the three Five-Year Plans over the ten years around each plan.[18] In other words, the sample is constructed by stacking three subsamples, each consisting of the treated and control industries for a specific plan from five years before the plan to the last year covered by the plan.

In equation (3), $Post_{p,t}$ is a dummy variable equal to one for the five years covered by Plan p and zero for the previous five years. The classification of a "treated" industry for Plan p requires that it passes two filters: $Treated_{p,j}$ is a dummy variable equal to one if the industry is encouraged in the plan, *and* it experiences an above-median subsidy growth in the post-plan period from the level in the pre-plan period, and zero for the industries not encouraged in the plan.[19] The encouraged industries constructed with the double filters on average account for about 9% of China's GDP. If an industry is encouraged in multiple plans during our sample period, we classify the industry as "treated" only for the first plan that supports the industry, and exclude it from the subsample for the other plans.[20]

The dependent variable $y_{c,p,j,t}$ is a measure of economic activity for industry j in country c during year t, where $c = \{CN, US\}$. The regression incorporates two fixed effects: $\alpha_{c,p,j}$ is the country-plan-specific industry fixed effect (ISIC 4-digit), and $\alpha_{c,t}$ is the country-specific year fixed effect. The first fixed effect ensures that the estimated outcome is based on within-industry (of one that is covered by a Plan) change from before to after the policy change, and absorbs unobserved cross-industry heterogeneity. The second fix effect controls for economy-wide shocks and trend at the country-year level.

[18] An exception is the Tenth Five-Year Plan, of which the subsample spans from 1998 to 2005 because CIED starts from 1998.

[19] The filter of above-median subsidy ensures that the encouraged industry actually received significant government financial support. Our results are robust to not imposing this filter which requires ex post information.

[20] The exclusion of the repeatedly encouraged industries and the definition of $Treated$ suggest that the sample size of the stacked panel is likely to be smaller than the baseline panel.

3.2. Industrial activities

Table 7 Panel A reports the estimation of equation (3). The outcome variables in columns (1)-(3), (4)-(6), and (7)-(9) are logarithm of the number of firms in a China industry, the number of establishments and employment in a U.S. industry in a given year denominated by the level in the first year of the pre-shock period.[21] Hence, coefficients could be interpreted as the effect of a regressor on the growth rate of the business activities. Across all specifications, the coefficients on $Post \times Treated$ are significantly positive for the economic activities in China and significantly negative for the corresponding industries in the U.S. After the shock, the treated industries in China expanded more than nontreated industries, in terms of the number of firms. In contrast, firms in corresponding industries in U.S. experience slower growth in the number of establishments and employment than firms in other industries. On average, the targeted industries in China see a surge of about 15% in the number of firms after the release of a Five-Year Plan relatively to the non-treated industries, whereas the number of establishments and employment in the corresponding U.S. industries decline by about 5%.

[Insert Table 7 here]

Note that the analyses are performed at the business establishment level, as opposed to firm level using standard databases such as Compustat. In fact, Internet Appendix Table A2 shows that the number of Compustat firms remains more or less stable post shock, suggesting that our key finding that the China production shocks predict decrease in the number of U.S. factories could not have been uncovered in the absence of such granular data. This result shows that the granular level of analysis is crucial for our study.

[21] For the 10th, 11th, and 12th Five Year Plan, the outcome variables are denominated by the level in 1998, 2001, and 2006, respectively. We use the level in 1998 instead of 1996 as the denominator for the 10th Five Year Plan because the CIED data start from 1998.

Next, we examine whether the negative effects of Five-Year Plans on U.S. industries are stronger when plans encourage industries with preexisting high export intensity. We expect the response of U.S. firms to be stronger if they face more direct competitive pressure from imports from China, or if the growth in production capacity in China feeds into export to the U.S. Panel B reports the differential effect on industries with various export intensity. The outcome variables in column (1) (column (2)) are the logarithm of the ratio between the average number of establishments (employment) for the post-period and the pre-period in a U.S. industry. $Export_{CN,t-1}$ is defined as the average percentage of revenue that is attributed to export in a Chinese industry during year $t-1$. The negative coefficient on $Treated * Export_{CN,t-1}$ shows that indeed the effect of the Five-Year Plans is significantly more pronounced when export-intensive industries in China are encouraged. In particular, a one standard deviation increase in the export intensity of a target Chinese industry is associated with 4.7% (6.2%) additional decline in the number of firms (employment) for the corresponding U.S. industry after a plan.

3.3. Impact on firm demand for labor: Evidence from job posting

In this section we explore the impact of the Five-Year Plans on U.S. employment via demand for labor. The job posting data (especially the first-time postings) from Burning Glass (introduced in Section 1) capture U.S. firms' desire to hire, distinguished from employment level which could also be affected by labor supply conditions. According to Gutiérrez et al. (2020), job posting is a forward-looking indicator for future firm growth, and its movement even leads market valuation. Hence, if negative changes in firm desire to hire materialized in subsequence to the announcements of Five-Year Plans, a reverse causality is highly unlikely.

Table 8 reports the estimation of equation (3) at the industry-month level, where the dependent variables are the logarithm of industry-wide job postings, scaled by the level in the first year of the pre-shock period. All regressions incorporate both county-specific year-month fixed effect and country-plan specific industry fixed effect, hence variation comes from job postings by treated and untreated firms within an industry-month cell. Because the Burning Glass data span 2007, and 2010-2019, it covers the time periods associated with the Twelfth and the Thirteenth Five-Year Plans. Note that the later plan was not in the sample of the previous Table 7, hence the first two columns of Table 8 reports results with the Twelfth Plan only, to ensure that expanding the sample to 2019 adds statistical power but conveys the same economic message as using the same sample period coverage as our main analyses (e.g., Tables 3 to 7).

[Insert Table 8 here]

The first two columns show that job postings, the most direct measure for firms' desire to hire, drop by about 8% in treated relative to the other industries during the five-year period after the announcement of a Five-Year Plan, and the effect is significant at the 1% and 5% levels. Columns (3) and (4) show that the drop is significant in both skill and unskilled job openings. We define skill jobs as those that requires above 14 years of education. In fact, the drop for skilled labor (at 9.2%) is higher than that for unskilled labor (at 6.6%). To the extent that industries that are prized in the U.S. require more skills, the results suggest that the China shocks created by the recent Five-Year Plans are displacing disproportionately skilled workers likely in industries high up in the food chain. This is in contrast with the early-year wisdom that expansion of production in China mostly displace labor intensive, low-skill jobs in the U.S. and echoes the findings in Hoberg et al. (2020) that Chinese firms actively compete with U.S. firms in technology and product innovation, and more so in industries that develop or deploy new technologies (Han et al., 2020). Section 4 will provide more insights into the changing nature of the industries that the government supports. Finally, Columns (5) and (6) further reveal a contrast that only first-time job postings (a cleaner measure for firms' desire to hire) of the treated industries exhibit significant decline, but not the repeat postings which reflect more of (the shortage of) labor supply.

