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Trade barrier and misallocations: The case of the photovoltaic manufacturing industry in China

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ABSTRACT

We measure resource misallocations among Chinese photovoltaic (PV) exporters before and after the EU imposed antidumping duties (ADs) and countervailing duties (CVDs) in 2011.We find that improvements in total factor productivity can be attributed to improvements in the production efficiency of state-owned enterprises (SOEs) and the convergent returns of labor and capital inputs between SOEs and non-state-owned enterprises (NSOEs) after 2011. Surprisingly, our results indicate that improvements in extensive-margin misallocations due to exiting zombie SOEs do not contribute substantially to improving industry-level production efficiency, and we conclude that reallocating inputs among existing firms is more important.

1. Introduction

Spurred on by imminent climate change and by increasing knowledge about low-carbon environments, all major economies have shown a growing demand for and interest in developing clean energy, such as wind and solar natural power and LED energy-efficient illumination.

Newly industrialized China, which is equipped with cheap labor and strategic governmental support, thinks of itself as a giant player in the clean energy arena.[2] Among the various clean-energy-related fields, the Chinese photovoltaic (PV) manufacturing industry, which is a major source of clean energy, has experienced large-scale restructuring. Over the most recent decade, Chinese firms have acted swiftly to seize the largest share of the global PV manufacturing market share. Following the meteoric rise of Chinese PV firms, European and American PV producers have complained about Chinese companies' predatory pricing, which was made possible by the huge subsidies that these companies received from various levels of the Chinese government. Significant Chinese government intervention not only negatively affects Western competitors but also introduces distortions among domestic Chinese producers. For example, it has been argued that as only a few privileged Chinese PV firms have access to limited cheap production resources, government involvement has allowed inefficient state-owned enterprises (SOEs) to remain in the market, thus hindering further technological development

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[1] Statements or opinions in this article are those of the authors. Nothing in this article should be construed or interpreted as being the position or policy of the MOEA R.O.C.

[2] Those supportive industry policies include pushing the PV industry to increase exports and revenue under the last three Five-Year Plans for Chinese SOEs.

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within the industry.

In response to the upsurge of Chinese PV firms in the global market, trade measures targeting Chinese PV firms have been implemented since 2011, when the EU imposed anti-dumping duties (ADs) and countervailing duties (CVDs) on Chinese firms. Although there have been theoretical discussions regarding how ADs and CVDs might affect performance metrics for exporters, such as profits and employment, no prior study has quantified the effects of ADs or CVDs on industry productivity or the extent to which resources are misallocated among Chinese exporting firms (which are further divided into private firms and SOEs in this article). We know from Syverson (2011) that resource misallocation is a major challenge in the delivery of high productivity; therefore, quantifying disparate efficiencies in allocating resources across trade units within the Chinese PV industry is an essential issue.

In this paper, we assess the influence of ADs and CVDs on Chinese PV exporting firms. To this end, we study misallocations in trade-oriented SOEs and non-state-owned enterprises (NSOEs) within the Chinese PV manufacturing industry. As conceptually noted by Hsieh and Klenow (2009), relative to an ideal environment in which input markets are assumed to be competitive to ensure the equality of the marginal contribution of the last unit of production inputs, differences in firm-level distortions result in misallocations and lower aggregate performance.[3] Moreover, some of these distortions reflect intentional government policies, such as capital subsidies or preferential tax treatments that favor particular firms or production activities. Other distortions reflect exclusive seller power, which can lead to gigantic monopoly rents in the output markets.

We derive a measure of industry-level total factor productivity (TFP) based on Hsieh and Klenow's (2009) computations of overall misallocations. We further extend the literature by distinguishing between intensive-margin misallocations, which arise from inefficient allocation among existing firms, and extensive-margin misallocations, which are due to distorted firm entry and exit decisions. As highlighted in Melitz (2003), firm entry and exit should be important when investigating the change in average industry productivity following trade liberalization. Thus, we calculate a theory-based measure of production efficiency in the Chinese PV manufacturing industry. This measure of production efficiency has a larger value when the dispersion of revenue productivity (TFPR), which is a function of firm-level input and output distortions, is smaller across Chinese PV firms. In other words, when the extent of distortion is similar across firms, the measure of production efficiency will be higher.[4] When we compute the measure of production efficiency, we also obtain the TFPR for each firm in each year.[5] Because a firm's TFPR can be understood as an inverse measure of that firm's distortions, we further our analysis by identifying the potential sources of firm-level distortions.

We construct a new micro dataset that contains information on PV firm production inputs and outputs in China. We obtain these data from available annual financial reports of all companies in the Chinese PV industry and a unique research dataset procured from TrendForce., a research company focused on the IT manufacturing industries Our analysis includes most PV exporting firms in China that were in business between 2009 and 2014.[6] Our measure of production efficiency increases substantially after the EU imposed ADs and CVDs on Chinese PV exporters in 2011. Specifically, the measured production efficiency was at 0.66 in 2009, then dropped to its lowest point of 0.27 in 2010, and then increased substantially to more than 0.70 after 2011.[7] This increase indicates substantial convergence of the distortions across PV exporters in China following the EU's imposition of ADs and CVDs on Chinese PV firms. Our results also suggest that surviving Chinese SOEs contribute the most to improving production efficiency after 2011.

The second part of the analysis further extends the literature by investigating the factors that affect production efficiency. A variety of productivity-related indices have been adopted, and they robustly confirm that the converging gap in firm-level distortions between surviving SOEs and NSOEs helps production efficiency in the Chinese PV industry. This converging gap in firm-level distortions reflects the remarkable convergence of labor and capital productivity between surviving SOEs and NSOEs. Moreover, several zombie SOE firms that were particularly inefficient were forced to leave the market after the EU's imposition of ADs and CVDs in 2011. Therefore, production efficiency further increased because of the reduced extensive-margin misallocation.

Our paper is closely related to the literature that discusses resource misallocations and trade frictions. Studies on resource misallocation have become a focal point in the growth literature since the seminal work of Banerjee and Duflo (2005), who found that there is a large dispersion in the marginal product of capital among Indian firms that leads to significant loss of aggregate output.[8] The more recent research regarding misallocation has been initiated by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Restuccia and Rogerson (2008) argue that policy distortions that cause an incorrect match between production input usage and firm-level productivity lower aggregate TFP.[9] By reducing the extent of capital and output distortions in India and China to a degree that is comparable to the levels of the US, Hsieh and Klenow (2009) indicate that these two emerging countries' TFPs grew by 40% to 60% and 30% to 50%,

[3] Hsieh and Klenow (2009) focus on resource misallocations in India and China and attribute those countries' losses in production efficiency loss primarily to differences in governmental policies. These distortions influence the differences in TFP across industries in different countries.

[4] According to Bartelsman et al. (2013), the improved allocative efficiency is associated with the process in which limited production inputs are reallocated from less-productive to more-productive units within an economy.

[5] Our gauge of industry-level productivity begins with a measurement of idiosyncratic input distortions at the firm level. Thus, this first step requires intensive data support at the firm level, which we describe below.

[6] We do not include all the Chinese PV producing firms in our analysis as private companies (not listed on the stock markets) do not have to publish their annual financial report, and no other related researches or trade investigation reports have any extended reports regarding these small private PV firms in China.

[7] This measure denotes the ratio of the actual and efficient production levels of innovation, where efficient production is defined as the output level that is obtained with no misallocations of resources across firms within the PV industry. For example, a value of 0.5 means that actual production would have doubled (1/0.5=2) had the misallocations been eliminated.

[8] An early paper by Baily et al. (1992) also emphasizes the importance of resource misallocation and suggests that the productivity growth in US manufacturing in the 1980s may be largely attributed to factor reallocations from low-productivity plants to high-productivity plants.

[9] Specifically, these authors study a class of distortions that lead to no changes in the aggregate prices and no changes in the aggregate factor accumulation but that do have idiosyncratic distortions that create heterogeneity in the prices faced by individual producers.

respectively. Several papers have studied growth implications through various channels of misallocation. For example, Banerjee & Moll (2010); Midrigan & Xu (2014); Buera et al. (2013) and Moll (2014) construct dynamic general equilibrium models of misallocation with capital market imperfections; Jones (2013) argues that the negative effects of misallocations may be amplified by an economy's input-output structure, which helps to explain cross-country TFP gaps; and Jovanovic (2014) examines misallocation using an assignment framework with heterogeneous firms and workers and argues that more efficient assignments of human capital lead to faster long-term growth, greater inequality, and less turnover in the distribution of human capital.

