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Adapting to Competition: Solar PV Innovation in Europe and the Impact of the 'China Shock'

Pia Andres[1]

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Abstract

Low cost solar energy is key to enabling the transition away from fossil fuels. Despite this, the European Union followed the United States' example in imposing anti-dumping tariffs on solar panel imports from China in 2013, arguing that Chinese panels were unfairly subsidised and harmed its domestic industry. This paper examines the effects of Chinese import competition on firm-level innovation in solar photovoltaic technology by European firms using a sample of 10,137 firms in 15 EU countries over the period 1999–2020. I show that firms which were exposed to higher import competition innovated more if they had a relatively small existing stock of innovation, but less if their historical knowledge stock fell within the top 10th percentile of firms in the sample. This suggests that newer firms were more able to respond to increased competition by innovating, while firms with a large historical stock of innovation may have been locked into old technological paradigms. As firms with a smaller knowledge stock tended to innovate more overall, trade with China appears to have been beneficial in encouraging innovation among the most innovative firms. However, I also find evidence that import competition increased the probability of exit among firms in the sample.

1 Introduction

Preventing the worst effects of climate climate change by limiting global temperature rises (be it to 2 °C or even 1.5 °C) requires rapid and dramatic reductions in greenhouse gas emissions around the world. In the face of continuing economic and population growth, this implies an even more rapid reduction in the global economy's emission intensity. Technological change can lead to significant long run cost reductions in clean technologies, thereby altering the presumed trade-off between climate benefits and economic cost in magnitude (Popp et al. 2010) if not removing it entirely. This is rarely more evident than in the case of electricity production from renewable sources, specifically onshore wind and solar power, which saw reductions in the levelised cost of electricity of 23% and 73%, respectively, between 2010 and 2017 alone (Gielen et al. 2019). The main drivers of these trends, in particular with

✉ Pia Andres
p.andres@lse.ac.uk

1 Centre for Economic Performance, London School of Economics and Political Science, London, UK

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respect to solar technology, are thought to be policy support and the expansion of low cost manufacturing in China. The latter has, however, also resulted in trade tensions, culminating in the US–China solar trade war in 2012 and the EU–China solar trade war in 2013. This paper adds to the empirical literature on clean technological change by examining whether low wage import competition presented a driver or a barrier to technological progress in solar photovoltaic technology. It also constitutes a case study relating to the wider literatures on the China Shock and on the relationship between competition and innovation in a world of heterogeneous firms.

The effects of competition (through trade or otherwise) on innovation and growth are ambiguous. Trade theory suggests that higher competition through trade leads to a redistribution of market share towards the most productive firms and the exit of the least productive, thereby raising overall productivity (Melitz 2003; Baldwin and Gu 2004). A similar effect could exist for innovation, with the most innovative firms escaping competition through innovation (Bloom et al. 2016), or innovating in order to simply keep up with competitors (Baldwin 1992; Aghion et al. 2005). Trade may further unlock benefits from comparative advantage, knowledge spillovers, and increased incentives to innovate due to a larger market (Grossman and Helpman 1990). On the other hand, more trade and fiercer competition could also harm innovation through a reduction of rents available to invest in it, and by reducing firms' ability to appropriate post-innovation rents (Baldwin 1992).

Empirically, the effect of competition on innovation appears to depend on market structure. Aghion et al. (2005) show that the relationship between product market competition and innovation resembles an inverted U-shape. In a related paper, Aghion et al. (2009) test the effects of entry on incumbent innovation using UK firm-level data, showing that the threat of entry encourages incumbent innovation and productivity growth in sectors close to the technological frontier, but may discourage it in laggard sectors. Schumpeterian growth models, such as the one presented in Aghion et al. (2014), provide a theoretical framework which can explain these empirical patterns. The authors distinguish between R&D efforts by laggard firms to 'catch up' with the leader, and efforts to innovate by neck-and-neck firms attempting to become a leader, which is more beneficial in a more competitive environment. An increase in product market competition leads to a 'Schumpeterian effect' reducing innovation among laggards, as the benefits of catching up with the leader are reduced when less rent can be extracted; at the frontier, firms may conversely be encouraged to innovate more in order to 'escape competition' (Aghion et al. 2014). Given the very low initial levels of competition identified by Carvalho et al. (2017), we might expect that increased competition would tend to encourage innovation within the solar PV manufacturing sector – in particular in countries which started out as the technological leaders. In line with the theory of international trade with heterogeneous firms, we would also expect to find this effect to be more pronounced among the most technologically advanced firms (Melitz 2003; Bloom et al. 2016).