3.4. Tracing out the impact of Five-Year Plans from the preexisting trends

Estimates from regression (3) can be interpreted as causal only if the following parallel trends assumption holds: the industries in the treated and control groups would have seen their economic activities evolve similarly absent the Five-Year Plans. While the parallel trend assumption is inherently nontestable, we shed light on the premise by examining pre-existing trends. More specifically, we examine how the outcome variables evolve around the release of the Five-Year plans for the treated and control groups by estimating the following regression:

$$y_{c,p,j,t} = \sum_{\tau=-3}^{4} \theta_\tau D_{p,t}^{\tau} \times \text{Treated}_{p,j} + \alpha_{c,p,j} + \alpha_{c,t} + \varepsilon_{c,p,j,t}. \tag{4}$$

We estimate the regression based on the same stacked panel data as for equation (3). $D_{p,t}^{\tau}$ is a dummy variable equal to one for the τ^{th} $(-\tau^{th})$ year after (before) the announcement of Five-Year Plan p, and zero otherwise. The definitions of other variables are consistent with equation (3). The coefficient θ_τ measures the gap between the treated and control industries on the economic activities during the τ^{th} $(-\tau^{th})$ year after (before) the shocks. The results are reported in Table 9 and plotted in Figure 2.

[Insert Table 9 here]

[Insert Figure 2 here]

The outcome variables in columns (1), (2), and (3) are the logarithm of the firms in a China industry, the establishments and employment in a U.S. industry in a given year denominated by the level in the first year of the pre-shock period. Insignificant coefficients on $Treated * D^{-\tau}$ for the pre-shock periods suggest that, before the Plans, the industries in the treated and control groups share a similar trend in their economic activities both in China and in the U.S., supporting a parallel pre-trend. In addition, almost all coefficients on $Treated * D^{\tau}$ for post-shock periods are significantly positive for the economic activity in China and significantly negative for the corresponding industries in the U.S. This estimation result provides further support for the hypothesis of the stimulating effect of the industrial policies on Chinese firms and the adverse effect on the corresponding U.S. industries.

It could still be argued that the absence of preexisting trends does not imply a full parallel trend in that the Chinese government could have chosen to implement supportive policies in industries which were just about to see a reflection point such that China would have overtaken the U.S. in those industries right at the time but in the absence of the plans. We test such a hypothesis by resorting to market valuations and stock returns. Our premise is that if stock prices are efficient—to the extent that information about the future of U.S. economy (that is available to Chinese government) is priced without systematic bias—the information about future trends should also have been priced. In other words, if certain industries in the U.S. were about to be outcompeted by their peers in China, the stock market valuation should have reflected that imminent negative prospect.

Based on such an argument, columns (6)-(8) in Table 9 report estimates of regression (4) with the following market-based and forward looking economic variables for U.S. industries: Tobin's Q, cumulative stock returns, and job postings. Tobin's Q is, averaged over all public firms in the industry, the ratio of the sum of the market value of equity and the book value of debt, over the book values of equity and debt. Similarly, cumulative stock returns are value-weight averaged over all public firms in a given industry. $Job\ Postings_{US}$ is the total number of job postings for all firms in an industry in a given month.

The results indicate that these variables for treated and control groups do not diverge before the shock, suggesting that neither the U.S. stock market nor the U.S. firms were anticipating the relative weakening of the industries that were targeted by China's Five-Year Plans soon after. Moreover, the stock market appears to be relatively efficient in processing new information in that the stock returns and industry valuation adjust by the end of the year of announcement, rather than after the implementation of the plans. In contrast, employment, establishments, output, wage, and job postings all reacted a year or two down the road.

We would like to note that it is generally considered implausible in the vast economics literature to assume that a government can better process information to predict and anticipate evolutions in economic activities than the aggregate wisdom of the securities market. In fact, the ability to aggregate information to guide resource allocation is considered the fundamental strength of markets over any government alternatives. Thus, the most likely explanation for the findings in Table 7 could be attributed to a real impact of China's government policies on the Sino-U.S. race to lead in the targeted industries.

3.5. U.S. firms with presence in China: How are they affected?

The impact of China's Five-Year Plan on the U.S. firms should be heterogeneous for those with presence in China versus those without for two reasons. First, U.S. firms with their own facilities in China or joint ventures with local partners benefit from the extra public goods (e.g., infrastructure and government services) as a result of government policies promoting the specific industries. Second, most of the government preferential policies (e.g., tax rebates, research grants, and talent recruiting) are applicable to all firms residing in China, including foreign-owned and joint ventures.[22] Therefore, U.S. firms with

[22] For example, the government subsidy for the production and sales of electric vehicles since 2009 applies to domestic, joint ventures and foreign-owned firms in China. Foreign firm recipients include Toyota, Tesla,

significant China presence may offset the negative impact demonstrated in the previous section.[23] This section tests this hypothesis on U.S. public firms for which the relevant data are available.

The key variable to the test is a measure for a U.S. firm's production presence in China, *China Presence*, a firm-year dummy variable which we construct based on the textual information in 10-Ks from our main sample period 1998–2013. We set *China Presence* to be one if the 10-K of a firm-year includes a discussion about a manufacturing facility in China or mentions an operation site/facility in China, and to be zero if such a discussion or mentioning is absent. More specifically, we extract all sentences in a 10-K that include "China" and at least one of the key words that indicate production activities.[24] We then manually process the information and code *China Presence* to a firm-year observation accordingly. The procedure identifies 15.6% of U.S. public firms as having significant business presence in China in 1998 and the percentage went up to 51.3% by the end of 2013.

Based on this measure, we conduct a partitioning analysis to examine how China's industrial policies in the five year plans affect the stock returns and Tobin's Q of U.S. public firms with and without significant China business presence separately. The results are reported in Table 10.

[Insert Table 10 here]

Columns (1)–(2) present the effect on U.S. public firms without a business presence in

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Daimler, among others.

[23]If such mitigating effect of China presence exists, we expect the effect manifests itself more in firm value and stock market response than a firm's production activities in the U.S. There is, a priori, no clear prediction how a firm's production in the U.S. could be affected by the increased competition from Chinese counterparts, even if its own production facility in China benefits from the government support.

[24]The list of key words is as follows: facility, facilities, manufacture, manufacturing, manufactured, manufactures, operation, operations, operate, operating, factory, factories, production, producing, produce, produces, produced, plant, plants, site, sites, subsidiary, subsidiaries, establishment, establishments.

China at the release of a five-year plan, and columns (3)–(4) show the effect on U.S. public firms with such a presence. The significant coefficient on $Post * Treated$ in columns (1) and (2) and the insignificant coefficient in columns (3) and (4) suggest that the negative effect of China's industrial policies on the stock returns and Tobin's Q of U.S. firms are concentrated on those firms without a significant presence in China. In particular, the accumulated stock returns (Tobin's Q) of U.S. firms without China business presence decrease by 28.7% (1.34) in the five years after their industries are targeted by a plan. In contrast, firms that set up production establishments in China are able to, on average, completely offset the competitive effects from China's industrial policies. The estimated net effects for these firms are positive (but not statistically different from zero). Such a heterogeneous effect may explain the offshoring to China of U.S. firms in "sunrise industries" in recent years, such as Tesla's factory in Shanghai set up in 2019. Jointly with our findings in Section 2, our analysis shows that instead of being used to displace the U.S. production activity, the U.S.-owned entities in China help U.S. firms mitigate the negative effect of China's industrial policies on firm value.

4. The Evolution of Target Industries

For a long time, labor-intensive firms in China had a natural comparative advantage over similar firms located in the U.S. because of the cheap labor in China. After decades of high growth based on its low-wage advantage and a young population, however, future growth will necessarily depend on increased productivity and more domestic innovation (Wei et al., 2017). In the recent decade, we observe that Chinese firms started to flex muscles in industries with high value-added and high labor productivity in the U.S. In this section, we investigate whether the impact of China's Five-Year Plans on the U.S. firms has varied over time, especially sorted on industries' labor productivity.