Staiger and Wolak (1994) search for the timing and the trigger for the initiation of ADs and CVDs. Their work identifies separate trade effects for each phase of the antidumping process and analyzes the associated post-investigation outcomes. Huang (2008) and Zhou (2011) study the overall industry welfare effects resulting from ADs and CVDs imposed by the EU on East Asian countries. Konings and Vandenbussche (2005) use micro-level data to empirically measure the protection effects of ADs and conclude that ADs benefit domestic firms by allowing them to acquire local market power. Although the literature mainly emphasizes the negative effects of ADs and CVDs on exporters' industrial profits and on employee and firm numbers, Li and Whalley (2015) report that ADs and CVDs improve exporters' labor productivity because foreign imposition of ADs and CVDs work as countermeasures to biased domestic industrial policies, such as illegal or dubious government subsidies and support.[10]

Our paper contributes to the previous literature in two important ways. First, we review the current literature and quantify the potential misallocation problems in the Chinese PV industry, which is a new energy-saving industry that has been deemed crucial for the future growth of the Chinese economy.[11] Second, this paper is the first to analyze how a change in foreign trade policy might affect resource misallocation within an industry. Using a new model, we quantify the improvement in efficiency from the extensive and intensive margins, which allows us to decompose the efficiency consequences resulting from firm dynamics following policy changes.[12]

The remainder of this article is organized as follows. In Section 2, we introduce the methodology, whereas in Section 3, we present the unique dataset and data sources and discuss the construction process. Section 4 presents the results of our empirical analysis on the evolution of production efficiency and its determinants, and Section 5 concludes.

2. Methodology

We construct a model that is designed specifically to capture key features of the PV manufacturing industry in the presence of misallocation. We consider decreasing returns to scale production technologies that facilitate the determination of firm size. This theory is based on the assumption that manufacturing firms are heterogeneous in their production efficiencies and in the distortion levels they face. A firm's entry and exit decisions are modeled based on a framework similar to that used by Melitz (2003). In so doing, we can quantify the effects of misallocations in the PV manufacturing industry at the intensive and extensive margins. Building upon our theoretical aggregation, we investigate the full effects of resource misallocation on industry-level TFP.

2.1. Measure of overall resource misallocation across firms

In this paper, we seek to devise a model that can specifically capture the key features of the PV industry. We wish to develop a theoretical model compatible with basic economic rules that captures firms' profit maximization behaviors when facing idiosyncratic shocks in the PV industry. To measure the effects of resource misallocation on industry-level TFP, we conceptually adapt the model of Hsieh and Klenow (2009) on misallocation. The PV industry consists of firms of different sizes and productivities. This industry also features product homogeneity, with prices quoted based on price per watt. To conform to these characteristics, we consider a model setup with a homogeneous product governed by decreasing return-to-scale production technology, as in Lucas (1978).[13] This setup allows for the existence of firm heterogeneity due to both different productivities (TFPs) and idiosyncratic shocks (firm-level distortions).

We begin by assuming a competitive PV industry that features a homogeneous product.[14] There are M firms within the industry, and the aggregate output is represented by:

$$Y = \sum_{i=1}^{M} Y_i. \tag{1}$$

We then consider firm i in this industry, and the output of the firm is represented by:

[10] A detailed comment on the policy effects of ADs and CVDs is available in Moore and Wu (2015) on the trade dispute involving China X-Ray Equipment.

[11] Studies, such as Bown (2010) and Lu et al. (2013), focus on the impact of ADs and CVDs from the perspective of foreign targeted firms.

[12] For example, if we had similar data at the firm level, we could analyze how changing regulations regarding foreign ownership affect resource misallocation.

[13] PV manufacturers must undertake the production of their own components, from wafers to modules, and several complicated assembly processes. Thus, the assumption of decreasing returns to scale is required to guarantee that a large proportion of output is explained well by the specific production technology possessed by these manufacturers. For details, see Goossens (2014), "Solar Boom Driving First Global Panel Shortage Since 2006," *Bloomberg*, August 19, 2014,http://www.bloomberg.com/news/2014-08-18/solar-boom-driving-first-global-panel-shortage-since-2006.html.

[14] The solar PV modules are quoted by the price per watt, and for the convenience of follow-up analysis, we adopt the homogeneous products setup in the model. For details, see the European Commission's press release (2013) "European Commission Adopts Price Undertaking in EU-China Solar Panels Case," press release, August 2, 2013, http://trade.ec.europa.eu/doclib/press/index.cfm?id=957.

$$Y = \ A_i\left(L_i^{\alpha}K_i^{1-\alpha}\right)^{\gamma}, \quad \gamma \in \ (0,1) \tag{2}$$

This setup essentially captures the decreasing returns to scale production technology where γ governs a firm's operative returns to scale in the PV industry. The operative returns to scale is also referred to as the "span-of-control" parameter described by Lucas (1978).[15]

Firms in the Chinese PV industry are heterogeneous not only in production efficiency A_i but also in the distortions associated with capital and labor productivities. Here, we follow Hsieh and Klenow (2009) by assuming that firms face two types of distortions such that the output distortion τ_{Yi} simultaneously affects capital and labor productivities and the capital distortion τ_{Ki} drives up the productivity of capital relative to labor. Hence, a firm's profit is given by:

$$\pi_i = (1-\tau_{Yi})P_iY_i - wL_i - (1 + \tau_{Ki})RK_i. \tag{3}$$

We assume that the labor and capital markets are both competitive. Given the assumptions that products are homogeneous and that the standard first-order condition on demand holds, the output price is expressed as:

$$P_i = \ P, \quad \text{for every firm } i \text{ in the PV industry}. \tag{4}$$

We then solve the demand for production inputs in perfectly competitive factor markets. The demand derived from (4) can be inserted into (3) to solve the input demand and the output supply, which follow the following properties:

$$L_i \propto \left(\frac{A_i(1-\tau_{Yi})}{(1 + \tau_{Ki})^{\gamma(1-\alpha)}}\right)^{\frac{1}{1-\gamma}}, \tag{5}$$

$$K_i \propto \left(\frac{A_i(1-\tau_{Yi})}{(1 + \tau_{Ki})^{(\alpha\gamma-1)}}\right)^{\frac{1}{1-\gamma}}, \tag{6}$$

$$Y_i \propto \left(\frac{A_i(1-\tau_{Yi})}{(1 + \tau_{Ki})^{\gamma(\alpha-1)}}\right)^{\frac{1}{1-\gamma}}. \tag{7}$$

Under profit maximization, firms that face greater output distortions (higher τ_{Yi}) exhibit a higher marginal product of labor. Similarly, firms experience a higher marginal revenue product of capital when they face greater output or capital distortions (τ_{Ki}):

$$MRPL_i \triangleq \alpha\gamma\frac{PY_i}{L_i} = w\frac{1}{1-\tau_{Yi}}, \tag{8}$$

$$MRPK_i \triangleq (1-\alpha)\gamma\frac{PY_i}{K_i} = R\frac{1 \ + \ \tau_{Ki}}{1 \ - \ \tau_{Yi}}. \tag{9}$$

A firm facing a high degree of distortions would end up with higher marginal revenue products of production inputs. Moreover, highly distorted firms would have smaller equilibrium scales of production than the optimal scales in a frictionless economy with no firm-level distortions.

In equilibrium, the aggregate final output is derived by simply aggregating an individual firm's output production. Similarly, one can sum over every firm's input demand to obtain the industry aggregate input usage. Specifically, firm i's input demand is related to the industry's total input as follows:

$$L_i = L \times \frac{A_i(1-\tau_i)^{\frac{1}{1-\gamma}}(1 \ + \ \tau_{Ki})^{\frac{\gamma(\alpha-1)}{1-\gamma}}}{\sum_{j=1}^{M}\left[A_j\left(1-\tau_j\right)^{\frac{1}{1-\gamma}}(1 \ + \ \tau_{Ki})^{\frac{\gamma(\alpha-1)}{1-\gamma}}\right]}, \quad \forall \quad i. \tag{10}$$

$$K_i = K \times \frac{A_i(1-\tau_i)^{\frac{1}{1-\gamma}}(1 \ + \ \tau_{Ki})^{\frac{\alpha\gamma-1}{1-\gamma}}}{\sum_{j=1}^{M}\left[A_j\left(1-\tau_j\right)^{\frac{1}{1-\gamma}}(1 \ + \ \tau_{Ki})^{\frac{\alpha\gamma-1}{1-\gamma}}\right]}, \quad \forall \quad i. \tag{11}$$

Thus, the industry-level production function is

$$Y = TFP \times L^{\alpha} \times K^{1-\alpha}. \tag{12}$$

[15] As detailed by Lucas (1978), the value of the span-of-control parameter helps to determine the level of a firm's returns to scale in the industry and characterizes the firm size distribution to the industry.