Existing work on the evolution of the solar value chain includes Carvalho et al. (2017), who argue using descriptive statistics that although the expansion of solar panel manufacturing in China squeezed profit margins and forced many western firms out of the market, innovation became more intensive and radical among survivors. This is in line with some of the more general literature on Chinese import competition: Bloom et al. (2016), using European firm-level data, find that higher import competition from China after its accession to the WTO increased innovation within the most exposed European firms, while employment and survival among low tech firms decreased. In contrast, Autor et al. (2020) estimate the effect of Chinese import competition on US manufacturing innovation and find a significant negative impact on private sector innovation, both at the firm- and technology class-level. Chakravorty et al. (2023) find an inverted U-shaped relationship between innovation by publicly listed US firms and Chinese import competition, wherein the latter increased innovation if it was below 60%, but reduced it above 60%. Further, Acemoglu et al. (2016) argue that import competition from China has been responsible for significant manufacturing job losses in the US, as well as weak overall employment growth. A systematic review of existing research on this topic by Shu and Steinwender (2019) concludes that the empirical literature finds mixed effects of import competition on firm productivity and innovation in the US in particular, but that positive effects are generally found for developing countries and, to some extent, Europe. The authors posit that perhaps the US are to the right of Aghion's inverted U, whilst Europe and the developing world are to its left.

The lack of consensus emerging from the broader 'China Shock' literature motivates this case study of the solar sector. I carry out a firm-level analysis of the effects of the China shock on firm-level innovation in solar PV and related technologies by 10,137 firms in 15 EU countries between 1999 and 2020. The main challenge to this endeavour is the endogeneity of trade patterns, which I address by instrumenting for country-level Chinese imports (scaled by market absorption) using overall Chinese exports to the rest of the world interacted with start-of-period import competition in semi-conductors. Using import penetration in other countries or world exports as an instrument is a widely used approach in the broader China Shock literature. In addition, I interact country-level measures of import competition with a firm-level exposure measure based on the similarity of each firm's patent portfolio to those of Chinese solar innovators, based on Jaffe (1986)'s proposed measure of technological proximity.

The results indicate that firms which were exposed to higher import competition tended to innovate more if they had a low, and less if they had a high, historical stock of innovation – with the exception of the small minority of firms whose knowledge stock fell within the top 1st percentile, which also increased their innovation. Moreover, a high a priori technology stock is negatively associated with future innovation. This suggests that innovation in the solar PV sector was driven by newcomers, rather than incumbents with a large existing knowledge stock. Newer firms appear to have been more adaptive in responding to competition by increasing innovation, while incumbents may have been locked into old technological paradigms. Given that firms with a smaller existing knowledge stock seemed to innovate more overall, the fact that import competition was associated with higher innovation among those firms suggests that China's entry into the sector introduced a healthy dose of competition, calling into question the rationale behind the trade war.

I do, however, find evidence to suggest that a \$100M increase in exposure-weighted imports from China increased the odds of firm exit by about 10%. Moreover, I do not consider the effects of Chinese competition on employment or global market share in solar PV, outcomes which policy-makers may have considered to be of greater importance than innovation or market dynamism.

The remainder of the paper proceeds as follows. Section 2 further motivates the case study by providing a brief overview of the literature on clean technological change and the context and significance of the solar trade war. Section 3 provides details of the dataset and empirical strategy. Section 4 reports results, and section 5 concludes.

2 Background: Clean Technological Change and the Solar Trade Wars

There is some empirical evidence that pricing carbon – economists' poster child for a 'first best' policy – can on its own encourage innovation in low carbon technologies, for example in the case of the EU ETS (Calel and Dechezleprêtre 2016; Calel 2020). However, a broader literature on technological change and the environment argues that this is not sufficient: there are multiple externalities at play, including positive knowledge spillovers from R&D, (dynamically) increasing returns to scale, technological lock-in and path-dependency, network effects and learning-by-doing. Energy systems in particular are resistant to change (Neuhoff 2005). This calls for a portfolio of policies, combining environmental regulation legislating for emission reductions with R&D incentives and policies to support diffusion (Jaffe et al. 2005; Popp et al. 2010; Popp 2010; Jaffe 2012; Acemoglu et al. 2012, 2016). In practice, governments aiming to promote renewable energy technology have deployed a range of demand-pull policies such as feed-in tariffs and renewable energy portfolio standards, as well as supply-push policies like R&D or manufacturing subsidies.