Following equation (5), we explore the heterogeneous effect of China's government support on U.S. industries with high and low labor productivity, and separately for the Five-Year Plans in the early period (i.e., 10th and 11th Plans) and the more recent period (i.e., 12th and 13th Plans).[25]

$$\begin{aligned} y_{c,p,j,t} = {} & \theta_1 Post_{p,t} \times \text{Treated}_{p,j} \times LaborProd_{US,-1,p,j} + \theta_2 Post_{p,t} \times \text{Treated}_{p,j} \\ & + \alpha_{c,p,j} + \alpha_{c,t} + \varepsilon_{c,p,j,t}, \end{aligned} \tag{5}$$

where c, p, j, t denote county, plan, industry, and year. Similar to equation (3), the regression builds on the stacked panel data that covers relevant industries for each of the focal plans. $LaborProd_{US,-1,p,j}$ is the quintile of a U.S. industry by labor productivity, measured in the year before the release of plan p. Following the literature, we define labor productivity as the total output divided by the number of workers in a U.S. industry. This definition implies that a labor-productive industry is less labor-intensive (i.e., employs fewer employees for a unit of output). All other variables are defined in Table 1 and Section 3.

[Insert Table 11 here]

Panel A of Table 11 builds on the 10th and 11th Plans, and Panel B is based on the 12th (and 13th) Plans. In both panels, column (1) reports the heterogeneous effect on China's firms, and columns (2)–(3) examine the impact on establishments and employment in the corresponding U.S. industries. Since our main focus is to understand the impact of China's government support on U.S. firms, we measure an industry's labor productivity based on the relevant information on U.S. side.

Consistent with results reported in the previous section, the significantly positive coefficient on *Post* $*$ *Treated* in column (1) of Panel A suggests the industries experienced

[25] Table A1 reports the summary statistics of the subsamples for the two periods separately.

expansion after being targeted by 10th and 11th Five-Year Plans, which started from 2001 and 2006, respectively. Interestingly, the significantly negative coefficient on $Post * Treated * LaborProd_{US,-1}$ suggests that the high labor productivity industries in China experienced shrinkage or slower expansion relative to lower-labor-productivity industries after being targeted by 10th and 11th Five-Year Plans. Thus, during the earlier part of our sample, Five-Year Plans targeted industries that were of low labor productivity, or high labor intensity.

The patterns among the same variables are remarkably different in panel B, which is based on the 12th and 13th Plans. The significantly positive coefficient on the triple interaction term in column (1) of panel B suggests that after the 12th Plan (staring from 2011), it was the high labor productivity industries among the treated firms in China that experienced a stronger growth in the number of firms. This result indicates that during the later part of our sample, Five-Year Plans primarily targeted higher-labor-productivity, or less labor-intensive industries. The coefficients on the triple interaction terms in column (1) of panels A and B are significantly different at the 1% level. This finding indicates that the focus of the industrial policies embedded in the Five-Year Plans shifted from low labor productivity to high labor productivity industries, whereas the latter ones are also likely prized in the U.S.

Columns (2)–(3) in Panel A and (2)–(4) in panel B consider the effects of Plans on U.S. firms. The evidence indicates a concurrent shift in the opposite direction in terms of how U.S. industries are affected by the plans relative to industries in China. The positive coefficients on the triple interaction in columns (2)–(3) of Panel A show that, among the targeted industries in the 10th and 11th Plans, their U.S. counterparts with high labor productivity experience smaller deterioration in the growth of number of establishments and employment. In contrast, according to columns (2)–(3) of Panel B, the high labor productivity industries in the U.S. experienced a more pronounced decline in economic activities after the corresponding Chinese industries were encouraged in the 13th Plan. Again, the coefficients in column (2) (column (3)) of Panels A and B are significantly different at the 5% (10%) level, signaling a significant change in the composition of U.S. industries that are vulnerable to Chinese industrial policies. Such a pattern extends to the more recent years covered by the 13th Plan (up to 2019) using the Burning Glass data. According to column (4) of Panel B, the 12th and 13th Plans lead to a disproportionate decline (or lower growth) in job postings by high labor productivity industries in the U.S.

5. Conclusion

Merging U.S. and China establishment-level data, we find that high birth rates of Chinese firms predict same-industry firm exits and lowered employment in the U.S., particularly in the export-intensive industries. We resort to China's Five-year Plans for a tighter causal inferences as shocks to China's industry growth. These shocks were not preceded by low productivity or valuation in the same industries in the U.S., but were followed by shrinkage of establishments and employment in these industries. Our findings generally support the hypothesis that government support on the China side shapes the relatively competitive positions of industries that both countries aspire to lead.

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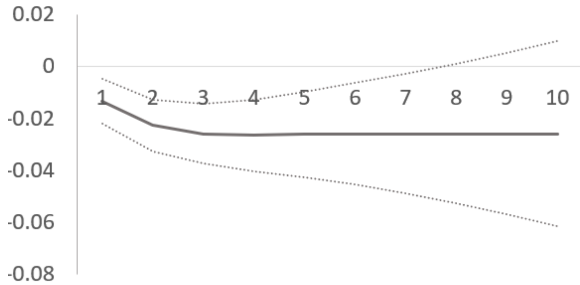
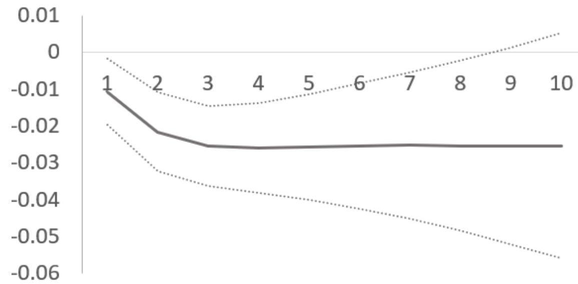
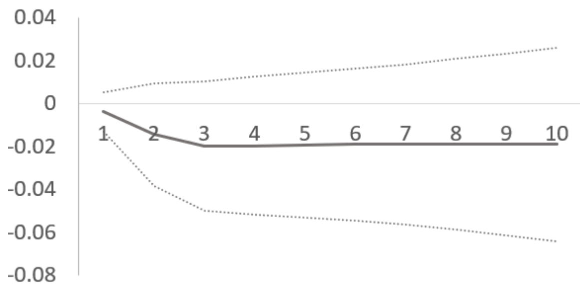


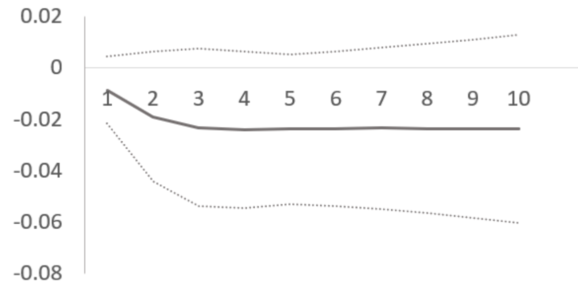
(a) The effect of Chinese firms on U.S. establishments (China innovation as exogenous).



(b) The effect of Chinese firms on U.S. establishments (U.S. innovation as exogenous).

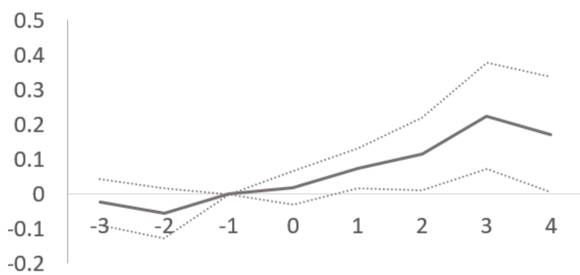


(c) The effect of U.S. establishments on Chinese firms (China innovation as exogenous).