The TFP in Eq. (12) denotes the industry-level TFP, which is important for determining the measure of aggregate production efficiency. Hsieh and Klenow (2009) differentiate between physical productivity, which they refer to as TFPQ and revenue productivity, which they refer to as TFPR. TFPQ is firm-specific, whereas TFPR is industry-specific (if there are no resource distortions). As in Hsieh and Klenow (2009), we define TFPQ and TFPR for each firm i as follows:

$$TFPQ_i \triangleq \frac{Y_i}{\left(L_i^{\alpha} K_i^{1-\alpha}\right)^{\gamma}}, \tag{13}$$

$$TFPR_i \triangleq \frac{PY_i}{L_i^{\alpha} K_i^{1-\alpha}}. \tag{14}$$

Without distortions, TFPR will not vary across firms within an industry. The only reason firms within a specific industry have different TFPRs is because output and capital distortions are different at the firm level. It must be remembered that factor markets are competitive and that all firms face the same input price. Without firm-specific output and capital distortions, firms with higher TFPQs use more production resources up to the level at which the TFPRs are equalized within the same industry. To be more precise, we can represent TFPR_iin terms of the geometric average of firm i's marginal revenue products of labor and capital. Firm i's TFPR is an indicator of the distortions faced by firm i in this industry:

$$TFPR_i = \left[\left(\frac{MRPL_i}{w}\right)^{\alpha}\left(\frac{MRPK_i}{R}\right)^{1-\alpha}\right]^{\gamma} = \left[(1-\tau_{Yi})^{\alpha}\left[\frac{(1-\tau_{Yi})}{(1+\tau_{Ki})}\right]^{1-\alpha}\right]^{-\gamma}. \tag{15}$$

As higher outputs and greater capital distortions raise the marginal products of capital and labor, this firm will exhibit a smaller scale of output than the efficient scale. By using (15) and by simplifying the linear aggregate of the industry production function, we calculate the industry-level production efficiency, i.e., the industry-level TFP, as follows:

$$TFP = \frac{Y}{L^{\alpha}K^{1-\alpha}} = \frac{\left[\sum_{i=1}^{M}\left(TFPQ_i\frac{\overline{TFPR}}{TFPR_i}\right)^{\frac{1}{1-\gamma}}\right]^{1-\gamma}}{\left(L^{\alpha}K^{1-\alpha}\right)^{1-\gamma}}, \tag{16}$$

where $\overline{\text{TFPR}}$ is found to be a harmonic average of the average marginal revenue products of capital and labor in the industry.[16] Eq. (16) implies that the industry production efficiency is that of a CES function aggregated across all TFPQ_i when revenue productivities are equalized across firms within the industry. In this case, TFP is represented as:

$$\overline{A} = \left(\sum_{i=1}^{M} A_i^{\frac{1}{1-\gamma}}\right)^{1-\gamma} / \left(L^{\alpha}K^{1-\alpha}\right)^{1-\gamma}.$$

Based on (16), we can empirically measure industry-level production efficiency and evaluate the loss of efficiency in the PV industry that is the result of resource misallocation.

2.2. Firm entry-exit, production, and misallocation

In the previous section, we derived the industry-level TFP measure as a function of misallocations. However, we have yet to address the question of where these misallocations originate. Conceptually, misallocations may arise from the inefficient allocation of inputs among existing firms, which we refer to as intensive-margin misallocations, and as illustrated in Hsieh and Klenow (2014), from firms' entry and exit decisions, which we refer to as extensive-margin misallocations.[17] In our new extension model, we will decompose overall misallocations into their intensive- and extensive-margin components. Following Melitz's (2003) notion that the number of firms should be endogenous, surviving firms should be able to earn profits that are sufficient to offset the fixed costs associated with remaining operational. In addition, given policy changes that might not only affect the distortions that firms face but also cause the reallocation of resources among existing firms, firms' entry and exit decisions will result in improving extensive-margin misallocations within the PV industry.[18]

To enter the industry, we assume that each firm must pay a fixed cost F to stay in operation. The entering and operating firms then initiate production given their heterogeneous production technologies and their individual output and capital distortions. The unit cost of production will endogenously vary across firms, and the costs depend on firm-specific variations in the technology scale as well as output and capital distortions. Hence, variation in the unit cost of production across firms can be inferred by the different TFPQs and TFPRs measured across firms in the industry.

[16] $\overline{TFPR} = \left[\sum_{j=1}^{M}\left(\frac{Y_j}{Y}(1-\tau_{Yj})\right)\right]^{-\alpha\gamma}\left[\sum_{j=1}^{M}\left(\frac{Y_j(1-\tau_{Yj})}{Y(1+\tau_{Kj})}\right)\right]^{-(1-\alpha)\gamma}$

[17] For example, micro-level distortions detected in the industry may shield certain less-efficient firms and allow them to remain operative at a lower industry-level TFP.

[18] Hsieh and Song (2016) detail capital subsidies and entry control for governments to support SOEs to dominate in the strategic or pillar industries. The highly inefficient SOEs will become zombie firms and be forced out of the market after deregulation.

Table 1
Parameters used in calibrations.

	α	$R = \delta + \rho$		γ
		δ	ρ	
Parameter values	0.10	0.20	0.03	0.8

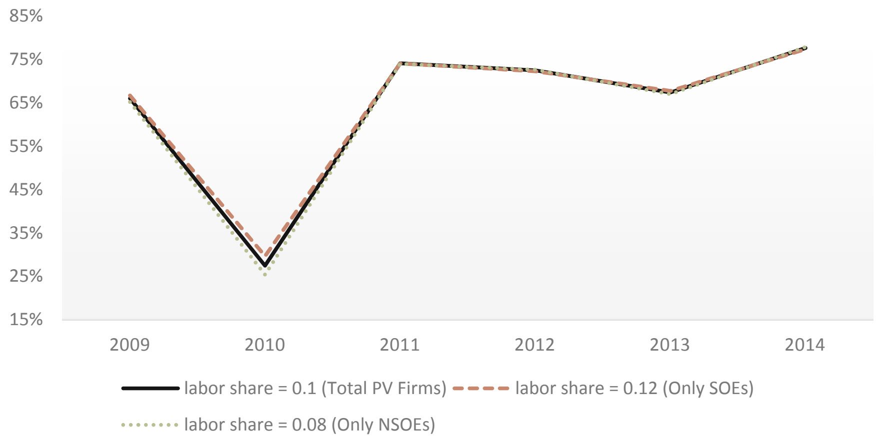

Fig. 1. Production efficiency in the Chinese PV industry.

For simplicity, we consider a simple version of the timeline for firms' decisions, i.e., (i) firms pay F to remain in operation and (ii) firms' production and exit decisions depend on realized profits. If realized profits are too low, firms exit immediately without engaging in production. Conversely, if the realized profits are high enough, firms will produce a positive number of products, realize sufficient profits, and remain in operation.

As described in Melitz (2003), firms experience heterogeneous productivity shock prior to the beginning of each period. It is then straightforward to follow Melitz (2003) and to find a cutoff productivity level A^* by determining the threshold level of A at which a firm is indifferent between remaining and not remaining in operation. When we consider a frictionless equilibrium without firm-level distortions, firms remain in operation only if their productivity levels are higher than the cutoff level A^*. Firm-level distortions that are prevalent in an industry may cause the set of surviving firms to be much different from the set of surviving firms in a frictionless economy without micro-level distortions. Therefore, the composition of productivity A of these survivors is also transformed because of the distortions. This effect could be identified as extensive-margin misallocation and should be quantified when measuring the extent of resource misallocation in the PV industry in China.

2.3. Computation of overall misallocation

Before we can calculate the unit-free industry-level production efficiency in the Chinese PV industry, we must first determine the values of several exogenous parameters. All necessary exogenous parameters are listed in Table 1. We set the labor share at 0.1, which is much lower than that set in Hsieh and Klenow (2009). Hsieh and Klenow (2009) argue that the share of labor in manufacturing is approximately two-thirds, based on the National Income and Product Accounts. However, in this study, we assume a lower labor share because of the capital-intensive nature of the industries under analysis. According to the Annual Review and Outlook for China's Solar PV Industry, the labor wage, inclusive of all types of labor compensation, accounts for approximately 8% to 11% of the value added in the PV industry. Accordingly, we set the labor share at 10%. Subsequently, we recalculate our results with labor share parameters of 0.08 (the average labor share among NSOEs) and 0.12 (the average share among SOEs) to determine whether our findings remain valid. These alterations produced only extremely minor changes in industry-level production efficiency, as illustrated in Fig. 1.

We set the rental rate of capital as $R = 0.23$. This rental rate is a combination of an interest rate (ρ) of 3% and a depreciation rate (δ) of 20%, which is established in accordance with Chinese accounting rules. Thus, we adopt full depreciation amortization within five years for any newly purchased fixed capital in the business year calendar. The interest rate is set at 3% within the sample period investigated in this paper.

