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DISCUSSION
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Using Export Market Performance to Evaluate Regional Preferential Policies in China*

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Abstract

We apply program evaluation methods to analyze the effectiveness of two types of preferential regional policy programs in China's manufacturing sector. Economic and Technological Development Zones (ETDZs) aim to facilitate firms' internationalization strategies. Science and Technology Industrial Parks (STIPs) aim to generate technology spillovers. We focus on various dimensions of export market performance as objective indicators for the upgrading of product quality and firm operations. We compare startups that locate into one of these zones with other startups, while controlling for self-selection. The findings suggest that firms locating in an ETDZ do much better on sheer quantity of trade, i.e. the total volume of exports and number of destinations are higher. Firms locating in a STIP perform best on 'quality' dimensions, in particular they fetch higher export prices, even by destination and especially for firms producing machinery.

JEL codes: F14, R11, L2

Keywords: Spillovers, international trade, upgrading

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1 Introduction

Preferential regional policies have played an important role in the wide-ranging restructuring of China's economy from the start of the reforms in 1978. Even though the early reforms were geared towards agriculture, the first three Special Economic Zones (SEZ) were already set up in 1979 in Guangdong and a fourth one in Fujian in the next year. Coastal Open Cities were added to the policy portfolio in 1984 as well as Economic and Technological Development Zones (ETDZ). Like the original SEZs their primary aim was to help local firms integrate in the global economy. Cornerstones of this policy were duty-free access to imported intermediates for dedicated exporters and less restrictive entry regulations for foreign multinationals—hence their label 'preferential' policy areas.

As the Chinese economy developed and generated large export volumes, achieving sustainable growth became a more prominent objective. Rising labor costs and environmental degradation further motivated policies to stimulate manufacturing firms to upgrade along the value chain. In 1988, the central government established the Torch Program that had four major objectives: (1) improve the support system for high-tech industrialization, (2) foster growth of and enhance innovation in technology-based small and medium sized enterprises (SMEs), (3) improve mobility of factor inputs, especially human capital, and (4) set up technology zones (Hu and Jefferson 2008, Ministry of Science and Technology 2011).

This last objective was an important part of the central government's drive to generate more economic benefits from the national innovation system. The State Council established 54 national Science and Technology Industrial Parks (STIP) between 1988 and 2007. The objective of these parks is to support SMEs in high-tech industries and increase their international competitiveness. The program puts strong emphasis on commercial research and development to encourage independent innovation, in contrast with more centralized, failed attempts in the 1970s.

Both types of preferential policy areas aim to facilitate firms' movement along an upgrading trajectory from low to higher value added activities. Our objective is to investigate whether locating in an ETDZ or a STIP is effective in this respect. Identifying upgrading using an input measure such as R&D expenditures is not appropriate, because it is a pre-condition to locate in a STIP. Some studies have measured success in attracting Foreign Direct Investment (FDI), but this can hardly be considered a performance criteria in its own right. Productivity would be an attractive measure of good performance, but it can have several underlying causes. Even firms with simple production processes or producing simple products can achieve high productivity if they operate efficiently.

We have chosen to use different dimensions of export market success as objective performance criteria. There is a wealth of evidence demonstrating that the most efficient firms self-select into the export market (Roberts and Tybout 1997, Wagner 2007). The necessity to overcome fixed or sunk costs of exporting is an important part of the mechanism that generates this correlation. To the extent that accessing each export market entails additional fixed costs (Arkolakis 2010), the number of export destinations provides another signal of firm quality. Moreover, evidence in Hallak (2006) illustrates that richer countries have a higher willingness to pay for quality. Therefore, we not only look at the total export volume, but also at the total number of export markets served, the fraction of exports going to high-income countries, and the (relative) price a firm fetches on international markets.

Previewing the results, we find that firms locating in an ETDZ perform significantly better than other entrants primarily on the first two dimensions. The positive effect on the number of export destinations is weak for 'treated' firms, those actually locating in an ETDZ, but is estimated to be stronger for the full population of firms. The superior performance of firms locating in a STIP, on the other hand, is more pronounced on the quality dimension of exports. The effect on total exports is comparable in size to that for firms in ETDZs, but it is estimated much less precisely. In contrast, firms in a STIP fetch much higher prices on the export markets than the control firms and even significantly higher prices than firms in ETDZs. The differences decline somewhat over time and they are particularly pronounced for firms producing machinery and electronic equipment.

In order to give these results a causal interpretation, it is important to control for the endogenous nature of locating into these areas. If locating in a STIP or an ETDZ is more advantageous for firms that would have performed above average anywhere, estimated performance effects for these areas would be biased upward due to self-selection. We rely on two different approaches from the literature on the evaluation of treatment effects, recently reviewed in Imbens and Wooldridge (2009). Adopting the terminology of the Rubin Causal Model, we need to find an estimate for the potential performance of treated firms, i.e. those locating in a preferential area, if they had located elsewhere. This counterfactual is inherently unobservable, but we can exploit unconfoundedness and overlap assumptions to construct an appropriate benchmark from the performance of untreated firms that share observable characteristics.

A few studies have evaluated the effects of these preferential policy areas. Hu (2005) documents the general positive contribution of ETDZs to the local economy, notably in terms of attracting FDI, but no effort is made to control for confounding factors. Démurger et al. (2002) have stressed in particular that one should control for location within China before any positive effects can be attributed to a preferential zone. Based on interviews and self-collected information for STIPs and other science parks, Walcott (2003) is sceptical that proximity of firms fosters "innovation-promoting learning." She finds that multinational companies often use China only as assembly base and keep critical technology in the home country. As a result, technology transfer and skill enhancement for Chinese employees tend to be low. Other studies are discussed in the next section.