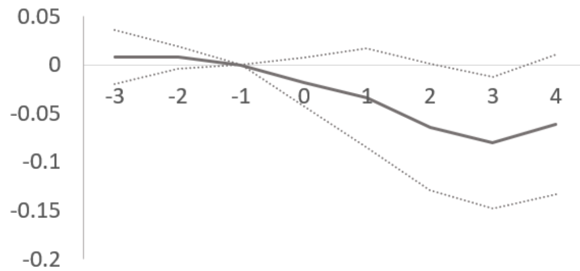


(d) The effect of U.S. establishments on Chinese firms (U.S. innovation as exogenous).

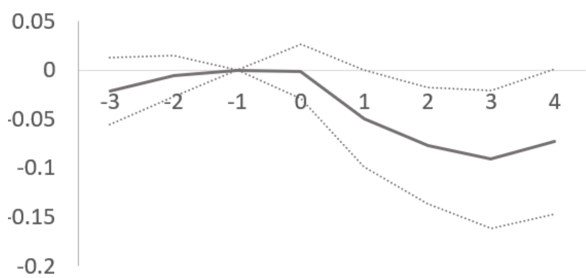
Figure 1: **Impulse response analysis.** The figures report the result of the impulse response analysis corresponding to Panel A of Table 3. The horizon axis represents the year relative to the shock. The solid line represents the impulse response in a given year, and the dotted lines represent the 95% confidence internals of the estimates.



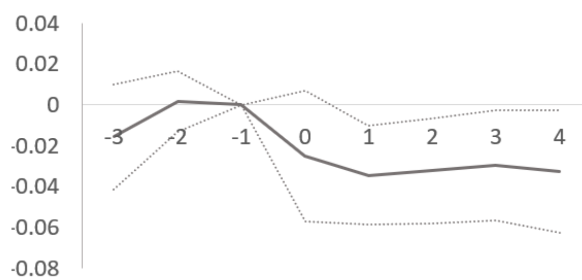
(a) The number of Chinese firms in an industry around the release of a Five-Year Plan.



(b) The U.S. establishments in an industry around the release of a Five-Year Plan.



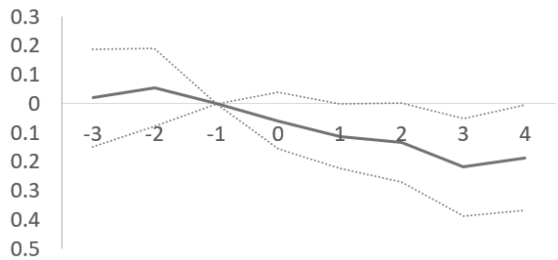
(c) The employment in a U.S. industry around the release of a Five-Year Plan.



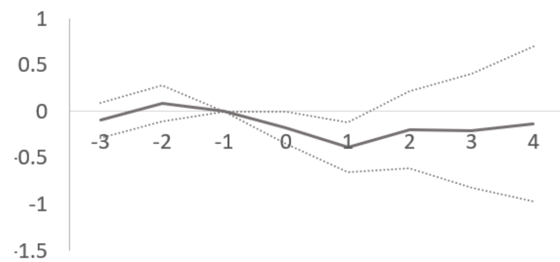
(d) The average income of a U.S. industry around the release of a Five-Year Plan.

(Figure continues)

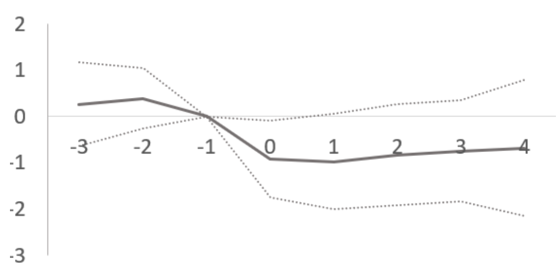
Figure 2: Continued.



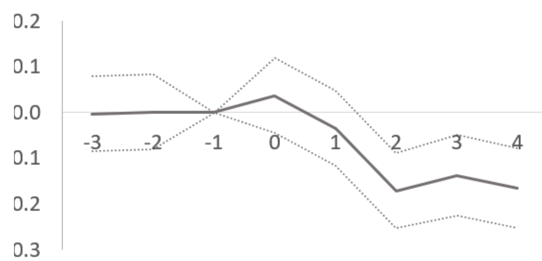
(a) The output of a U.S. industry around the release of a Five-Year Plan.



(b) The accumulated stock return of a U.S. industry around a Five-Year Plan.



(c) The Tobin's Q of a U.S. industry around the release of a Five-Year Plan.



(d) The job postings of a U.S. industry around a Five-Year Plan.

Figure 2: **Parallel trends test.** The figures report the result of the parallel trends analysis corresponding to Table 9. The horizon axis represents the year relative to the release of a Five-Year Plan. The solid line represents the difference between the treated and the control groups in terms of the corresponding outcome variable. The dotted lines represent the 95% confidence intervals of the estimates.

Table 1: **Variable Definitions.**

Variable	Definition
$Firms_{CN}$	Number of firms in an ISIC-4 digit industry in China in a given year
$Employment_{CN}$	Total employment in an ISIC-4 digit industry in China in a given year
$Establishments_{US}$	Number of establishments in an ISIC-4 digit industry in the U.S. in a given year
$Employment_{US}$	Total employment in an ISIC-4 digit industry in the U.S. in a given year
$Export_{CN}$	The export intensity of a Chinese industry in a given year. An industry's export intensity is defined as the total export shipment as a percentage of the total revenue of all firms in the industry.
$Export_{US}$	The export intensity of all firms appearing in the ASM and belonging to a U.S. industry in a given year. An industry's export intensity is defined as the total export shipment as a percentage of the total shipment of all firms in the industry.
$Firms_{CN,foreign}$	Number of foreign-owned firms in an ISIC-4 digit industry in China in a given year. A firm is classified as foreign-owned if foreign entities or individuals provide more than 50% of the total paid-in-capital.
$Firms_{CN,state}$	Number of state-owned enterprises in an ISIC-4 digit industry in China in a given year. A firm is classified as a state-owned if Chinese government provides more than 50% of the total paid-in-capital.
$Firms_{CN,private}$	Number of private domestic firms in an ISIC-4 digit industry in China in a given year. A firm is classified as private domestic if non-government domestic entities or individuals provide more than 50% of the total paid-in-capital.
Subsidy (nominal)	The sum of the subsidies an industry received in a given year (in millions RMB)
Subsidy (# of firms)	The total number of subsidized firms in an industry in a given year
$Output_{CN}$	The total output of an ISIC-4-digit industry in China in a year (in billions RMB)
$Output_{US}$	The total output of all firms appearing in the ASM for an ISIC-4-digit industry in U.S. in a given year (in billions USD), which is derived from the variables in CMF (ASM) using the formula: tvs (total value of shipment)+ fie (inventories - finished goods at the end of a year)- fib (inventories - finished goods at the beginning of a year) + wie (inventories - work in process at the end of a year) - wib (inventories - work in process at the beginning of a year)
$Income_{US}$	The annual income for an average worker in an ISIC-4 digit industry in the U.S. in a given year
$Job\ Postings_{US}$	The number of job postings for all firms in an ISIC-4 digit industry in the U.S. in a given month
$Job\ Postings\ Skilled_{US}$	The number of skilled job postings for all firms in an ISIC-4 digit industry in the U.S. in a given month. Skilled jobs are those that requires above 14 years of education.
$Job\ Postings\ Unskilled_{US}$	The number of unskilled job postings for all firms in an ISIC-4 digit industry in the U.S. in a given month. Unskilled jobs are those that requires at most 14 years of education.
$Job\ Postings\ Repeat_{US}$	The number of repeat job postings for all firms in an ISIC-4 digit industry in the U.S. in a given month. The repeat posting are those with the same job title, employer, county, job hours but different hiring date within a year.
$Job\ Postings\ First_{US}$	The number of first (non-repeat) job postings for all firms in an ISIC-4 digit industry in the U.S. in a given month.