Aside from its importance for climate change mitigation, clean technological change may bring a number of co-benefits. Using citations from clean, grey and dirty transport and electricity generation patents to identify knowledge spillovers from those respective technologies, Dechezleprêtre et al. (2017) find that clean technologies tend to generate larger spillovers than their dirty counterparts (though they acknowledge this may be due to those technologies' novelty more than anything else). Renewable energy technologies are also thought to have particularly large macroeconomic multipliers (Hepburn et al. 2020). Co-benefits such as economic growth and job creation are often put forward by governments seeking popular support for pro-climate technology policies; this strategy, while possibly effective, has also contributed to trade tensions in the renewable energy space (Lewis 2012, 2014).

Gerarden (2023) estimates a dynamic structural model of oligopolistic (Cournot) firm competition to study the effects of consumer subsidies on solar manufacturers. Using data on the electrical conversion efficiency of solar panels as measure of technological innovation, he shows not only that induced innovation significantly increases the social benefits of subsidies, but also that induced innovation may not only occur in the country paying out the subsidies, but spill over to other parts of the world (Gerarden 2023). In addition to potential concerns over where the benefits of domestic subsidies accrue, foreign subsidies are inevitably susceptible to challenge under WTO law, as the case of solar PV demonstrates.

The Evolution of the Solar PV Sector

Solar photovoltaics is a technology central to decarbonisation, which has undergone a dramatic evolution since its conception in the 1950s. Its cost has declined by a factor of almost 100 since then, making it a unique historical example in the sphere of energy technologies (Nemet 2006).

Nemet (2006), focusing on the period 1975–2001 (during which the cost of PV modules decreased by a factor of 20), identifies the three largest drivers of cost reductions (out of the seven considered) as being plant size, cell efficiency, and the cost of silicon. However, those seven drivers (which additionally include yield, poly-crystalline share, silicone consumption and wafer size) leave nearly half the change in cost over the period unexplained.

One of the potential explanations for this residual is increased competition (Nemet 2006). Indeed, the dramatic reductions in the cost of solar PV equipment are often attributed to the expansion of low-cost manufacturing in China (Carvalho et al. 2017; Dent 2018), which drastically increased competition in the sector, reducing the share of top 5 producers from

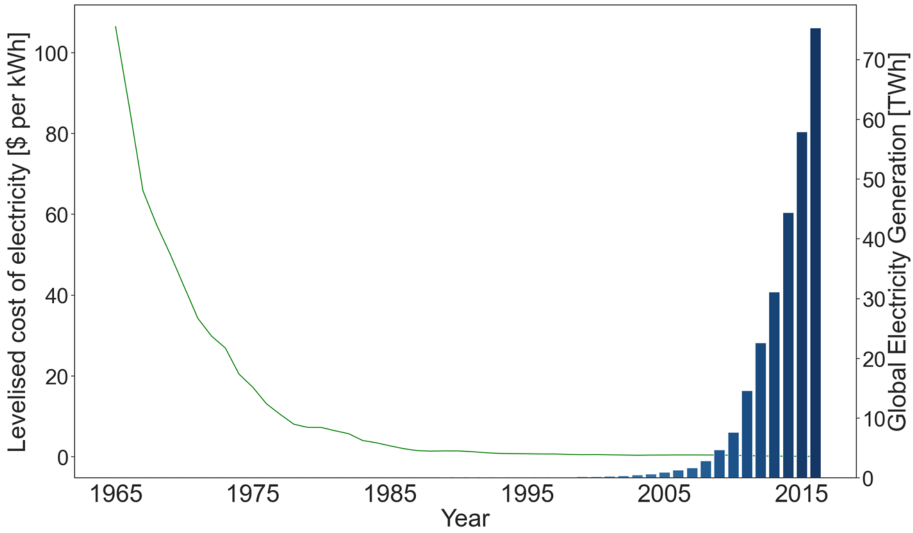


Fig. 1 Solar PV cost and deployment over time.
Note The figure plots global levelised cost of electricity (LCOE) from solar PV in USD per kWh over time (left axis, green line) against global solar PV electricity generation in TWh (right axis, blue bars). It demonstrates the dramatic fall in costs between the 1960s and early 2000s, as well as the rapid increase in deployment since about 2005.
Source Way et al. (2022), Dudley and Others (2018)

about 80% in 2004 to about 30% in 2012 in up- and midstream production (Carvalho et al. 2017). Between 2010 and 2015 alone, the price of solar panels fell by 75% – two thirds of all solar panels were produced by Chinese manufacturers during this period (Gerarden 2023).