Focusing specifically on STIPs, two systematic empirical studies fail to find consistent benefits. At a regional level, Hu (2007) does find labor productivity convergence across different STIPs, but no evidence of local externalities from geographically concentrating high-tech firms. STIPs do not contribute sufficiently to economic growth to reverse the secular trend of rising regional inequality. Zhang and Sonobe (2011) do find positive agglomeration effects for the presence of high-tech firms, foreign direct investment, and research activity of academic institutions, but these spillover benefits also accrue to firms in the same city but outside the parks. At the same time, congestion effects within STIPs depress productivity for on-park firms.

An important drawback of all previous studies is the lack of comprehensive firm-level data. They rely on case studies or information at the city-level, broken down between on-park and off-park firms. Hu (2007) further conjectures that it might have been too early to assess the full potential of technology parks as his sample only covers the 1992-2000 period. Finally, none of the studies control for the self-selection of firms into the preferential areas. We remedy all three problems.

The remainder of the paper is organized as follows. In Section 2, we provide an overview of the development and organization of the preferential policy areas in China. In Section 3 we describe the empirical strategy to control for firms self-selecting into these areas. The data and sampling frame is described in Section 4, followed by the estimation results in Section 5. We close with conclusions on firm behavior and policy in Section 6.

2 Overview of preferential policies

2.1 Open Door policy & Economic and Technological Development Zones

ETDZs were established to expand the policy environment of the successful Special Economic Zones to additional areas. Over the 1984–2002 period a total of 54 ETDZs were established covering all coastal provinces and gradually also inland locations. The first zones were created after Deng Xiaoping's first southern tour in 1984. They were limited to coastal provinces, but set up specifically in rural areas to isolate them from the rest of the economy (Liu and Wu 2011). After Deng's second southern tour in 1992 a second wave of ETDZs was established, extending the policy to central and western regions. The establishment of the final wave of 17 ETDZs in 2000–2002 coincided with China's entry into the World Trade Organization.

These zones are dedicated areas were Foreign Direct Investment (FDI) is encouraged and tax reductions are granted. Firms that produce solely for exports are exempt from import tariffs on intermediate inputs and machinery and they are automatically awarded an export license. All ETDZs show a high concentration of multinational corporations and are not devoted to specific industries, in contrast to STIPs. Their geographical concentration facilitated the logistics of separating duty-exempt import flows from regular imports and monitoring that outputs are actually exported. It also avoided leakage of such imports or exports into the wider economy.

The growing export processing sector gradually became a virtual sector, not tied to specific geographic areas. In all major coastal port cities 'bonded areas' were established to facilitate duty-free importing by qualified exporters (Démurger et al. 2002). Over time, export processing firms could locate anywhere and compliance with the trade regime was monitored on-site by customs officials. Eventually, firms were even allowed to produce for the domestic market and under the export-processing regime from a single production facility. Import tariffs due were determined purely from company accounts and customs inspections. It facilitated the realization of scale economies in production and diminished local constraints on land and skilled workers.

An advantage of the geographical concentration of ETDZs is the possibility of localized externalities. Recent studies using sophisticated identification strategies suggest that manufacturing firms are able to learn from successful neighbors. (Swenson 2008, Greenstone et al. 2010). The continued popularity of ETDZs implies by a revealed preference argument that firms must still derive benefits from locating there.

The direct evidence on ETDZs' effectiveness in improving firm performance is very limited. Hu (2005) highlights a positive contribution to the economy, in terms of GDP per capita and the attraction of FDI, but without any benchmark. Liu and Wu (2011) show that ETDZs accounted for 21.6 and 15.8 percent of China's total FDI and trade by 2005, even though they covered only one hundred of one percent of the total territory. The quantification of benefits is complicated by interaction effects across time and between ETDZs and STIPs. We discuss these below, but first provide some background on the regional dimension of China's innovation policy.

2.2 Innovation policies & Science and Technology Industrial Parks

Chinese research institutions were originally focused on heavy industries, space technology, mining, and national defense. With the onset of reforms, attention turned to the economic orientation of the innovation system with efforts to close the gap with Western economies in industries producing for private consumption. A first effort in 1982, the "Key Technologies R&D Program", promoted technology transfers from research institutes and enterprises. The government also started to encourage researchers from universities and state-owned research institutions to found spin-offs (Fan and Watanabe 2006).

This policy proved rather successful and an important cluster of high-tech firms developed in Zhongguancun Street in Beijing close to Tsinghua University (Saxenian 2002). The State Council officially launched the first STIP "Beijing New Technology Industry Experiment Zone" at this site in May 1988, which was renamed as "Zhongguancun Science Park" in 1999. As part of the Torch Program, the Ministry of Science and Technology established a further 53 parks since then. Figure 1 illustrates that the STIPs are distributed across the entire country with some aggregation in the Beijing, Shanghai, and Shenzhen areas. The Urumqi State High-tech Industrial Development Zone marks the only STIP in the far west of the country.[1]

To become eligible for locating in a STIP, a firms needs to meet three criteria and be certified as high-tech (Zhang and Sonobe 2011). It must use or develop products,

[1] The full list of active STIPs can be found at Ministry of Science and Technology (2011).