(Table continues)

Table 1: continued

$EstablishGrowth_{US}$	The ratio between the average number of establishments for the post-period and the pre-period in a U.S. industry
$EmployGrowth_{US}$	The ratio between the average employment for the post-period and the pre-period in a U.S. industry
Treated	A dummy variable equal to one for the industries encouraged in a plan and experiencing an above-median subsidy growth in the post-shock period from the level in the pre-shock period, and zero for the industries not encouraged
Q_{US}	The average Tobin's Q of all public firms in a U.S. industry in a given year, where Tobin's Q is measured by $(AT + (CSHO * PRCC\_F) - CEQ)/AT$ using variables from Compustat
$AccumReturn_{US}$	The average accumulated stock return of all public firms in a U.S. industry starting from three years before the enaction of a Five-year Plan.
Post	A dummy variable equal to one for the five years covered by a Five-year Plan, and zero for the previous five years
$Return_{US}$	The average annual return of all public firms in a U.S. industry in a given year.
$LaborProd_{US}$	the quintile of a U.S. industry by labor productivity in a given year. Labor productivity is defined as the total output divided by the number of workers in a U.S. industry in an given year.
D^{τ}	A dummy variable equal to one for the τ^{th} $(-\tau^{th})$ year after (before) the announcement of a Five-Year plan, and zero otherwise
Revenue (CN)	The revenue of a Chinese firm in a give year
Total Assets (CN)	The total assets of a Chinese firm in a given year
Wage Expense (CN)	The wage expense of a Chinese firm in a given year
Wage Expense (US)	The wage and salary expense of a U.S. establishment in a given year
Long Term Liability (CN)	The long-term liability of a Chinese firm in a given year
Book Leverage (CN)	The long-term liability denominated by the stockholders' equity of a Chinese firm in a given year
Value Added (CN)	Value added of a Chinese firm in a given year derived from the formula: output - intermediate input + value added tax expense
Value Added (US)	Value added of a U.S. firm in a given year derived from the formula: output - intermediate input
Net Fixed Assets (CN)	The net property, plant, and equipment of a Chinese firm in a given year
Current Assets (CN)	The current assets of a Chinese firm in a given year
Total Liability (CN)	The total liability of a Chinese firm in a given year
Current Liability (CN)	The current liability of a Chinese firm in a given year
Intangible Assets (CN)	The intangible assets of a Chinese firm in a given year
Value Added Tax Expense (CN)	The value added tax expense of a Chinese firm in a given year
Wage Expense - Operating (CN)	The operating wage expense of a Chinese firm in a given year
$PublicFirms_{US}$	The number of public-listed firms in an ISIC-4 digit industry in the U.S. in a given year

Table 2: **Summary statistics.** The table reports summary statistics at the industry (4-digit ISIC) level for the main LBD-CIED matched sample. All variables are defined in Table 1. All potentially unbounded variables are pre-winsorized at the 0.5% and 99.5% extremes. Column (1) and (2) report the mean and standard deviation of each variable. Columns (3)-(5) report their values at the 25th, 50th, and 75th percentiles.

	Mean (1)	Std Dev (2)	25% (3)	Median (50%) (4)	75% (5)
A. Statistics at the industry level					
$Establishments_{US}$	5,210	15,210	882	2,196	4,691
$Firms_{CN}$	1,208	1,704	233	577	1,444
$Employment_{US}$	124,000	137,200	30,970	74,040	164,900
$Employment_{CN}$	496,100	764,100	114,500	251,000	536,400
$Export_{CN}$	17.83%	17.20%	4.779%	11.30%	26.89%
$Export_{US}$	10.05%	8.455%	4.052%	8.567%	13.73%
$Output_{CN}$	279	612	21.8	78.6	268
$Output_{US}$	29.9	54.4	5.489	14.6	35.0
Subsidy (nominal)	490.0	1,191	37.17	130.6	435.5
Subsidy (# of firms)	150.1	205	31.04	76.92	186.1
$Job\ Postings_{US}$	333.7	699.2	21	87	270
$Job\ Postings\ Skilled_{US}$	226.8	583.5	12	46	147
$Job\ Postings\ First_{US}$	256.4	551.9	17	68	201
$Income_{US}$	48.51	97.27	36.52	43.86	52.84
$LaborProd_{US}$	173	162.9	83.92	118.1	194.8
$Return_{US}$	12.07%	41.99%	-11.4%	5.352%	31.94%
Q_{US}	2.976	2.665	2.07	1.487	3.318
B. Statistics at the firm/establishment level					
Revenue (CN)	220,713	1,749,833	32,754	58,575	130,093
Total Assets (CN)	194,947	2,185,953	15,143	35,031	91,759
Wage Expense (CN)	10,918	96,860	1,450	3,118	7,106
Wage Expense (US)	1,320	228,100	35	125	481
Long Term Liability (CN)	29,965	622,918	0	0	1,520
Book Leverage (CN)	12.13%	25.96%	0.00%	0.00%	4.01%
Value Added (CN)	47,306	499,932	6,664	12,673	27,952
Net Fixed Assets (CN)	81,758	1,047,797	3,614	10,312	30,844
Current Assets (CN)	87,830	773,331	6,630	17,340	46,579
Total Liability (CN)	121,466	1,244,626	6,377	17,936	52,306
Current Liability (CN)	96,499	874,796	5,270	15,992	46,554
Intangible Assets (CN)	2,590	33,021	0	0	0
Wage Expense - Operating (CN)	7,258	44,362	1,010	2,346	5,295

Table 3: **The lead-lag relationship between economic activities in U.S. and China.** The table reports the estimates of simultaneous equation system 1 using panel VAR method in the GMM framework. The empirical method is described in Section 2. Panel A reports the dynamic interdependent relationship between the logarithm of establishments in a U.S. industry and the logarithm of firms in the corresponding industry in China, at the industry-year (ISIC 4-digit) level. Panel B reports the relationship between the logarithm of employment in a U.S. industry and the same industry in China. All variables are as defined in Section 2 and Table 1. We incorporate industry fixed effects in all columns and year fixed effects in columns (2) and (4). The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: U.S. and China firm birth

Dependent variable:	$log(Establishments_{US,t})$		$log(Firms_{CN,t})$	
	(1)	(2)	(3)	(4)
$log(Establishments_{US,t-1})$	0.639***	0.830**	-0.066	-0.064
	(6.21)	(2.07)	(-0.89)	(-0.46)
$log(Establishments_{US,t-2})$	-0.136	0.251	-0.149	-0.106
	(-1.30)	(0.57)	(-1.36)	(-0.69)
$log(Firms_{CN,t-1})$	-0.122***	-0.144**	0.796***	0.934**
	(-3.42)	(-2.09)	(7.06)	(2.24)
$log(Firms_{CN,t-2})$	-0.071**	-0.002	0.123**	-0.067
	(-2.48)	(-0.27)	(2.53)	(-1.20)
N	1,400	1,400	1,400	1,400
Fixed effects:				
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes

Panel B: U.S. employment and China firm birth

Dependent variable:	$log(Employment_{US,t})$		$log(Employment_{CN,t})$	
	(1)	(2)	(3)	(4)
$log(Employment_{US,t-1})$	0.022	-0.709	0.491	1.027
	(0.05)	(-1.52)	(0.31)	(0.67)
$log(Employment_{US,t-2})$	0.287	1.402***	-0.831	-1.299
	(1.45)	(2.75)	(-1.46)	(-0.90)
$log(Employment_{CN,t-1})$	-0.105**	-0.104***	0.080	-0.101
	(-2.10)	(-2.75)	(0.32)	(-0.44)
$log(Employment_{CN,t-2})$	-0.016	-0.002	-0.202***	-0.097**
	(1.19)	(0.33)	(-4.53)	(-2.15)
N	1,400	1,400	1,400	1,400
Fixed effects:				
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes

Table 4: **The lead-lag relationship: Low versus high export intensity.** The table reports how the relationship between the economic activities in a Chinese industry and in the corresponding U.S. industry varies with the (demeaned) export intensity of the Chinese industry, at the industry-year (ISIC 4-digit) level. The outcome variables in columns (1)-(4) and (5)-(8) are the logarithm of establishments and employment in a U.S. industry during year t, respectively. All independent variables are as defined in Section 2 and Table 1. We incorporate industry fixed effects in all columns and year fixed effects in columns (2), (4), (6), and (8). The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$log(Establishments_{US,t})$				$log(Employment_{US,t})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$log(Firms_{CN,t-1}) * Export_{CN,t-1}$	-0.321***	-0.242***			-0.605***	-0.465***		
	(-4.44)	(-3.22)			(-6.15)	(-4.85)		
$log(Firms_{CN,t-1})$	-0.095**	-0.058***			-0.144***	-0.137***		
	(-3.68)	(-3.95)			(-8.11)	(-3.55)		
$log(Firms_{CN,t-2}) * Export_{CN,t-2}$			-0.333***	-0.245***			-0.611***	-0.483***
			(-4.73)	(-3.33)			(-6.58)	(-5.25)
$log(Firms_{CN,t-2})$			-0.097***	-0.061***			-0.132***	-0.145***
			(-3.95)	(-4.00)			(-7.92)	(-3.84)
N	2,100	2,100	2,100	2,100	2,100	2,100	2,100	2,100
Fixed effects:								
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 5: **The lead-lag relationship: Foreign versus domestic firms.** The table reports the estimates of simultaneous equation system 1 using panel VAR method in the GMM framework. The empirical method is described in Section 2. Panel A reports the dynamic interdependent relationship between the logarithm of establishments in a U.S. industry and the logarithm of foreign-owned firms in the corresponding industry in China, at the industry-year (ISIC 4-digit) level. Panels B and C report the relationship between the logarithm of establishments in a U.S. industry and the logarithm of state-owned firms and private domestic firms in the corresponding industry in China, respectively. All variables are as defined in Section 2 and Table 1. We incorporate industry fixed effects in all columns and year fixed effects in columns (2) and (4). The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: China's foreign-owned firm birth

Dependent variable:	$log(Establishments_{US,t})$		$log(Firms_{CN,foreign,t})$	
	(1)	(2)	(3)	(4)
$log(Establishments_{US,t-1})$	0.787***	0.462*	0.077	-0.066
	(8.41)	(1.88)	(1.49)	(-1.16)
$log(Establishments_{US,t-2})$	0.070	0.010	-0.005	-0.015
	(0.78)	(0.05)	(-0.12)	(-0.08)
$log(Firms_{CN,foreign,t-1})$	-0.023	0.094	0.781***	1.529
	(-0.51)	(0.56)	(2.69)	(1.21)
$log(Firms_{CN,foreign,t-2})$	-0.010	0.006	-0.057	0.012
	(-0.62)	(0.42)	(-0.49)	(0.10)
N	1,400	1,400	1,400	1,400
Fixed effects:				
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes

Panel B: China's state-owned firm birth

Dependent variable:	$log(Establishments_{US,t})$		$log(Firms_{CN,state,t})$	
	(1)	(2)	(3)	(4)
$log(Establishments_{US,t-1})$	0.917***	-0.061	0.291	-0.028
	(10.60)	(-0.18)	(1.44)	(-0.12)
$log(Establishments_{US,t-2})$	0.044	-0.096	-0.795	-0.841
	(0.54)	(-0.51)	(-1.60)	(-1.60)
$log(Firms_{CN,state,t-1})$	0.001	0.006	-0.285***	-0.096
	(1.37)	(1.04)	(-10.80)	(-0.66)
$log(Firms_{CN,state,t-2})$	0.002	0.002	-0.047**	-0.044
	(1.62)	(0.47)	(-2.54)	(-0.34)
N	1,400	1,400	1,400	1,400
Fixed effects:				
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes

Panel C: China's domestic private firm birth

Dependent variable:	$log(Establishments_{US,t})$		$log(Firms_{CN,private,t})$	
	(1)	(2)	(3)	(4)
$log(Establishments_{US,t-1})$	-0.065	1.107**	-0.020	-0.019
	(-0.73)	(2.57)	(-0.24)	(-0.75)
$log(Establishments_{US,t-2})$	-0.137*	0.381	-0.060	-0.059
	(-1.91)	(0.90)	(-0.92)	(-0.64)
$log(Firms_{CN,private,t-1})$	-0.126***	-0.250**	0.749***	0.247
	(-6.22)	(-1.97)	(4.39)	(0.53)
$log(Firms_{CN,private,t-2})$	-0.033***	0.012	0.044	-0.093
	(-3.02)	(1.00)	(1.23)	(-1.23)
N	1,400	1,400	1,400	1,400
Fixed effects:				
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes

Table 6: **The aggregate output of subsidized industries.** Panel A and Panel B report how much the logarithm of the aggregate output of a Chinese industry and the corresponding U.S. industry predict the amount of subsidy provided by the Chinese government, respectively, while Panel C combines the independent variables from the first two panels to predict China's subsidy. All variables are as defined in Section 3 and Table 1. We incorporate industry fixed effects in all columns. The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	*Log Subsidy (nominal)*			*Log Subsidy (# of firms)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: China industry output and Chinese government subsidy						
$log(Output_{CN,t-1})$	0.291*	0.529**		0.168***	0.308***	
	(1.73)	(2.21)		(2.95)	(3.84)	
$log(Output_{CN,t-2})$	0.328**		0.559***	0.193***		0.327***
	(2.53)		(2.74)	(3.50)		(4.60)
N	1,400	1,400	1,400	1,400	1,400	1,400
Fixed effects:						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: U.S. industry output and Chinese government subsidy						
$log(Output_{US,t-1})$	0.034	0.041		-0.023	0.046	
	(0.36)	(0.32)		(-0.71)	(1.12)	
$log(Output_{US,t-2})$	0.101		0.081	0.092		0.079
	(1.53)		(0.81)	(0.84)		(1.09)
N	1,400	1,400	1,400	1,400	1400	1,400
Fixed effects:						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: China/U.S. industry output and Chinese government subsidy						
$log(Output_{CN,t-1})$	0.306*	0.537**		0.178***	0.309***	
	(1.78)	(2.32)		(3.37)	(3.93)	
$log(Output_{CN,t-2})$	0.324**		0.556***	0.187***		0.321***
	(2.48)		(2.74)	(3.33)		(4.45)
$log(Output_{US,t-1})$	0.146	-0.051		-0.087	0.007	
	(1.41)	(-0.39)		(-0.83)	(0.16)	
$log(Output_{US,t-2})$	0.116		0.031	0.101		0.050
	(1.56)		(0.31)	(0.86)		(1.27)
N	1,400	1,400	1,400	1,400	1400	1,400
Fixed effects:						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **The impact of industrial policies in the Five-year Plans.** Panel A reports the impact of industry policies in the Five-year Plans on the industries in China and U.S., corresponding to equation 3. We incorporate industry-plan fixed effects in columns (2)-(3), (5)-(6), and (8)-(9), and year fixed effects in columns (3), (6), and (9). Panel B reports how the industry policies' effect on U.S. industries varies with export intensity of the Chinese industry. To perform the analysis, we collapse the panel by calculating the logarithm of the ratio between the average number of establishments (employment) for the post-period and the pre-period in a U.S. industry. $Export_{CN,-1}$ is the (demeaned) export intensity of a China's industry for the year before the release of a plan. All variables are as defined in Section 3 and Table 1. The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Panel regressions