With respect to the production efficiency calculation, the production efficiency measurement does not depend on the true rental rate of capital R. Instead, R only affects the capital distortion rate as derived here.[19]

Next, we determine the parameter γ. Based on Basu and Fernald (1995), Basu (1996), and Basu and Kimball (1997), we choose $\gamma = 0.8$, which implies that the return to organization capital is 20%. The parameter γ captures the degree of diminishing returns in variable factors at the firm level. Many empirical studies have used micro data to estimate production functions. From a review of studies conducted by Baily et al. (1992); Bahk and Gort (1993), Olley and Pakes (1996), and Bartelsman and Dhrymes (1998), we argue that in the context of a model such as ours, $\gamma = 0.8$ is a reasonable value for this parameter. Moreover, our choice of $\gamma = 0.8$ is also consistent with the discussion in Atkeson and Kehoe (2005) who, in their analysis, incorporate a variety of assumptions regarding the form of the production technology and draw on cross-sectional, panel, and time-series data from virtually every industry and developed country. Atkeson and Kehoe (2005) and Hsieh and Klenow (2009) also adopt the Lucas span-of-control parameter in setting $\gamma = 0.8$.[20]

We apply the notion of resource misallocation in Hsieh and Klenow (2009) to compute the idiosyncratic distortions in the labor and capital adoption costs. Specifically, we compute the firm-level distortions in labor and capital adoption costs as follows:

$$\text{(i)}\quad (\text{Capital distortion})_{\text{i}} \qquad \tau_{Ki} = \frac{1-\alpha}{\alpha}\frac{wL_i}{RK_i} - 1, \tag{17}$$

$$\text{(ii)}\quad (\text{Output distortion})_{\text{i}} \qquad 1 - \tau_{Yi} = \frac{1}{\alpha\gamma}\frac{wL_i}{PY_i}, \tag{18}$$

$$\text{(iii)}\quad (\text{TFPQ}_i) \qquad A_i = C\frac{PY_i}{\left((wL_i)^{\alpha}K_i^{1-\alpha}\right)^{\gamma}}. \tag{19}$$

The distortion measurement in this case is easy to understand because the Cobb-Douglas production technology is used. Eq. (17) is obtained from the standard Cobb-Douglas result that yields the relationship between the labor share and the capital share. It is determined that if the capital share is higher than the parameter adjustment factor $(1-\alpha)/\alpha$, we can infer that capital distortion exists. Eq. (18) reveals that the labor share relative to the total output will identify output distortion if it is higher than the parameter adjustment factor $1/(\alpha\gamma)$. The TFPQ$_i$ measurement in (19) is different from its definition in (13) by a constant C. However, in our database, we have the firm's net sales PY_i and total labor compensation; therefore, we cannot measure TFPQ$_i$ based on the definition. Although we cannot directly measure TFPQ$_i$, the relative productivities across firms are not affected by the constant C, which is assumed to be the same within the same industry. Because we assume that firms produce homogeneous products, these distortion measurements and firm-level productivities are enough for us to proceed with gauging the industry-wide efficiency loss.

We calculate the efficiency loss by introducing the efficient industry output in the Chinese PV industry. Efficient industry output is associated with the case in which there are no idiosyncratic distortions among firms within the Chinese PV industry. Therefore, the marginal products of production factors are equalized across firms.

Thus,

$$TFPR_i = \overline{TFPR}, \tag{20}$$

$$\overline{A} = \frac{\left(\sum_{i=1}^{M} A_i^{\frac{1}{1-\gamma}}\right)^{1-\gamma}}{\left(L^{\alpha}K^{1-\alpha}\right)^{1-\gamma}}, \tag{21}$$

$$\frac{Y}{Y_{\text{efficient}}} = \left[\sum_{i=1}^{M}\left(\frac{A_i}{\overline{A}}\frac{\overline{TFPR}}{TFPR_i}\right)^{\frac{1}{1-\gamma}}\right]^{1-\gamma}. \tag{22}$$

We itemize our results in a figure showing the ratios of production efficiency measurement ($Y_R = \mathrm{Y}/\mathrm{Y}_{\text{efficient}}$) in the Chinese PV industry across all sample periods. As predicted, TFP increases after deregulation, utilizing (21); therefore, this increase can represent an overall improvement in industry-level production efficiency and can be given by:[21]

$$100 \times \left(\frac{1}{\frac{\mathrm{Y}}{\mathrm{Y}_{\text{efficient}}}} - 1\right). \tag{23}$$

[19] In the production efficiency calculation, the production efficiency measurement does not depend on the true rental rate of capital R. Instead, R affects only the capital distortion rate as derived here. The reason is as follows. From Eqs. (17) and (18), the measured capital and output distortions change proportionally with R. However, the derived innovation efficiency depends on the ratio of the measured TFP of the entire innovation system relative to the efficient TFP of the entire innovation system. Therefore, the measured innovation efficiency will not depend on the chosen interest rate R.

[20] The span-of-control parameter (γ) records the operative returns to scale by labor (L) and fixed capital (K). This operative returns to scale parameter is often referred to as the "span-of-control" parameter, as in Lucas (1978), Atkeson and Kehoe (2005), and many others.

[21] Deregulation here means the removal of all idiosyncratic barriers or frictions that cause disparity in the marginal products of labor and capital.

2.4. Decomposing improvement in misallocation: the intensive and extensive margins

We empirically decompose improvement in misallocation into two components, i.e., the intensive and extensive margins. The former component arises from reallocating resources among firms that will always survive regardless of existing heterogeneous distortions, and the latter results from firms entering and exiting. There are two major conceptual improvements when one decomposes these two margins. First, in this extended model, the number of firms operating in the market is now endogenous. Second, micro-level distortions change the set of surviving firms and the set of productivity belonging to the surviving firms, as a result.[22] Accordingly, we first compute the improvement in industry-level TFPs both with and without considering extensive-margin misallocations; then, by taking the difference between the two, we can isolate the gain in TFP from the improvement in extensive-margin misallocations.

As noted above, our setup is similar to Melitz (2003) in the sense that firms must pay F units of final goods if they want to stay in business. In other words, firms survive if their profits can cover their fixed costs:

$$\pi_i - F \geq 0, \text{ for every firm } i \text{ remaining in operation.}$$

We adopt the estimator for F suggested by Bartelsman et al. (2013) to compute the fixed costs in the model. To be specific, given that firms operate under decreasing returns to scale production technology, we set the fixed cost F to be:

$$F = (1-\gamma)\min_i\left\{A_i\left(L_i^{\alpha}K_i^{1-\alpha}\right)^{\gamma}\right\}.$$

To compute fixed costs F, we focus on the smallest firm in an industry. For a marginally surviving firm, its optimal production level generates profit just high enough to cover its fixed costs, which allows it to remain in operation. Hence, information on the output level of the smallest firm combined with the operative returns to scale parameter γ results in a proxy for the fixed cost F within the industry. As argued by Bartelsman et al. (2013), this approach is applicable irrespective of any assumption regarding the heterogeneity of firm productivity and applies to a wide range of industries.

The observed data on factor demand are typically annual values that do not differentiate between fixed and variable cost factors. However, production input X (which can be capital or labor) can still theoretically consist of a fixed component, X_F, and a variable cost component, X_{vi}:

$$L_i = L_{vi} + L_F,$$

$$K_i = K_{vi} + K_F.$$

Following Bartelsman et al. (2013), we decompose total fixed cost F into L_F and K_F. Intuitively, L_F and K_F take the value by assuming cost minimization in adopting labor and capital inputs:[23]

$$w \times L_F = \alpha \times F,$$

$$R \times K_F = (1-\alpha) \times F.$$

We adopt the wage bill rather than the number of workers as our measure of labor input to account for differences in human capital across firms. The same assumption is applied to our measure of capital inputs, which is defined as the reported book value of the firm's capital stock.

Finally, to calculate distortion and productivity measures in each period, only variable input usage should be considered. Hence, we substitute the derived wL_{vi} for wL_i and RK_{vi} for RK_i in (17), (18) and (19) to obtain firm-level distortions and physical productivities in the Chinese PV industry.

To decompose the overall improvement in misallocation into the contributions of intensive and extensive margins, we must find cut-off productivity A^*, which determines the minimum level of firm productivity in a frictionless economy. In other words, a surviving firm i in an economy without heterogeneous firm-level distortions should have physical productivity, $A_i \geq A^*$, such that once it pays for fixed cost F, it can remain in operation. To calculate A^*, note that the profit level of a PV firm i with firm-level distortions is calculated as follows:

$$\pi_i = (1-\gamma)\, A_i^{\frac{1}{1-\gamma}}(1-\tau_{Yi})^{\frac{\gamma}{1-\gamma}}(1+\tau_{Ki})^{\frac{(\alpha-1)\gamma}{1-\gamma}}\left(\frac{\alpha}{w}\right)^{\frac{\alpha\gamma}{1-\gamma}}\left(\frac{1-\alpha}{R}\right)^{\frac{(1-\alpha)\gamma}{1-\gamma}}\gamma^{\frac{-\gamma}{1-\gamma}}. \tag{24}$$

Then, by plugging $\pi_i = F$ and $\tau_{Yi} = \tau_{Ki} = 0$, the cut-off productivity level A^* can be found.