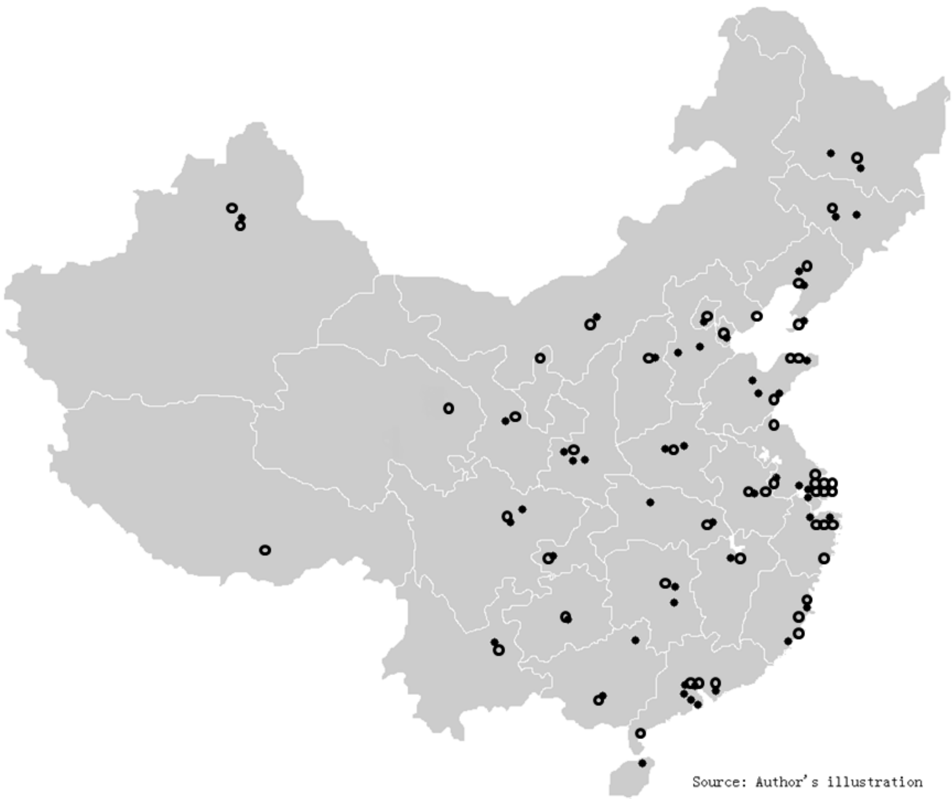

Figure 1: Geographical distribution of the 54 STIPs (•) and 54 ETDZs (∘)

services, or technologies mentioned in the *Catalog for High and New Technology Products* of the Ministry of Science and Technology. It must invest at least 3 percent of its annual gross revenue in R&D related activities. At least 30 percent of its employees must hold a tertiary-level degree and at least 10 percent of its workforce must be employed in the R&D department. Every year, a provincial government agency in charge of science and technology issues re-evaluates whether the firm still satisfies the three requirements.

On-park firms are given preferential treatment on various dimensions, including state-of-the-art infrastructure, lighter regulatory burdens, lower rates of corporate income tax, exemption of import tariffs and export licenses, and rebates for investments (Liu and Wu 2011). Local governments are in charge of organizing the parks, but the central government's State Council decides over the implementation of development zones and provides the tax holidays.

One objective of the STIPs is to facilitate knowledge transfers from multinationals to domestic firms. As mentioned, Walcott (2003) finds only limited learning from case studies of seven technology parks of different types (Multinational Development

Zones, Multinational Learning Zones, and Innovation Learning Zones). Macdonald and Deng (2004) also express a critical point of view, but no evidence, arguing that the majority of STIPs are science parks only in name. In contrast, Inkpen and Wang (2006) do find evidence of technological knowledge transfers in the Suzhou Industrial Park that is an explicit collaboration between the Chinese and Singapore governments. Managerial knowledge, however, was found to be particularly difficult to transfer.

Other studies have compared the Chinese STIPs to similar policies in other countries. In a comparison with Japanese industrial policy, Fan and Watanabe (2006) stress the importance of balancing the import of foreign technology and domestic development and the key role of the private sector in enhancing technological capabilities. Saxenian (2002) examines whether government policies can help transform a brain drain into a "brain circulation" by giving incentives to Chinese graduates in Silicon Valley to return and start high-tech firms in China. Specially for them, "Returning Students Science Parks" were created in some existing STIPs.[2]

2.3 Challenges to evaluate preferential policy areas

Evaluating the effects of preferential policies faces a number of challenges. Démurger et al. (2002) stress the importance of controlling for location within China to ascribe effects to a particular preferential policy area. The disparities in regional growth rates and level of development are too great to overlook. The previously mentioned evidence in Hu (2007) underscores this: he finds positive effects of STIPs, but they are dominated by regional trends.

Head and Ries (1996) illustrate the importance of endogenous location decisions of firms. They estimate static and dynamic effects of FDI and find large differences if the effects of early FDI on the attractiveness of a location for subsequent FDI is taken into account. In their evaluation of early preferential policy areas, prior to the establishment of ETDZs and STIPs, they find that endogenous location decisions have a strong magnification effect on agglomeration externalities. Liu and Wu (2011) document a similar externality. They show that ETDZs and STIPs are complementary, especially in the coastal areas. The effectiveness of an ETDZ in attracting FDI is boosted by the presence of a STIP in the same city.[3]

[2]For example, Saxenian (2002) identifies 48 companies run by returning students in the Zhongguancun Science Park in Beijing.

[3]Figure 1 illustrates that many locations host both types of preferential policy areas.

Many different types of preferential or incentives areas have been established in China. The early Special Economic Zones and Open Coastal Cities are well known and cover relatively large areas. Other geographically concentrated initiatives include Open Coastal Belts, Open Economic Coastal Areas, Open Delta Economic Zones, and Border Economic Cooperation Zones. Head and Ries (1996) and Démurger et al. (2002) provide some information. In addition to the national, also called state-level, ETDZs and STIPs with uniform policies, provincial variants exist for both types of areas. We do not include them in our study as they have idiosyncratic policy differences, but their ubiquity makes it important to select the performance benchmark carefully.

An important aim of the STIP policy is to pool high-skilled labor markets and to facilitate productivity and knowledge spillovers by agglomerating high-tech firms and R&D activities. To some extent these objectives are shared with ETDZs where the focus in on knowledge transfers from multinational firms through FDI. The policy environment of the two types of preferential areas show many similarities (Saxenian 2002), but locating in a STIP is a lot more restrictive. A randomly selected firm is likely to be a much worse benchmark for firms in a STIP than for firms in an ETDZ. It is important to carefully construct an appropriate benchmark and we describe this process in the next section.