Dependent variable:		$log(Firms_{CN})$			$log(Establishments_{US})$			$log(Employment_{US})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Post * \text{Treated}$	0.143***	0.149***	0.150***	-0.060**	-0.055**	-0.055**	-0.055**	-0.052**	-0.052**
	(2.75)	(3.01)	(3.02)	(-2.24)	(-2.18)	(-2.17)	(-1.98)	(-2.00)	(-2.00)
$Post$	0.481***	0.233***		-0.115***	-0.052***		-0.193***	-0.082***	
	(5.33)	(3.34)		(-4.38)	(-3.08)		(-7.47)	(-7.61)	
Treated	0.047			-0.002			0.010		
	(0.98)			(-0.17)			(0.72)		
N	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900
Fixed effects:									
Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Industry-Plan FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Panel B: Cross-sectional variation in export intensity

Dependent variable:	$log(EstablishGrowth_{US})$	$log(EmployGrowth_{US})$
	(1)	(2)
$\text{Treated} * Export_{CN,-1}$	-0.275**	-0.360**
	(-2.13)	(-2.13)
Treated	-0.054*	-0.040*
	(-1.91)	(-1.82)
N	230	230
Fixed effects:		
Plan FE	Yes	Yes

Table 8: **Job Postings.** This table reports the impact of industry policies in the Five-year Plans on the job postings of the corresponding US industries. Regressions include industry and year-month fixed effects. All variables are as defined in Section 3 and Table 1. Column (1) reports results with the Twelfth Plan only, and column (2)-(6) are based on Twelfth and Thirteenth plans. Columns (1)–(2) analyze the impact on the logarithm of total job postings in a U.S. industry. Columns (3)–(4) examine the logarithm of skilled and unskilled job openings, and Columns (5)–(6) focus on the logarithm of first-time and repeat job postings in a year. The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$log(Job\ Postings_{US})$					
Job Posting type:	Any	Any	Skilled	Unskilled	First	Repeat
	(1)	(2)	(3)	(4)	(5)	(6)
$Post *$ Treated	-0.074***	-0.097**	-0.108**	-0.060***	-0.112***	-0.015
	(-3.09)	(-2.18)	(-2.26)	(-2.02)	(-2.10)	(-0.30)
N	6,216	14,796	14,796	14,796	14,796	14,796
Five-Year Plan	12th	12th, 13th	12th, 13th	12th, 13th	12th, 13th	12th, 13th
Fixed effects:						
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Plan FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: **Parallel Trend Test: Encouraged versus nonencouraged Industry.** The table shows how the economic activity in China and U.S. industries evolves around the release of the Five-Year Plans for the treated and control groups, corresponding to equation 4. We incorporate industry fixed effects and year fixed effects in all columns. All variables are as defined in Section 3 and Table 1. The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$log(Firms_{CN})$ (1)	$log(Establishments_{US})$ (2)	$log(Employment_{US})$ (3)	$log(Income_{US})$ (4)	$log(Output_{US})$ (5)	$AccumReturn_{US}$ (6)	Q_{US} (7)	$log(Job\ Postings_{US})$ (8)
Treated $*\ D^{-3}$	-0.024	0.008	-0.021	-0.016	0.021	-0.094	0.268	-0.003
	(-0.72)	(0.56)	(-1.20)	(-1.18)	(0.24)	(-0.97)	(0.58)	(-0.06)
Treated $*\ D^{-2}$	-0.056	0.008	-0.006	0.002	0.055	0.086	0.387	0.001
	(-1.52)	(1.30)	(-0.56)	(0.23)	(0.81)	(0.88)	(1.16)	(0.02)
Treated $*\ D^{0}$	0.019	-0.018	-0.002	-0.025	-0.058	-0.179**	-0.918**	0.037
	(0.78)	(-1.39)	(-0.11)	(-1.52)	(-1.16)	(-2.02)	(-2.16)	(1.89)
Treated $*\ D^{+1}$	0.074**	-0.034	-0.049*	-0.035***	-0.112*	-0.381***	-0.973*	-0.035
	(2.48)	(-1.32)	(-1.96)	(-2.80)	(-1.96)	(-2.79)	(-1.84)	(-0.83)
Treated $*\ D^{+2}$	0.115**	-0.064*	-0.077**	-0.032**	-0.134*	-0.197	-0.825	-0.171***
	(2.14)	(-1.93)	(-2.56)	(-2.45)	(-1.93)	(-0.94)	(-1.48)	(-4.09)
Treated $*\ D^{+3}$	0.225***	-0.080**	-0.091**	-0.029**	-0.219**	-0.209	-0.747	-0.137***
	(2.89)	(-2.32)	(-2.55)	(-2.14)	(-2.54)	(-0.67)	(-1.34)	(-3.04)
Treated $*\ D^{+4}$	0.171**	-0.062*	-0.073*	-0.033**	-0.186**	-0.132	-0.682	-0.165***
	(2.02)	(-1.67)	(-1.94)	(-2.14)	(-2.00)	(-0.31)	(-0.91)	(-3.69)
N	1,700	1,700	1,700	1,700	1,600	1,400	1,400	14,796
Fixed effects:								
Industry-Plan FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year-Month FE	No	No	No	No	No	No	No	Yes

Table 10: **U.S. firms with and without China business presence.** The table reports the impact of industry policies in the Five-year Plans on U.S. public firms with and without China business presence separately. Columns (1)–(2) presents the effect on U.S. public firms without a business presence in China, and columns (3)–(4) shows the effect on U.S. public firms with China presence. All variables are as defined in Section 3 and Table 1. The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$AccumReturn_{us}$	Q_{us}	$AccumReturn_{us}$	Q_{us}
Firm type:	Without China presence		With China presence	
	(1)	(2)	(3)	(4)
$Post * \text{Treated}$	-0.287**	-1.338**	0.183	0.227
	(-2.06)	(-2.07)	(1.30)	(0.68)
N	1,400	1,400	1,400	1,400
Fixed effects:				
Year FE	Yes	Yes	Yes	Yes
Industry-Plan FE	Yes	Yes	Yes	Yes