Firms with productivity levels greater than A^* are those firms that should survive regardless of the existence of heterogeneous distortions. Therefore, we define the efficiency gains from reallocating resources among these more efficient firms as the potential

[22] This point is emphasized by Fattal Jaef (2012) and Hsieh and Song (2016).

[23] As suggested by Bartelsman et al. (2013) and Fattal Jaef (2012), fixed cost F is decomposed by following a firm's cost minimization problem. The first-order condition of the firm's cost minimization problem indicates that the capital-labor share should follow the product of the ratio of Cobb-Douglas exponents and the ratio of wage to the nominal interest rate.

improvement in intensive-margin misallocation. Formally, it is defined as:

$$100 \times \left(\frac{1}{\frac{Y}{Y_{\text{efficient}}}} \Bigg|_{A_i \geq A^*} - 1 \right) \tag{25}$$

The difference in the potential improvement in the overall (Eq. (24)) and intensive-margin (Eq. (25)) misallocations is then defined as the potential improvement in the extensive-margin misallocation:

$$100 \times \left(\frac{1}{\frac{Y}{Y_{\text{efficient}}}} - \frac{1}{\frac{Y}{Y_{\text{efficient}}}} \Bigg|_{A_i \geq A^*} \right) \tag{26}$$

Conceptually, this efficiency gain might be realized because the removal of idiosyncratic distortions will force all zombie firms with a productivity level below A^* to exit the market.

3. Chinese PV industry dataset

In this paper, we created a new micro dataset for the PV industry in China. The main empirical challenge with studying the PV market is that no existing database includes comprehensive firm-level information regarding operational details, sales, employment, capital inputs, unit costs and unit prices. These detailed data are crucial to the calibration of our productivity measure. To overcome this limitation, we created our own micro datasets by first merging information from different commercial micro datasets and then by hand-collecting the data for additional variables that are relevant to this study.

The first dataset that we use consists of the annual financial reports of all publicly listed companies in the PV industry.[24] We collect all companies' net sales, labor compensation, and the average of the book value of fixed capital net of depreciation at the beginning and end of the fiscal year as the measure of PV manufacturing firms' capital inputs.[25] The second dataset is procured from TrendForce and this dataset contains firm-level operational details, including market shares and firms' profitability, for all companies in the PV industry.[26] We then merge firm-level operational details with input and output information from datasets provided by several consulting and marketing intelligence companies with which we signed confidentiality agreements.[27] The merged dataset has been completed, and it includes the relevant variables necessary for this study. The completed micro dataset is then applied to our computations of empirical results.

We identify all major Chinese companies specializing in and focused on PV production. These firms account for approximately 60% of the global PV market, reflecting the fact that China is the largest PV producer worldwide. Our database consists of firm-level operational details as well as measures of sales, employment, capital inputs, and unit costs and unit prices from 2009 to 2014. To examine the impact of changes in trade barriers, we further split the data into the pre-ADs/CVDs period (2009 to 2010) and the post-ADs/CVDs period (2011 to 2014).[28] The data are summarized in Table 2.

3.1. *Industry features*

China and the EU are the two major players in the PV manufacturing sector accounting for more than 85% of the global market share during the period of study; thus, our research aim is to study the interaction of these two largest players in a recent major trade conflict.

A central theme in China's PV industry over the past decade has been the role of SOEs.[29] This fact naturally suggests that China's growth was driven by state capitalism. Proponents of the role of state capitalism note that although many SOEs were eventually shut down, the SOEs that remain in operation are among the largest firms in China today. In this regard, SOEs have played a crucial role in the advancement and development of the PV industry. However, a recent view propagated by many studies is the fear that these SOEs might in fact be too successful. This concern arises because it is widely accepted within the Chinese PV industry that the success of SOEs comes at the expense of the failure of NSOEs.[30] In particular, although PV manufacturing run by SOEs is typically large, their labor and capital productivity is significantly lower than that of the average NSOE.

A coherent way to identify SOEs in China is to use firms' legal registration with the Annual Survey of Industries conducted by China's National Bureau of Statistics from 1998 to 2007. This survey is a census of all legally registered firms in the industrial sector that generate more than five million RMB in annual revenue. Specifically, firms in China are legally registered as state-owned, collectively

[24] The annual financial reports of each company in the dataset can be retrieved from the public website of each company. The sample companies in the research dataset are all publicly listed on American, Chinese, Hong Kong and Singapore stock exchanges.
[25] We have collected more than 900 annual financial reports across company-years to construct the variables in this paper.
[26] We have procured exclusive access to this detailed solar energy dataset from Trend Force.
[27] We have procured the confidential dataset from TrendForce, and Trendforce also provides us original research data on the DRAM, LCD display, and LED sectors.
[28] We split the data coverage period by the year that the EU first imposed the ADs and CVDs on Chinese PV firms, i.e., 2011.
[29] In our empirical work, we focus on identifying state ownership, which is frequently disguised by the firm's legal registration.
[30] As noted by Hsieh and Song (2016), "guo jin min tui" is a major concern for the development of a new industry in China. This expression can be generally understood as SOEs advance, NSOEs retreat.

Table 2
Summary statistics before and after ADs/CVDs.

Total	**2009–2010**			
Before ADs/CVDs	Obs.	Mean	SD	C.V.
Revenue	115	2,055,038,095	3,510,081,927	171%
Salary	115	84,177,357	119,141,447	142%
Capital	115	4,569,769,564	9,908,997,564	217%
Total	**2011–2014**			
After ADs/CVDs	Obs.	Mean	SD	C.V.
Revenue	277	2,227,992,415	3,535,233,670	159%
Salary	277	155,210,519	242,494,359	156%
Capital	277	5,147,001,252	8,042,986,352	156%

Note: The results are computed by the authors based on the collected micro dataset of Chinese PV firms. C.V. reports the coefficient of variation for each respective variable.

owned, privately owned, limited-liability corporations, share-holding (including publicly traded) firms, or foreign firms. According to this classification, state ownership is typically defined as firms that are legally registered as state-owned. However, many firms are intentionally not legally registered as SOEs although they are controlled by government-related agents or holding companies dominated by the state in reality. For example, the joint ventures of the Shanghai local government with GM and Volkswagen (Shanghai-GM and Shanghai-VW) are registered as NSOEs because part of their funding is from a foreign source. In this regard, we remedy the obscure definition of SOEs via the equity structure specified in our collected PV firms' annual financial statements. In addition to the firms legally registered as SOEs in the Annual Survey of Industries, we further complement the definition of SOEs by including those ownership forms of share-holding cooperative enterprises, joint-operation enterprises, limited liability corporations, and shareholding corporations in which the majority shares of a firm are owned by the government, public organizations, or the SOEs themselves. Because we have recovered all the firms' capital structures in our constructed PV dataset, we have a thorough and accurate classification of SOEs and NSOEs. Thus, the real influence brought about by SOEs and NSOEs can be backed out accordingly.

3.2. Descriptive statistics

We use firms' publicly listed ID on the stock market to match firms over time. Table 2 summarizes the descriptive statistics of the Chinese PV industry, including companies' net sales (Y), labor compensation (L), and net value of fixed capital (K). Y and K are the most volatile, as evidenced by the standard deviations presented in Table 2. The results are consistent with our basic understanding regarding the pro-cyclical trend in terms of market demand and capital investment expenditure in the highly capital-intensive PV industry. This pro-cyclical feature can be partly attributed to the fact that firms in this industry frequently expand their production capacities to ensure lower future unit production costs. The general effects of the ADs and CVDs is reflected, first, by the lower volatility of post-AD/CVD net sales within the Chinese PV industry. Second, the post-AD/CVD Chinese PV industry may have more efficient input adoption in terms of both K/Y and L/Y. However, we cannot address this issue based on simple observations, as the computations of labor and capital productivity of Chinese PV firms require more detailed analysis.

4. Result analysis and robustness

4.1. Production efficiency in the Chinese PV industry

This paper is the first to investigate whether the EU's ADs and CVDs improve disparate efficiencies among China's PV exporters in the allocation of production inputs. Disparate firm-level efficiencies in labor and capital usage would exacerbate the extent of resource misallocation and causes industry-level loss based on production efficiency. In this study, we further extend the literature as we can compute the potential efficiency loss induced by firm-level intensive-margin and extensive-margin misallocations within the Chinese PV industry.