3 Empirical methodology

3.1 Treatment Effects framework

Our objective is to investigate the effect of locating in an ETDZ or a STIP on various dimensions of export performance. The main identification problem we face is that we cannot observe what the performance of a 'treated' firm, i.e. one locating in a preferential policy area, would have been if it had chosen to locate elsewhere. If treatment is not random, which is likely, we cannot simply use the performance of firms outside the areas as a benchmark.

Because a firm only selects its location once, we cannot use a difference-in-differences approach in the time dimension. Instead, we use two methods from the treatment effects literature to control for self-selection into treatment. A good overview of the different methods is provided in Imbens and Wooldridge (2009) and Wooldridge (2010). Note that it is not the endogeneity of the location decision itself that is problematic, but the correlation between this decision and the potential performance in the absence of treatment. We discuss how we break this correlation.

Denote an outcome variables of interest by y. If unit i is treated its potential outcome is y_{i1}, while it is y_{i0} if the same unit i is not treated. The innovation in the Rubin Causal Model is to specify both potential outcomes explicitly even though only one is observable for each firm. The assumptions needed for identification can then be specified directly on these objects, separately from the process that governs the selection into treatment. We denote by w_i the binary treatment variable.

The average treatment effect measures the expected effect of treatment on a random sample of the population or the average effect across the entire population. Because many firms might have no interest in locating in an ETDZ and even more firms would not even qualify to locate in a STIP, we are primarily interested in the effect of the program on those who actually participated, i.e. the average treatment effect on the treated (ATT).[4] We can define it as follows,

$$\tau_{att} \equiv \mathrm{E}(y_1 - y_0 | w = 1). \tag{1}$$

We rely on two identifying assumptions to deal with the missing information on y_0 for treated firms (Wooldridge 2010). Unconfoundedness, or ignorability of treatment, assumes that once we condition on a sufficiently rich set of covariates, treatment assignment is essentially randomized. It allows self-selection into treatment based on unobservables, but only if the unobservables are not correlated with performance differences after conditioning on the covariates. This clearly is a tall order, but in the absence of (quasi-)experimental assignment it is the only way forward. If firms self-select during their lifespan and we observe performance before and after treatment, we could relax the unconfoundedness assumption by only making it on the time-differenced performance measures. [5] Unfortunately, this is impossible for the location decision. Formally, the assumption is expressed as

A.1 $\quad (y_0, y_1) \perp w | \, \mathbf{x}.$

Given that we are only interested in the ATT, we will only use the following mean-independence assumption: $E[y_0|\mathbf{x}, w] = E[y_0|x]$.

[4]Many evaluations of programs with voluntary participation focus on the ATT effect. When treatment is randomly assigned, ATE equals the ATT.

[5]That scenario would allow selection into treatment based on time-invariant firm-specific unobservables, see Van Biesebroeck, Yu, and Chen (2011) for an application to the evaluation of short-term export promotion programs.

The second assumption we make is overlap: Based on a set of explanatory variables $\mathbf{x}$, each unit in the population may potentially enjoy treatment. Formally:

$$\text{A.2} \qquad \forall\, \mathbf{x} \in \mathcal{X}, \quad 0 < \mathrm{P}(w = 1|\mathbf{x}) < 1,$$

where $\mathcal{X}$ is the support of the covariates. If the assumption is satisfied, it guarantees that for each treated firm we observe non-treated, control firms with similar covariates.

3.2 Estimating Average Treatment effects

The sample estimator for the ATT is defined as

$$\hat{\tau}_{att} = \frac{1}{\sum_i w_i} \sum_{i=1}^{N} w_i \left[\hat{m}_1(\mathbf{x}_i) - \hat{m}_0(\mathbf{x}_i)\right], \tag{2}$$

where the functions $\hat{m}_1(.)$ and $\hat{m}_0(.)$ are the predicted values of the performance variable for treated and untreated firms using the same set of covariates $\mathbf{x}$, but allowing for different coefficients. We can estimate this simply with the following OLS regression

$$y_i = \beta_1 \mathbf{x}_i + \beta_2(\mathbf{x}_i - \bar{\mathbf{x}}_1) * w_i + \tau_{att}\, w_i + \varepsilon_i. \tag{3}$$

The covariates in the interaction term are normalized by $\bar{\mathbf{x}}_1$, the sample means for the group of treated firms. The coefficient on the uninteracted treatment dummy immediately gives the ATT estimate.[6]

Assumption A.1 is fundamentally untestable because we do not observe the counterfactual outcome (Wooldridge 2010). Given that all but one of the covariates in the $\mathbf{x}$ vector are discrete variables, we can include dummy variables for different values such that the conditional expectation function is guaranteed to be linear (Angrist and Pischke 2008).

Assumption A.2 implies that the support of the conditional distribution of $\mathbf{x}$ given $w = 0$ overlaps completely with that of the conditional distribution of $\mathbf{x}$ given $w = 1$. Imbens and Wooldridge (2009) propose to verify this by calculating the population equivalent of the normalized differences:

$$\frac{E(\bar{x}|w=1) - E(\bar{x}|w=0)}{\sqrt{V(x|w=1) + V(x|w=0)}}.$$

[6]To estimate the ATE, the normalization of $\bar{\mathbf{x}}$ is over the full population average of the covariates.

For only 7% of the firms in our sample does the absolute values exceed 0.25, the threshold were Imbens and Rubin (forthcoming) suggest some concern, but even in those cases the normalized difference is at most 0.44. As a robustness check, we implement an additional estimator.

This second method was originated by Robins, Rotnitzky, and Zhao (1995) and combines the regression adjustment with propensity score weighting. Compared to the specification in (3), it does not require the equation to fit the entire covariate-space equally well. Untreated firms receive a weight that is increasing in their probability of treatment. Compared to matching estimators that explicitly match treated firms to one or several untreated control firms, it is more robust to misspecification of the treatment selection equation. Therefore it is said to be double robust. Imbens and Wooldridge (2009) point out that the estimator is consistent as long as the parametric model for either the propensity score or the regression function is specified correctly.