Table 11: **The evolution of affected industries: high versus low labor productivity.** The table reports how the impact of industry policies in the Five-year Plans on U.S. firms varies with the labor productivity of the U.S. industry. Panel A focuses on the 10th and 11th Five-year Plans, and panel B focuses on the 12th and 13th Plans. In panel A (panel B), columns (1) presents the effect on a China's industry, and columns (2)–(3) (columns (2)–(4)) reports the effect on the corresponding U.S. industry. $LaborProd_{US,-1}$ is the quintile an industry belong to when ranked by labor productivity. The labor productivity of an industry is measured in the year before a plan and is defined as the total output divided by the number of workers in an industry in the U.S. All the other variables are as defined in Section 3 and Table 1. The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: 10th and 11th Five-Year Plans

Dependent variable:	$log(Firms_{CN})$ (1)	$log(Establishments_{US})$ (2)	$log(Employment_{US})$ (3)
$Post * \text{Treated} * LaborProd_{US,-1}$	-0.072***	0.0232*	0.0142*
	(-2.90)	(1.82)	(1.67)
$Post * \text{Treated}$	0.370***	-0.129***	-0.112**
	(4.31)	(-2.71)	(-2.09)
N	1,400	1,400	1,400
Five-Year Plan	10th, 11th	10th, 11th	10th, 11th
Fixed effects:			
Year FE	Yes	Yes	Yes
Industry-Plan FE	Yes	Yes	Yes

Panel B: 12th and 13th Five-Year Plans

Dependent variable:	$log(Firms_{CN})$ (1)	$log(Establishments_{US})$ (2)	$log(Employment_{US})$ (3)	$log(JobPosting_{US})$ (4)
$Post * \text{Treated} * LaborProd_{US,-1}$	0.091**	-0.011*	-0.019*	-0.058**
	(2.53)	(-1.95)	(-1.84)	(-2.07)
$Post * \text{Treated}$	-0.098	-0.024	-0.019	0.081
	(-1.13)	(-0.47)	(-0.38)	(1.29)
N	800	800	800	14,796
Five-Year Plan	12th	12th	12th	12th, 13th
Fixed effects:				
Year FE	Yes	Yes	Yes	Yes
Industry-Plan FE	Yes	Yes	Yes	Yes

Internal Appendix for the paper

"A Race to Lead: How Chinese Government Interventions Shape the U.S.-China Production Competition"

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Appendix A. The mitigation of data limitations of China Industrial Enterprises Database (CIED)

The paper relies on CIED data to track the longitudinal change in operating and financial variables of a large sample of private and public Chinese firms from 1998-2013. The dataset is highly informative, although it may subject to a number of quality issues (Nie et al., 2012). In this section, we list the major limitations of CIED data raised in Nie et al. (2012) that are relevant to our study and discuss how the limitations may affect our results and how we address the data issues.

1. Missing Indices. Nie et al. (2012) mention a few variables subject to missing indices problem in certain years. This issue is relevant to two variables in our tests: export (missing in 2004) and subsidy (missing from 2008 to 2010). Export-related measures are involved in the analysis reported in Table 4. To cope with the missing variable issue, we define the export intensity as the average export intensity of a Chinese industry over the entire sample period (from 1998 to 2013), which can help dilute the impact of the missing variable in 2004. Subsidy measures are used in Tables 6 to 11. To ensure the estimates in Table 6 are not affected by the missing variable during 2008-2010, we perform robustness tests using the subsample up to 2007, which delivers similar results to Table 6. For the analysis based on Five-year Plans, we conduct robustness tests building on the industry policies only in the 10th Five-year Plan as of 2000, of which the sample period does not overlap with the years seeing missing subsidy information. The robustness tests provide results consistent with Tables 7 and 9.

2. Unrealistic Outliers. Nie et al. (2012) point out there are outliers of the variables in CEID data. This issue is potentially driven by the misreporting of variables, especially financial variables, by some firms, which is not unexpected considering not all firms have a reliable accounting system. Since we mainly rely on basic information, such as the number of firms and total employment, of which the calculation is straightforward and not reliant on any complicated accounting procedure, we believe this issue does not have major impact on our analysis. To further ensure the outliers do not affect the results, we repeat all analyses while trimming the potentially unbounded variables at the 0.5% extremes on both ends, or 1% extremes on one end for the variables unbounded only on one side. The results of the robustness tests confirm that the findings in the paper are not driven by the outliers of variables.

3. Measurement Errors. Nie et al. (2012) provide several examples of variables that might be subject to measurement errors, which do not include the variables we used. If measurement errors exist, it may potentially affect our results. However, since we aggregate the variables to the industry level, the data aggregation can automatically reduce the measurement error unless the errors are cross-correlated within the same industry.

4. Sample selection. Another concern is some firms in our sample may not present in the database for certain years in the life of the firms, because in some years (especially early years after entry), a firm's revenue may not pass the "above-scale" threshold. This is a major caveat to interpreting the change in the number of firms and employment in a Chinese industry.

In addition, the sample match problem raised by Nie et al. (2012) is largely irrelevant to our paper. Nie et al. (2012) point out the difficulty in matching the same firm across years and constructing a panel data at the firm-year level. This issue arises due to the lack of a unique identifier at the firm level and the change in firm names over time. This issue is not expected to affect our paper because our analysis builds on the industry-level measures and does not rely on the within-firm links. Also, the definition ambiguity issue discussed in Nie et al. (2012) does not apply to the variables used in this research.

Table A1: **Summary statistics of earlier and later periods.** The table reports summary statistics at the industry (4-digit ISIC) level for the LBD-CIED matched sample. Panel A considers the early period around the 10th and 11th Plans (i.e., 1998-2010), and panel B focuses on the more recent period around the 12th Plan (i.e., 2006-2013). All variables are defined in Table 1. All potentially unbounded variables are pre-winsorized at the 0.5% and 99.5% extremes. Column (1) and (2) report the mean and standard deviation of each variable. Columns (3)-(5) report their values at the 25th, 50th, and 75th percentiles.

	Mean (1)	Std Dev (2)	25% (3)	Median (50%) (4)	75% (5)
A. Early period					
$Establishments_{US}$	5,778	15,610	851	2,430	5,362
$Firms_{CN}$	933.4	1,411	190	452	1,041
$Employment_{US}$	135,000	142,300	31,990	78,040	197,900
$Employment_{CN}$	401,700	729,700	84,570	189,700	392,500
$Output_{US}$	27.3	50.5	4.836	13.5	32.9
$Income_{US}$	45.05	132.4	33.24	39.54	46.3
B. More recent period					
$Establishments_{US}$	6,126	19,680	1,149	2,745	5,662
$Firms_{CN}$	2,109	2,401	513	1,213	2,813
$Employment_{US}$	137,300	139,900	44,000	84,610	175,300
$Employment_{CN}$	740,500	1,065,000	178,000	399,500	782,900
$Output_{US}$	37.7	79.7	7.472	19.0	44.3
$Income_{US}$	47.95	13.68	39.08	45.54	53.58

Table A2: **The impact of the Five-year Plans on the number of U.S. public firms.** The table reports the impact of industry policies in the Five-year Plans on the number of U.S. public firms in the target industries, corresponding to equation (3). We incorporate industry fixed effects in columns (2)-(3), and year fixed effects in column (3). All variables are as defined in Section 3 and Table 1. The t-statistics are based on standard errors clustered at the industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$log(PublicFirms_{US})$		
	(1)	(2)	(3)
$Post *$ Treated	-0.042	-0.031	-0.032
	(-0.94)	-(0.65)	(-0.66)
$Post$	-0.123***	-0.110***	
	(-3.72)	(-4.73)	
Treated	0.576***		
	(2.99)		
N	1,900	1,900	1,900
Fixed effects:			
Year FE	No	No	Yes
Industry-Plan FE	No	Yes	Yes