Whether the exits of highly subsidized SOEs would contribute to a marked improvement in the extensive-margin misallocation is an open but difficult question to address. Our model explicitly identifies the extremely inefficient zombie firms that will leave the market once firm-level distortions are removed to a level that no longer can shield these zombie firms from outside competition. In this manner, we enrich the policy implications by quantifying the firm entry-exit efficiency improvement resulting from the entry of small and efficient private firms and the exit of zombie SOEs.[31] Our devised measure of industry-level TFP is proposed to aggregate the idiosyncratic distortions of production inputs among Chinese PV firms. We compute the efficiency dynamics before and after the imposition of the EU's ADs and CVDs in 2011. This measure of industry-level TFP can elucidate whether the EU's imposition of ADs and CVDs on Chinese PV firms in 2011 had the efficiency-enhancing effect that some people claimed.

From Fig. 1, we find that our measure of production efficiency in the Chinese PV industry increased substantially following the EU's

[31] According to Hsieh and Song (2016), Chinese SOEs may have strong political motivations to pursue the job security of local workers instead of profit maximizations as their main management objectives.

Table 3
Result of production efficiency and misallocations.[a]

Efficiency measure	Firms	2009	2010	2011	2012	2013	2014
(1) Production efficiency [b]	All	66%	27%	74%	72%	67%	78%
(2) Production efficiency	No zombies	68%	28%	74%	75%	68%	79%
(3) Potential improvement [c] (intensive)+(extensive)	All	52%	270%	35%	39%	49%	28%
(4) Potential improvement [d] (intensive)	No zombies	47%	257%	35%	33%	47%	27%
(5) Potential improvement [e] (extensive)	Zombies exit	5%	13%	0%	6%	2%	1%
(6) Firm entries and exits	Entry	10	5	4	2	0	0
	Exit	0	0	0	3	7	4

Note:
[a] The values within each cell are values of production efficiencies in the Chinese PV industry, the improvement in these production efficiencies and firm entries and exits in a specific sample year;
[b] from Eq. (22);
[c] from Eq. (23);
[d] from Eq. (25);
[e] from Eq. (26).

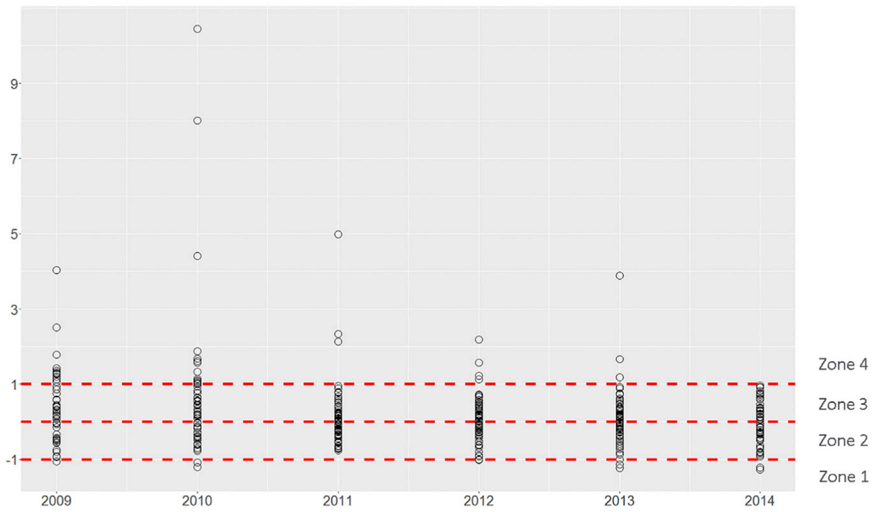

Fig. 2. Distribution of firm-level demeaned TFPRs (2009–2014). *Note:* Firm-level demeaned TFPRs are calculated by subtracting a firm's TFPR from that year's $\overline{TFPR}$.

imposition of ADs and CVDs on Chinese exporters in 2011. Production efficiency began at 0.66 in 2009, dropped (to its lowest level) to 0.27 in 2010, and then rose substantially to over 0.70 after 2011.[32] This increase indicates substantial convergence of the distortions across PV exporters in China after the EU imposed ADs and CVDs on Chinese PV firms. For the Chinese PV industry in the pre-ADs/CVDs period, lower production efficiency was recorded, and the year 2010, in particular, witnessed the lowest industry-level production efficiency.[33]

We consider whether the record high misallocation in 2010 may have triggered the EU's imposition of ADs and CVDs in 2011, which, in turn, initiated the exits of zombie firms and resulted in a strong rebound for production efficiency. To check for this, in Table 3, we report the production efficiency measures, the decomposition of improvement in production efficiency, and the number of entry/exit firms in each year. In the first two rows of Table 3, we find that the production efficiency measures including (row 1) and excluding (row 2) zombie firms are similar within each year. Next, in rows 3, 4, and 5, we confirm our findings in the first two rows, as the overall improvement (row 3) was primarily derived from the intensive margin (row 4). However, these results contradict commonly made arguments. The reason for this contradiction may be found in Row 6. Specifically, we note that although there were tens of firms in the market every year, the number of firms entering and exiting the market was minimal, which suggests that if there were to be an improvement in efficiency, it would be observed in those firms that remain.

In Fig. 1, we observe an increasing trend in industry-level production efficiency in the Chinese PV industry after 2011. This raises the

[32] This measure denotes the ratio of the actual and efficient production levels, where efficient production is defined as the output level that is obtained when there are no misallocations of resources across firms. For example, a value of 0.5 means that production would have doubled (1/0.5=2) had the misallocations been eliminated.
[33] The main impact of the recent financial crises was most universally felt in 2009. We conjecture that since the trough of PV demand in 2009 was generally experienced by all PV firms, the existing dispersion in output distortions became less of a problem; thus, overall industry production efficiency was better in 2009 than in 2010. Nevertheless, we still find a clear gap between production efficiency in 2009 and production efficiencies after 2011, the year when ADs and CVDs were first imposed.

Table 4
Distribution of demeaned TFPRs across Chinese PV firms.

2009–2014						
	SOE		NSOE		Total	
Zone 1	7	(5.4%)	3	(1.1%)	10	(2.6%)
Zone 2	59	(45.7%)	103	(39.2%)	162	(41.3%)
Zone 3	52	(40.3%)	132	(50.2%)	184	(46.9%)
Zone 4	11	(8.5%)	25	(9.5%)	36	(9.2%)
Total	129	(100%)	263	(100%)	392	(100%)
2009–2010						
	SOE		NSOE		Total	
Zone 1	2	(5.3%)	1	(1.3%)	3	(2.6%)
Zone 2	19	(50.0%)	21	(27.3%)	40	(34.8%)
Zone 3	10	(26.3%)	36	(46.8%)	46	(40.0%)
Zone 4	7	(18.4%)	19	(24.7%)	26	(22.6%)
Total	38	(100%)	77	(100%)	115	(100%)
2011						
	SOE		NSOE		Total	
Zone 1	0	(0%)	0	(0%)	0	(0%)
Zone 2	11	(50.0%)	22	(44.9%)	33	(46.5%)
Zone 3	11	(50.0%)	24	(49%)	35	(49.3%)
Zone 4	0	(0%)	3	(6.1%)	3	(4.2%)
Total	22	(100%)	49	(100%)	71	(100%)
2012–2014						
	SOE		NSOE		Total	
Zone 1	5	(7.2%)	2	(1.5%)	7	(3.4%)
Zone 2	29	(42.0%)	60	(43.8%)	89	(43.2%)
Zone 3	31	(44.9%)	72	(52.6%)	103	(50.0%)
Zone 4	4	(5.8%)	3	(2.2%)	7	(3.4%)
Total	69	(100%)	137	(100%)	206	(100%)

Note: The values within each cell are the frequency (outside the parentheses) and the share (within the parentheses) of the Chinese PV firms' demeaned TFPRs during a specific time period.

following two questions: How large are the firm-level differences in production efficiency? How do these differences evolve over time?

We use Fig. 2 and Table 4 to address this question. We can infer from Eq. (22) that the dispersion in the TFPRs within an industry causes a loss of productivity and lowers aggregate TFP in the Chinese PV industry. In Fig. 2, we plot the annual demeaned firm-level TFPRs for all Chinese PV firms, where a demeaned value is calculated by subtracting a firm's TFPR from the $\overline{\widehat{TFPR}}$ for that year. In Fig. 2, we draw three horizontal lines. The middle line represents zero; therefore, if a firm's demeaned TFPR is located on the line, that firm's TFPR equals the $\overline{\widehat{TFPR}}$ for that particular year. The upper and lower lines represent the lines above and below one standard deviation of the firm's demeaned TFPRs across all years, respectively. Thus, if a firm's demeaned TFPR is located above the upper line, then that firm's TFPR for that year is more than one (across years) standard deviation greater than the $\overline{\widehat{TFPR}}$ for that year. A similar interpretation applies for the firms' demeaned TFPRs that are located below the lower line. For convenience, we call the area below the lower line "zone 1"; the areas within one standard deviation below and above the middle line (which equals zero) are denoted as "zone 2" and "zone 3", respectively; and the area above the upper line is denoted as "zone 4".