We implement the estimator using the two-step approach of Hirano, Imbens, and Ridder (2003). First, we estimate the probability of treatment as a function of the covariates by maximum likelihood (logit) and calculate the predicted value, the propensity score. Second, we rely on the same equation (3) as before to estimate τ_{att}, but using the following weights[7]

$$\lambda_i^{att} = w_i + (1 - w_i)\,\frac{\hat{p}(\mathbf{x}_i)}{1 - \hat{p}(\mathbf{x}_i)}. \tag{4}$$

The parameter of interest will again be the coefficient estimate on the uninteracted treatment dummy. Given the two-step procedure, we need to bootstrap the procedure to calculate standard errors.

The covariates used in both estimators should be effective in breaking the correlation between a firm's potential performance without treatment and its self-selection into treatment. Government discretion in the selection process of firms that are allowed to locate in the preferential areas is an effective source of variation. We include a full set of interaction dummies for location and sector. Observable characteristics that enter the official rules for eligibility to locate in a STIP or ETDZ are also effective controls that make it more likely that the unconfoundedness assumption is satisfied. For this, we include average remuneration per employee, linear and squared. We also pre-select control and treatment firms on a positive export

[7] To estimate the ATE, the appropriate weights are the inverse probability of treatment or non-treatment for each observation: $\lambda_i^{ate} = w_i/\hat{p}(\mathbf{x}_i) + (1 - w_i)/(1 - \hat{p}(\mathbf{x}_i))$.

status. As exporters are known to exhibit above average performance on many dimensions (Bernard and Jensen 1995), this makes the two groups of firms already more comparable.

4 Data

We now discuss our information sources, the sample, and variable definitions. We have merged two data sets. The first one contains monthly trade transactions data from the Chinese Customs Office for the period 2000-2006 and has only been used in a few studies, e.g. Manova and Zhang (forthcoming). We identify exporters and aggregate all transactions to the annual level. For each firm-year observation we observe export transactions at the 8-digit HS product level and by export destination.[8] Export flows are reported in value and quantity (with an indication of units).

From this information we construct the four export performance variables. The total value of exports and total number of export destinations served are defined straightforwardly. The third variable is the ratio of exports going to high-income destinations, which are defined according to the World Bank (2011) country classification. The ratio is calculated using the number of export destinations and as a robustness check also in value terms.

The final performance measure is the price that a firm fetches on the export market. We divide export values and quantities at the most detailed product level to calculate the unit value ratio. This ratio is normalized by the median value for a particular product and then aggregated to the firm-year level, across products and destinations, using value shares. As a sensitivity check, we construct an alternative measure by normalizing the unit value ratio separately for each product-destination category before aggregating to the firm level. The second measure generates a relative price that does not depend on the composition of trading partners if prices differ systematically by destination.

Two text-variables in the transaction data, the ‘origin’ of a transaction and the address information of the exporter, provide sufficient information to determine whether a firm in a certain city is located inside a STIP or ETDZ.[9] We are the first

[8] Transactions are further broken down by type of trade—various types of export processing or general trade—but we aggregate over all types as most firms specialize in one.

[9] The full list of STIPs is provided on the web site of the Torch program (Ministry of Science and Technology 2011), and Liu and Wu (2011) provide the complete list of cities with an ETDZ.

to identify 'treatment' at the firm level.

The firms in the trade transaction file are matched to annual firm-level data from China's National Bureau of Statistics that is widely used, e.g. in Brandt, Van Biesebroeck, and Zhang (2012). The probabilistic matching method is based on name, address, sector, and size category; Brandt et al. (2010) has further details. In the first year (2000), we are able to match firms responsible for approximately 42% of exports. Coverage grows to almost 65% in the final year (2006) as more firms export directly rather than through trade intermediaries and because the coverage of the firm-level data set improves over time.[10] Note that this coverage is almost as high as achieved for the United States in the data set used in Bernard et al. (2007).

To construct performance benchmarks for firms that self-select into STIPs or ETDZs, we only consider new entrants that chose to locate elsewhere. Given the dynamism and the rapid growth of the Chinese economy, we do not want to compare them with older firms. Entrants are defined as firms that enter the data set during the study period, 1999-2005, and report a founding date at most two years prior to their first appearance.[11] In total we observe 14,110 entrants, 458 (3.0%) have chosen to locate in a STIP, and 891 (5.8%) in an ETDZ. These low percentages of treated firms make it easy to satisfy the overlap assumption required for the estimation of the ATT.

The covariates to control for the selection into treatment are constructed as follows. We use the 2-digit CIC industry classification to generate a set of 29 dummies. We work at this aggregate level to control for the 2003 change in sectoral classification and to preserve degrees of freedom. The detailed ownership classification is aggregated into five types: state-owned, collective, private, foreign, and firms from Hong Kong, Macau and Taiwan.[12] The location information was collapsed into dummy variables for the Western and Central region, while firms in the coastal

The firm address contains detailed location information, including street name, zip code, and city. For the limited set of cities with a STIP or ETDZ we text-searched the address and origin fields for the Chinese characters that uniquely identify the parks or zones.

[10]The NBS firm-level data captures all firms that are either state-owned or have annual sales of at least million RMB, approximately $650,000 over the sample period. The coverage of the manufacturing sector increased notably when the business registry was updated after all manufacturing firms were visited for the 2004 census (Brandt, Van Biesebroeck, and Zhang 2012).

[11]The firm-level data is a panel spanning the 1998-2008 period, which is longer than the period for which we observe performance data.

[12]Some firms changed their ownership status after entry. The most common switches were from state to private and private to foreign.

provinces are distributed over the three river deltas associated with the three important industrial regions. The size of firms is measured by three dummies based on the number of employees. The only continuous control variables used in the analysis are the average remuneration per employee, which includes both wages and non-wage benefits, and the square of this variable.