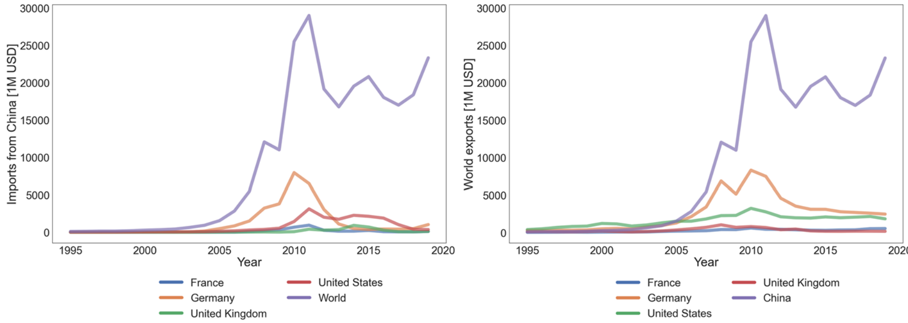
Due (at least to a large extent) to these dramatic falls in equipment costs, the levelised cost of electricity (LCOE) from solar PV has decreased rapidly, making it competitive with fossil fuels in many cases. Figure 1 illustrates this rapid reduction in the LCOE, falling from about 80,000 USD per MWh in 1965 to just 84 in 2016. The graph also shows how electricity generation using the technology has risen sharply since the turn of the century.

This is good news for the cost of greening the energy sector, which is responsible for two thirds of global greenhouse gas emissions (Gielen et al. 2019). However, the expansion of low-cost manufacturing in China has not only enabled dramatic cost reductions, but has also resulted in trade tensions.

Solar Trade Wars

Figure 2a graphs the evolution of imports of solar panels from China to France, Germany, the UK, the US, and worldwide. While a notable drop can be observed following the trade dispute in 2012, the global trend mirrors country and regional trends. As Figure 2b shows, world exports of solar panels also followed a similar trend for the regions shown, with China clearly rising to dominance between 2005 and 2010, but all countries' exports peaking just after 2010. This is likely reflective of the solar panel 'production glut': the global oversupply of solar panels which occurred during this period.

In 2012, the US and China entered into a trade dispute over solar PV subsidies when the US imposed anti-dumping and countervailing duties on Chinese module manufacturers, following a petition led by a subsidiary of the German firm SolarWorld in 2011. Tariffs were



(a) Chinese Imports

(b) World Exports

Fig. 2 Regional and global trends in solar PV trade.
Note Figure 2a plots Chinese imports of solar panels by a subset of countries and worldwide over time. Figure 2b plots the same countries' global exports of solar panels. Both graphs show a peak in solar panel trade around 2010

supported by a coalition of congress members and manufacturing firms despite opposition from a majority of US solar firms. China responded with a WTO complaint and imposed its own anti-dumping duties on US (and Korean) polysilicon (Hughes and Meckling 2017; Stemler et al. 2016).

The EU-China solar trade war started out in a very similar fashion. An industry coalition named ‘Pro Sun’, again led by Solar World, called for anti-dumping and anti-subsidy investigations. In September 2012, the European Comission launched investigations and imposed provisional tariffs on Chinese solar panel imports in 2013, despite opposition by a number of other industry coalitions. The dispute was resolved when the European Commission and China agreed on a minimum price for imports, as well as restrictions on import volumes (Meckling and Hughes 2018).

The extant literature studying the effects of these trade disputes suggests that the US and European anti-dumping measures reduced stock market valuations of Chinese solar companies (Huang et al. 2016; Crowley et al. 2019), as well as those of European manufacturers (Mccarthy 2016), and that they reduced demand for solar in the US and were generally damaging to downstream utilities and consumers (Houde and Wang 2022). More generally, anti-dumping measures are thought to have heterogeneous effects on firms in the protected market. Using European firm-level data and a distance-to-frontier measure, Konings and Vandenbussche (2008) find that laggard firms experience productivity gains and frontier firms experience productivity losses during periods of protection. Jabbour et al. (2019) distinguish between importing and import-competing firms when analysing the effect of EU anti-dumping measures on total factor productivity, employment, exports and investment in R&D over the period 1999–2007, and find a negative net effect on French employment and exports.