There are two notable patterns in Fig. 2. First, in earlier years, i.e., prior to 2011, many firms' demeaned TFPRs were in zone 4 or zone 1, which suggests great divergence in the TFPRs within the Chinese PV industry. Moreover, some firms' demeaned TFPRs were deep into zone 4 in 2010, resulting in particularly low industry-level production efficiency in that year. Second, we observe that after 2011, the demeaned TFPRs across firms converged; thus, most observations are found in zones 2 and 3. This convergence pattern is clearest between 2011 and 2014, and 2014 is the year with the fewest firm-level demeaned TFPRs outside of the middle zones.

In Table 4, we further our analysis by assessing whether there are specific patterns of TFPRs for different ownership types of PV firms in China. We distinguish among three time spans (2009 to 2010, 2011, and 2012 to 2014) and observe how the distribution of firms' TFPRs evolve over time. From the top panel of Table 4, which summarizes the distribution of the demeaned TFPRs for the entire sample period, we observe some differences in the TFPR distributions between SOEs and NSOEs.[34] Although the demeaned TFPRs for both SOEs and NSOEs are located primarily in the middle zones, the SOEs have more demeaned TFPRs lying within zone 1. Specifically, among the SOEs, 6% of their yearly TFPRs are one standard deviation below the yearly $\overline{\widehat{TFPR}}$ (zone 1, which may imply more subsidies), and 8% of their TFPRs are one standard deviation above the yearly $\overline{\widehat{TFPR}}$ (zone 4, which may imply more distorted taxes). Among the NSOEs, 1% of their demeaned TFPRs are located in zone 1, but 10% are located in zone 4.

[34] The definitions of firm identity are provided in Section 3.

When we compare the TFPRs of different time periods, we find that the SOEs' production efficiencies improved over time. Whereas in the early years (2009 to 2010), 18% of these regions' demeaned TFPRs were in zone 4, in the most recent period (2012 to 2014), only 6% of the demeaned TFPRs were in this least efficient zone. Similarly, whereas in 2009 to 2010, 75% of the demeaned TFPRs were in zones 2 or 3, in 2012 to 2014, this figure increased to 86%. With respect to the NSOEs, the improvement in production efficiency is even more evident. For the period 2009 to 2010, 71% of the demeaned TFPRs were in zones 3 or 4, and by 2009 to 2012, 95% of the TFPRs were in the middle efficient zones, i.e., either zone 2 or zone 3, and only 2% were in the least efficient zone, which is zone 4.

As previously described herein, the differences in the levels of the TFPRs across firms arise from the different levels of firm-level distortions, and these distortions may exist in the input and/or output markets. Accordingly, several firm features are identified that reveal the factors that lead to the pattern described above.

4.2. Determinants of improving production efficiency

We now interpret the results of industry-level TFP and TFPR distributions computed in the previous section via the idiosyncratic firm-level features in the Chinese PV industry. We apply our model computations to each PV firm and then aggregate firm-level output into aggregate industrial output. By changing the firm-level features between SOEs and NSOEs, we can then infer the major features that drive the improvements in overall production efficiency in the Chinese PV industry after 2011.

4.2.1. Labor productivity, capital productivity and total factor productivity of SOEs and NSOEs

We begin with the differences in labor productivity between SOEs and NSOEs. Judging from Eq. (8), the difference in the average product of labor reflects the difference in the firm-level distortions in labor inputs and the MRPL.[35] The convergence in labor productivity from 2011 to 2014 between SOEs and NSOEs, as presented in Fig. 3, indicates that the MRPL in SOEs increased relative to that of NSOEs after 2011.[36]

Similarly, Eq. (9) indicates that the gap in capital productivity of SOEs relative to NSOEs reflects differences in the MRPK. Therefore, the evidence in Fig. 4 shows that the MRPK in SOEs was much lower than that in NSOEs before 2011; however, this gap shrinks remarkably after 2011. In particular, the MRPK of the SOEs in 2011 and 2014 was almost the same as that of the NSOEs, suggesting that the NSOEs now have access to capital on the same terms as SOEs.

The fact that there is remarkable convergence in labor and capital productivity between SOEs and NSOEs indicates the convergent firm-level TFPRs after the EU's adoption of ADs and CVDs beginning in 2011. This finding is surprising because it could be argued that lower labor and capital productivity reflects a lower marginal cost of inputs in labor and capital. For example, the finding that the MRPK is lower among SOEs – and has remained low – might be due to SOEs having preferential access to capital. This preferential access increases the profits of the favored firms with access. Under this explanation, it appears that after 2011, both SOEs and NSOEs began to benefit from access to low-cost capital that was formerly accessible only by SOEs before 2011. Due to the exit of extremely inefficient zombie SOEs, the remaining SOEs and NSOEs compete under fair terms with respect to borrowing funds to invest in fixed capital formation. Similar arguments might be applied to the cost of labor inputs adopted by both SOEs and NSOEs after 2011. The patterns of converging labor and capital productivities between SOEs and NSOEs contribute to the reduced dispersion of firm-level TFPRs observed in Fig. 5. The reduced dispersion of firm-level TFPRs, in turn, would be converted into improving the measures of resource misallocation in the Chinese PV industry after 2011.

Finally, we measure firm physical productivity (TFPQ) A_i using Eq. (13). We use the labor share of all firms in the Chinese PV industry to measure industry specific α, and we set the value of returns to scale γ equal to 0.8, as in Atkeson and Kehoe (2005) and Hsieh and Klenow (2009). After 2011, the gap in A_i between SOEs and NSOEs narrowed. Specifically, the weighted average A of surviving SOEs relative to that of surviving NSOEs increased over time, and this trend became even more pronounced after 2011.[37]

We next examine the change in the distribution of relative A among the SOEs from 2009 to 2014. Here, a firm's relative A refers to its total factor productivity normalized by the mean of surviving NSOEs' TFPs. It is evident from Fig. 5 that the relative A among the more efficient SOEs after 2011 increased significantly in comparison with the pattern in 2009. In addition, there is less heterogeneity across the size distribution of the relative A among SOEs after 2011, suggesting an overall improvement in relative A throughout the distribution. These findings mirror the fact that many zombie SOEs exited the market after 2011.

In summary, we find that the growth rate of TFP among SOEs is relatively high and that the reduction in the gaps in labor and capital distortions between SOEs and NSOEs contributes to the decreasing trend of measured resource misallocation in the Chinese PV industry after 2011. Before 2011, the returns on capital among SOEs tended to be significantly lower than those among NSOEs, which is likely due to the political support of local governments given to SOEs during the earlier years, and this preferential treatment thus exacerbated resource misallocation in the Chinese PV industry. However, after 2011, notable changes occurred. The surviving SOEs have particularly high growth rates in TFP relative to their NSOE counterparts, and this improvement in SOEs' TFP combined with the convergent returns of labor and capital inputs underpins the improvements in overall productivity in the Chinese PV industry after 2011. Finally, our paper

[35] As evidenced by basic principles of economics, the average product is a function of marginal products, and these two measures meet at the maximum of the average product.

[36] One potential reason that the average product of labor is lower among SOEs earlier in time might be overstaffing in these firms. The political pressure to employ redundant workers declined after 2011 as SOEs became more incentivized to maximize profits to fight against the soaring export costs resulting from ADs and CVDs. However, since our measure of firm-level distortions fully retains and respects all potential causes of distortions in real prices faced by Chinese PV firms, other sources of distortion are also possible, such as general technological improvement. We would like to thank a reviewer for raising this issue.

[37] We compute the industry average of A by the individual firm's weight on revenues.