Descriptive statistics for the final sample, broken down by treatment status, are reported in Table A.1 in the Appendix. The high fraction of foreign-owned firms, both among control and treated firms, is notable. This is to a large extent the result of pre-selecting on export status. STIP firms are more likely to produce machinery and electronics, which is as expected. They also show better average export performance, underscoring the importance of constructing an appropriate benchmark.

5 Empirical results

5.1 Productivity and capital intensity

After the detailed discussion of the objective, approach, and identification strategy of the paper, presenting the results is relatively straightforward. In the following sections we look at export market performance, but we first verify whether there is sufficient identifying power in the relatively small sample of entrants. Recall that we only compare new firms locating in a STIP or ETDZ with entrants locating elsewhere. We use performance indicators from one or two years after entry and rely on covariates from the initial year to construct a benchmark, as discussed earlier.

One of the goals of the preferential policy areas is to facilitate the upgrading of domestic firms along the value chain, such that they increasingly focus on higher value added activities. Success on this dimension could show up as higher firm-level productivity. In the first table, we present estimates for labor and total factor productivity.[13] In addition, we look at capital-intensity as access to capital is often a discretionary preferential policy in China.

Table 1 reports the ATT estimates for all three dependent variables, both type of areas, and both estimators. The labor productivity differences are always positive and significant at the 5% (even 1%) level. Firms that choose to locate in a STIP are

[13] Labor productivity is calculated as value added per worker and TFP is calculated using an index number, as in Brandt et al. (2012).

Table 1: Estimated ATT – Productivity & capital intensity

		LP	K/L	TFP
STIP	Regression adjustment	0.206	0.395	-0.010
		(0.057)**	(0.064)**	(0.051)
	Double robust	0.214	0.338	-0.009
		(0.057)**	(0.064)**	(0.051)
ETDZ	Regression adjustment	0.271	0.622	-0.083
		(0.062)**	(0.063)**	(0.051)*
	Double robust	0.257	0.593	-0.074
		(0.048)**	(0.063)**	(0.079)

Note: Statistics in parentheses are standard errors, obtained by 1000 bootstrap replications for the double robust estimates. **, * indicates 5% and 10% significance levels.

found to achieve after one year 22.9% to 23.9% higher level of labor productivity than other firms, a 0.206 to 0.214 log-points difference, controlling for the location, sector, ownership, size, and wage rate. The productivity advantage is even slightly higher for firms locating in an ETDZ.

The estimates in the second column indicate that firms locating in both types of preferential areas employ vastly more capital. The log-point differences translate in percentage differences of 44.3% for firms in STIPs and even 87.3% in ETDZs, averaged over both estimates. The much higher capital-intensity, means that their large labor productivity advantage does not translate into higher total factor productivity. For STIPs both estimates of the TFP gap are very close to zero and for ETDZs they are negative, but barely significant.

Another performance indicator we considered is the share of domestic value added in sales. An increase could signal a move away from simple assembly activities and the fewer imports of advanced parts. However, all estimates for this dependent variable were close to zero and never significant (results available upon request).

Even though we only observe 458 entrants in STIPs and 891 entrants in ETDZs, the differences in Table 1 are estimated rather precisely. Against expectations, standard errors are barely higher for the weighted double robust results. We conclude that firms locating in the preferential policy areas operate at much higher labor productivity, but the difference can be fully explained by their higher capital use, with no role for efficiency or technological differences. The supporting policy environment in the preferential zones seems to facilitate these firms' access to capital markets.

5.2 Export volume measures

We next turn to export performance as objective indicator of quality upgrading by domestic firms. This is in the spirit of Sutton (2007) who assumed that success in the export market requires firms to achieve a minimum level of quality. In this section we focus on two measures of export volume: the value of total exports and the number of export destinations (both measured in logarithms). Operating more efficiently will lower costs and raise sales, for a given level of quality, which makes it feasible to cover fixed trading costs or sunk costs of entering new export markets. In the next section we focus on the quality dimension of export performance.

In Table 2 we present ATT estimates for the log-value of total exports one and two years after the firm's entry date. Seven of the eight point estimates are positive and four are significantly different from zero. Especially for firms locating in an ETDZ there is clear evidence that they are able to export greater volumes. The point estimates suggest a 25% to 29% advantage in year 2. For STIP firms, the point estimates are similar, at least in the first year after entry, but the standard errors are a lot higher.

Two more patterns are worth mentioning. First, all point estimates are higher for the double robust method than for the simple regression adjustment. The method is less vulnerable to misspecification of the functional form, but gives rise to higher standard errors. Second, all estimates decline substantially from the second to the third year and this is far more pronounced for firms in STIPs. Only the double robust estimate for firms in an ETDZ are still significant in year 3.

In the next two columns, we report the results for the (log) number of export destinations as performance variable. All eight point estimates are now estimated positively, but not a single one is significantly different from zero. The preponderance of positive coefficients hints at a positive effect of locating in a preferential area, but the evidence is very weak. The highest t-statistic is 1.32—for ETDZ firms in year 3. In spite of the imprecision, the point estimates are remarkably stable over the two time periods and estimators. Their size is comparable for STIPs and ETDZs, with the average estimate suggesting firms in STIPs serving 3.9% more destinations than control firms and firms in ETDZs 5.1% more.

Overall we view the evidence of higher export volumes for firms in ETDZs as

Table 2: Estimated ATT – Export volume measures

		Total export value		No. of destinations	
		year 2	year 3	year 2	year 3
STIP	Regression adj.	0.204	-0.002	0.034	0.043
		(0.132)	(0.097)	(0.069)	(0.052)
	Double robust	0.358	0.075	0.030	0.048
		(0.190)*	(0.128)	(0.072)	(0.057)
ETDZ	Regression adj.	0.226	0.099	0.056	0.038
		(0.096)**	(0.070)	(0.051)	(0.37)
	Double robust	0.255	0.175	0.060	0.046
		(0.128)*	(0.088)**	(0.053)	(0.035)

Note: Statistics in parentheses are standard errors, obtained by 200 bootstrap replications for the double robust estimates. **, * indicates 5% and 10% significance levels.

fairly solid. Export volumes are clearly higher and some weak evidence suggests more export destinations are served as well. Stronger effects for ATE estimates are reported below. The positive effects for firms in STIPs are estimated less precisely and fade more quickly. They could simply be due to the supportive policy environment and the proximity of other successful firms giving these firms a head start.

5.3 Export quality measures

The next two performance measures aim to capture quality as opposed to a volume effects. We first verify whether the composition of export destinations differs systematically between firms in the preferential areas and other firms. The dependent variable in the first two columns of Table 3 is the fraction of trade going to high-income countries, constructed by counting the number of trade flows by product-destination pair.

The results are all insignificant and there is not even a clear pattern in the signs. The standard errors are quite low, but the point estimates are all extremely close to zero. As a robustness check, we also calculated the ratio in value terms, but the estimates were almost equally insignificant. For ETDZ firms, a few coefficients were somewhat larger, reaching 0.012 and 0.015, but with t-statistics still only around 1. For STIP firms, almost all coefficients turned negative, but still very small in absolute

Table 3: Estimated ATT – Export quality measures

		Ratio high-income		Relative price	
		year 2	year 3	year 2	year 3
STIP	Regression adj.	0.003	-0.002	0.432	0.334
		(0.020)	(0.015)	(0.077)**	(0.056)**
	Double robust	0.000	-0.005	0.408	0.270
		(0.022)	(0.016)	(0.106)**	(0.089)**
ETDZ	Regression adj.	0.004	-0.004	0.077	0.138
		(0.015)	(0.011)	(0.056)	(0.041)**
	Double robust	-0.003	-0.007	0.089	0.141
		(0.015)	(0.010)	(0.063)	(0.047)**

Note: Statistics in parentheses are standard errors, obtained by 200 bootstrap replications for the double robust estimates. **, * indicates 5% and 10% significance levels.

value. Only on the sub-sample of firms producing machinery and electronics did the negative point estimate for STIP firms become almost significant, which is discussed further below.

The final performance measure is the relative price of exports, i.e. the unit value ratio. Results are reported in the last two columns of Table 3 and here the differences are again very prominent. All point estimates are positive, often very large, and most are significantly different from zero. STIP firms in particular are able to sell their exports at above-average prices. The difference is 50% in year 2, averaged over the two estimators. Being able to enter with easy access to capital and in the proximity of other high performing firms seems to generate large benefits in terms of product quality or finding more eager buyers. The differential reduces to 35% in year 3, suggesting that locating in a STIP gives entrants a head start, but that other firms make up some ground over time.

The price differentials are also estimated positively for ETDZ firms, but only one quarter to one half as large as for STIPs. For them the estimated effects grow over time and only become significantly different from zero in the third year of operation. In line with the estimates in Table 2, the effects for firms in ETDZs are more persistent over time. In contrast with those earlier estimates, the quality effects are largest for firms in STIPs.

Table 4: Additional evidence: high-tech firms (STIP) and ATE estimates (ETDZ)

		Relative price		Rel. price by destination	
		year 2	year 3	year 2	year 3
STIP (TECH)	Regression adj.	0.309	0.217	0.445	0.163
		(0.195)*	(0.171)	(0.178)**	(0.158)
	Double robust	0.362	0.309	0.517	0.237
		(0.256)	(0.163)**	(0.239)**	(0.169)**

		Total export value		No. of destinations	
		year 2	year 3	year 2	year 3
ETDZ (ATE)	Regression adj.	0.295	0.325	0.101	0.089
		(0.108)**	(0.090)**	(0.057)*	(0.048)*
	Double robust	0.347	0.348	0.146	0.120
		(0.160)**	(0.104)**	(0.069)**	(0.059)**

Note: Statistics in parentheses are standard errors, obtained by 200 bootstrap replications for the double robust estimates. **, * indicates 5% and 10% significance levels. For ETDZs, we report average treatment effects, not limited to treated firms. For STIPs, we report ATT estimates on a limited sample of firms producing machinery and electronics.

5.4 Additional evidence: high-tech firms and ATE estimates

The earlier results suggested a positive effect of locating in an ETDZ on export volumes, especially total export value, and a positive effect of locating in a STIP on export quality, especially on the relative price. To buttress this interpretation of the results, we include some additional evidence in Table 4.

In the first panel, we show estimates for STIP firms for a sample limited to the "Machinery and electronic equipment" industries (CIC industry codes 35–41). The expectation is for effects to be stronger on this subset of firms as they are more naturally high-tech and produce goods for which China has a revealed comparative advantage in trade. The estimates on the relative price differentials are comparable to those in Table 3. The average point estimates over the two methods are 0.336 in year 2 and 0.263 in year 3, comparable to the 0.420 and 0.302 estimates on the full sample. Two of the point estimates remain significant, even though the number of treated firms is only half as large.

The results become even stronger—estimates tend to be higher and standard errors lower—if the relative prices are calculated separately by export destination, i.e. normalized by the median price across all Chinese firms that export that particular 8-digit product to that particular destination. The price advantage for STIP firms is estimated higher after conditioning on destination than unconditionally. In the first year after entry, the log-point difference is 0.445 for the regression adjustment and even 0.517 for the double robust estimator. In contrast, for the full sample of STIP firms or for the ETDZ firms, price differentials by destination are only between one half and two thirds as large as the unconditional price differentials.