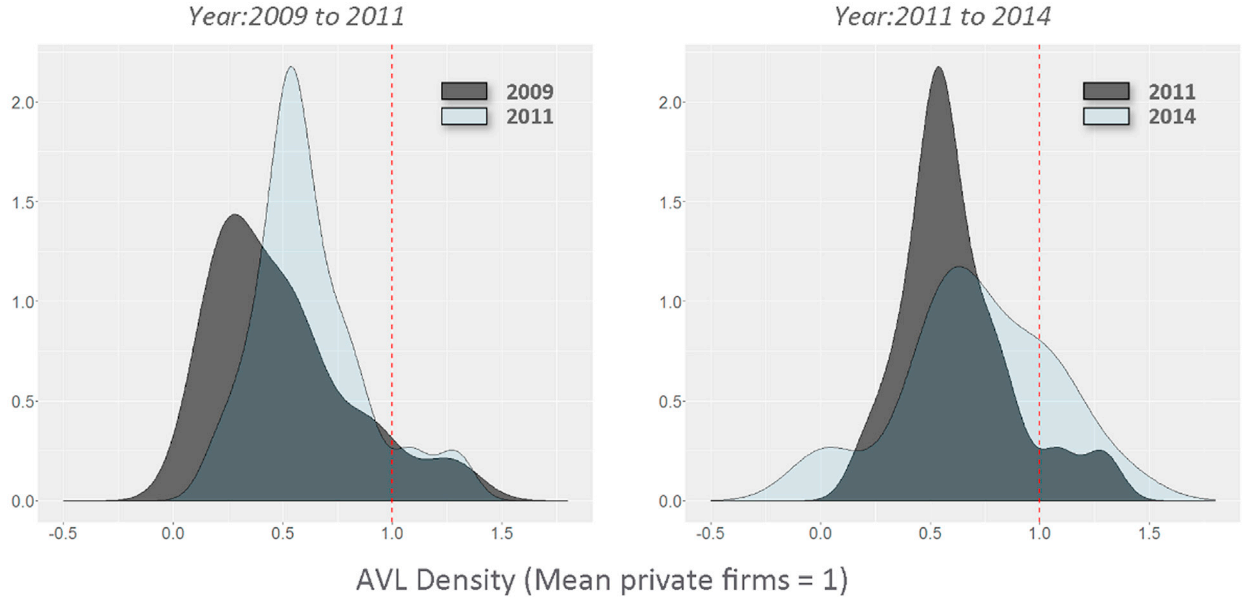

Fig. 3. Density of Average Labor Productivity (AVL). *Note:* The values in the figure are from the authors' calculations and are based on the collected micro dataset of Chinese PV firms. Labor productivity is normalized by the employment compensation weighted mean of labor productivity of surviving private firms in each year. Observations for each firm are weighted by firm employment compensation.

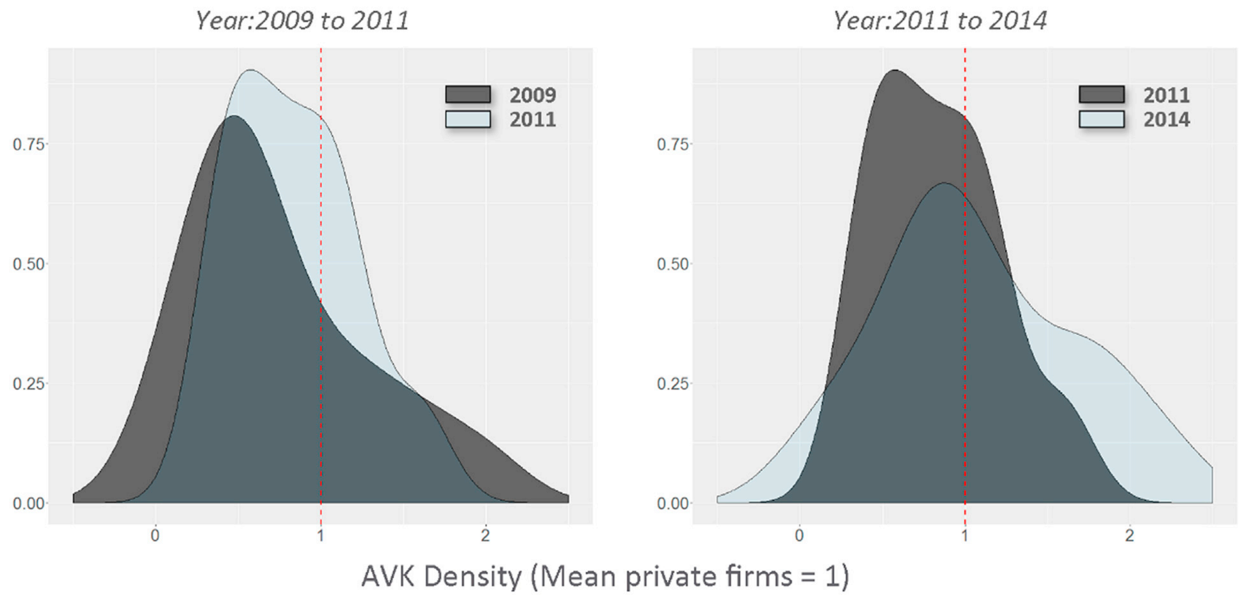

Fig. 4. Density of average capital productivity (AVK). *Note:* The values in the figure are from the authors' calculations and are based on a collected micro dataset of Chinese PV firms. Capital productivity is normalized by the value of the fixed capital weighted mean of capital productivity of surviving private firms in each year. Observations for each firm are weighted by the firm's value of fixed capital.

indicates that the improvement in extensive-margin misallocations due to firm entry-exit does not contribute significantly to improving industry-level production efficiency. Instead, we find that the reallocations of inputs within existing firms are more important.

5. Conclusion

In this paper, motivated by the recent EU imposition of ADs and CVDs on Chinese PV exporters in 2011, we provide a theoretical framework in which to analyze how the escalating trade frictions impact the production efficiency of the Chinese PV industry. Our

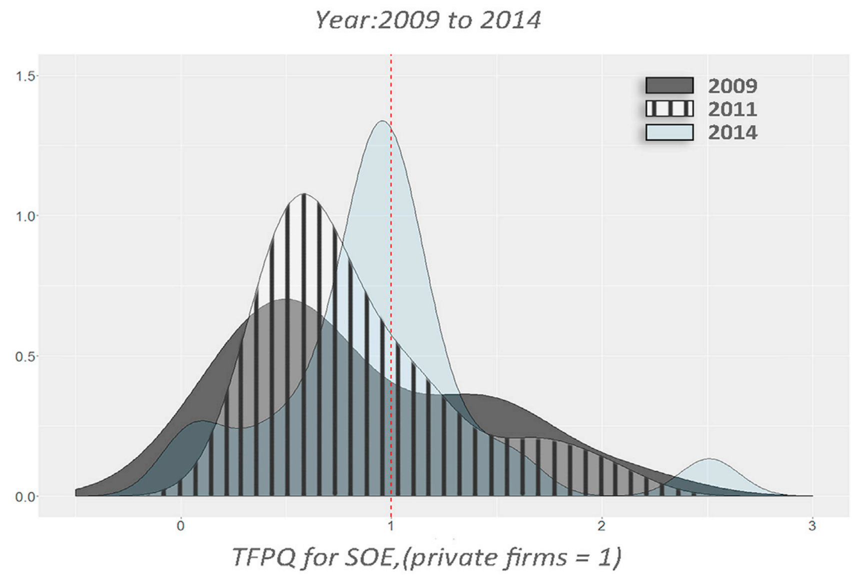

Fig. 5. Density of physical productivity (TFPQ). *Note:* The values in the figure are from the authors' calculations and are based on a collected micro dataset of Chinese PV firms. Total factor productivity is normalized by the mean of surviving private firms (NSOEs) in each year.

theoretical framework extends computations of industry-level misallocations based on Hsieh and Klenow (2009) by decomposing overall misallocations into their intensive- and extensive-margin components. We compute a measure of production efficiency in the Chinese PV industry for 2009 to 2014. Based on our results, production efficiency considerably improves after 2011, implying the substantial convergence of firm-level distortions in the Chinese PV industry. We further probe the potential factors that correlate with production efficiency and find that the converged gap of firm-level distortions between SOEs and NSOEs is beneficial to production efficiency in the Chinese PV industry; moreover, the converged gap of firm-level distortions reflects the remarkable convergence of labor and capital productivity between SOEs and NSOEs. Furthermore, several zombie firms, all of which are SOEs, were particularly inefficient and were forced to leave the market after the EU imposed ADs and CVDs in 2011. As a result, production efficiency increases due to the reduced extensive-margin misallocation losses. Thus, the improved total factor productivity (TFP) associated with SOEs combined with the convergent returns of labor and capital inputs of SOEs and NSOEs yields the improved production efficiency in the Chinese PV industry after 2011. However, our results indicate that the improvement in extensive-margin misallocations due to exiting zombie SOEs is not the greatest contributor to improving industry-level production efficiency. Instead, we conclude that the reallocations of inputs within the existing firms are more important than such improvements to extensive-margin reallocations. Nonetheless, our analysis is limited by an inability to distinguish among sources of firm-level distortions due to data constraints. However, the underlying forces driving the convergent gap in returns on production inputs may relate to the work of Hsieh and Song (2016), who reveal the positive impact produced by the privatization of Chinese SOEs. It could be rewarding to collect abundant detailed firm-level data to confirm whether Chinese PV SOEs would exhibit privatization effects comparable to those observed for their SOE counterparts in other industries. Although we could only conduct our analysis using publicly listed Chinese PV exporters due to data constraints, we provide a framework that can be used for more detailed policy analysis once more disaggregated datasets become available.

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