This is consistent with a lower fraction of these firms' exports going to high-income countries, where all prices tend to be higher. The estimates with the high-income ratio as dependent variable are still not significantly different from zero, but p-values where lower than for any other group of firms (as low as 16%). Taking the point estimates for high-tech STIP firms at face value suggests that the fraction of their export destinations that is high-income is 4.0% lower than average (in year 3) and the share of their exports going to these destinations is even 5.1% lower. It is well known that most electronics exports from China to the West is of the export processing variety and only contains limited Chinese value added. Firms in STIPs seem to focus, at least in relative terms, on lower-income destinations and they manage to secure much higher prices than other firms, conditional on the average price level by destination.

Finally, in the second panel of Table 4 we show ATE estimates for ETDZ firms for total export value and the number of country destinations.[14] In principle, any firm is eligible to set up in an ETDZ if it is willing to bear the congestion cost of locating close to a lot of other economic activity (Zhang and Sonobe 2011). The ATE estimates measure what the average effect would be for a random firm, taking into account that it might differ in characteristics from the typical firm in an ETDZ.

Compared to the earlier ATT estimates in Table 2, the effects on total export volumes are slightly higher in the first year following entry and they stay large in the next year. This is true both for the regression adjustment and for the flexible double robust estimates. In the latter case, the point estimates are also a lot higher and all coefficients now have p-values below 3%.

The ATE estimates of locating in an ETDZ on the total number of export destinations served are also estimated two to three times larger than the earlier ATT

[14] For STIP firms it is not appropriate to estimate ATE effects as the majority of firms simply do not qualify to locate there.

results. The precision is comparable such that all four coefficients are now significantly different from zero. The effects are again estimated to be very persistent over the two years. The average over the two estimation methods implies that ETDZ firms serve 13.1% more destinations than control firms in year 2 and 11.0% more in year 3.

6 Conclusion

We have applied program evaluation methods to analyze the effectiveness of Science and Technology Industrial Parks and Economic and Technology Development Zones in stimulating an upgrading process for China's manufacturing firms. The treatment in our analysis consists of the advantages granted to firms that locate in these preferential policy areas, e.g. tax reductions, duty exemptions, state-of-the-art infrastructure, etc. For firms locating in STIPs there is an additional potential benefit of locating near other high-tech firms that are screened by the park authorities.

We focus on new firms that choose to locate in a STIP or ETDZ and compare their subsequent performance with that of observationally similar entrants that chose to locate elsewhere. Using a unique data set that matches transaction-level trade statistics with firm-level information, we are able to identify treatment at the firm level and construct several dependent variables to capture multiple dimensions of performance.

The findings suggest that treated firms operate with a lot more capital than untreated firms, which raises labor productivity substantially, but without a noticeable effect on TFP. Their share of value added in total sales is also indistinguishable, but their export market performance is enhanced. The results reinforce the findings in Swenson (2008) for China that firms locating near multinationals are better able to access foreign markets. Most interestingly, firms locating in ETDZs and STIPs seem to follow a different export strategy.

The evidence strongly indicates higher total export levels for firms in ETDZs and positive, but weaker, effects on the total number of export destinations served. It suggests that these firms had some success in overcoming fixed and sunk entry costs into export markets. They are exploiting their performance advantage by exporting more goods to more places.

The effects on total exports are weaker for firms in STIPs and almost entirely absent for the number of destinations. STIP firms that produce machinery even serve fewer high-income destinations. Most notable for firms in STIPs are the much higher prices they fetch on the export market. These vastly exceed the modest premiums for ETDZ firms and for firms producing machinery the price differentials are even higher when we control for export destination. It suggests that firms in STIPs are exploiting their advantages by seeking out high-price niches, even at the expense of greater export volumes and foregoing entry in more export markets. This can be interpreted as indirect evidence of quality upgrading.

The positive results for in-park locations are in line with the conjecture in Hu (2007) that previous evaluations came too early to assess the full potential of technology parks. The strength of our analysis is that we can identify treatment at the firm level and benchmark performance with a control group of firms with similar observables. The use of export market performance as dependent variables provides a way to proxy various dimensions of firm quality. These measures are arguably more objective gauges of firm-upgrading than an input measure such as R&D or productivity, which can merely represent production efficiency. By focusing on new entrants the comparison is not diluted by different firm histories, but it substantially reduces the size of the sample we can work with.

A weakness of the analysis is the composition of the sample which only includes small firms if they are state-owned. In follow-up work, we intend to replicate the analysis using the information from the census of manufacturers that contains all firms, even small ones. However, in the cross-sectional census, we cannot focus on entrants, nor follow firms over time, or use export market performance.

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Table A.1: Summary statistics by treatment status

	Control firms	STIP	ETDZ
Number of observations	14,110	458	891
Fraction in "Machinery & electronics"	0.281	0.598	0.380
Average export performance:			
Total export value (in mio. USD)	5.87	10.81	11.49
No. of destination countries	6.95	7.42	7.02
Fraction high-income destinations	0.774	0.780	0.804
Fraction high-income exports	0.781	0.798	0.815
Relative price (relative to median = 1)	0.97	1.35	1.08
Relative price by destination (med. = 1)	1.00	1.29	1.03
Locations:			
Yangtze river Delta (Shanghai)	0.442	0.485	0.332
Pearl River Delta (Guangdong)	0.289	0.118	0.144
Yellow River Delta (Beijing)	0.208	0.317	0.442
Central region	0.039	0.038	0.051
Western region	0.022	0.042	0.031
Firm size (by employment):			
Small (<50 employees)	0.157	0.590	0.253
Medium (51-250 employees)	0.214	0.524	0.262
Large (250+ employees)	0.206	0.550	0.244
Ownership categories:			
State-owned	0.077	0.104	0.053
Collectives	0.012	0.009	0.005
Private	0.204	0.085	0.065
Hong Kong, Macau, Taiwan	0.316	0.221	0.219
Foreign	0.279	0.581	0.658
Wage rate per employee:			
Average, relative to sample average	0.956	1.690	1.339
Median, relative to sample median	0.980	1.631	1.251

Note: Sample is first year following entry for firms entering between 1999 and 2005.

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