There are a number of competing claims surrounding the solar trade war, its justifications and its effects. On the one hand, US and EU trade defence measures against China were opposed by many domestic firms, whose position in the international supply chain meant that they could be adversely affected by the anti-dumping measures (Meckling and Hughes 2018; Wu and Salzman 2013; Curran 2015). On the other hand, the narrative supporting trade remedies held that China was utilising unfair public subsidies to drive out foreign competition and establish a monopoly by ‘dumping’ underpriced solar panels on the European market.

Ensuring a competitive solar industry in the future would in such a case require trade defence (Goron 2018). Gaining better insight into how China's manufacturing expansion affected the solar sector, and thus, potentially, the energy transition, is crucial in order to evaluate the decision to impose trade defence measures.

3 Data & Empirical Strategy

This paper combines firm-level patent data with country-level trade and production data. Data on patent families, representing inventions, was obtained from the EPO's PATSTAT Global Database (2023 spring edition). Patents and their respective patent families were selected using a list of technology codes from the Cooperative Patent Classification (see Table 6 for the list of codes used). The technology categories included are solar photovoltaic cells; production equipment and inputs; storage; energy systems which include solar cells; enabling technologies; and hybrid technologies such as solar PV-thermal or solar-wind hybrids. Codes were selected via a keyword search and manual checks on the descriptions of codes within the Cooperative Patent Classification. Furthermore, patents related to solar cells were identified as belonging to generation 1, 2 or 3 as set out in Table 7 (Appendix 1).[1,2]

Patent families were matched to patent applicants and inventors, identified by their psn_id. psn_id records were retained if the assignee's country code was among the sample of countries studied, and if the variable psn_sector identified them as a company. In addition, patents were matched to firms in Bureau Van Dijk's ORBIS database, using ORBIS IP as a crosswalk. This allows me to include firm-level financials, such as turnover, assets and employment, as control variables. However, the ORBIS-based firm panel results in a significantly smaller sample size (8,475 firms in the ORBIS versus 10,137 in the PATSTAT-derived final dataset, with the overall number of observations in the baseline regression using the ORBIS dataset amounting to only a third of those using the PATSTAT dataset). About 31.49% of all patent families (across all relevant technologies) could be matched to ORBIS. The analysis therefore relies primarily on companies from PATSTAT, using ORBIS as a robustness check.

The ORBIS dataset allows for the construction of a *survival* indicator, based on its status variable. The *survival* variable is assigned as 1 (indicating survival) if a firm is active for at least three years post the reference year, or if its last observed year is at least three years after the reference year. A value of 0 (indicating exit) is assigned to inactive firms whose final status is recorded within less than three years from the reference year. The variable is set to missing for years beyond 2018 or when the survival status is indeterminate.

Bilateral trade data was acquired from CEPII's BACI database (Gaulier and Zignago 2010). The database contains annual bilateral trade values and volumes for all countries at the Harmonised System 6 digit code level. This data was used to compile a panel of Chinese exports to each of the countries in the sample at HS 1992 code 854140[3] and 854150.[4]

[1] I am grateful to Professor Dr Ulf Blieske from the Cologne Institute for Renewable Energy for his help in categorising the set of solar photovoltaic codes into 'generations'.

[2] Note that only two technology codes from the cooperative patent classification were categorised as falling under generation 3; the categorisation does not consider tandem, triple junction, perovskites or quantum dot solar cells, as no technology codes relating specifically to these third generation technologies could be found.

[3] Electrical apparatus; photosensitive, including photovoltaic cells, whether or not assembled in modules or made up into panels, light emitting diodes.

[4] Electrical apparatus; photosensitive semi-conductor devices n.e.s. in heading no. 8541, including photovoltaic cells, whether or not assembled in modules or made up into panels.

Table 1 Summary statistics

	Mean	SD	Min	Max
Patent family count, weighted by size	0.20	1.97	0.00	143.04
Patent family count	0.19	1.66	0.00	79.00
Patent family stock, weighted by size	0.95	8.80	0.00	508.35
Patent family stock	0.87	7.29	0.00	295.01
Hirschmann–Herfindahl index (weighted family stock)	0.09	0.10	0.00	1.00
Import penetration	0.09	1.20	−1.49	23.69
Exports (USD 100 M)	16.67	21.80	0.00	84.36
Chinese imports (USD 100 M)	9.48	17.72	0.00	79.63
Market size (USD 100 M)	24728.24	37137.04	−1501.20	153435.19
Observations	91,820			

The table shows the mean, standard deviation and range of key firm- and country-level variables. While the regression uses size-weighted patent family counts and stocks, the table also includes simple counts as a point of comparison. Import Penetration is defined as $IMP_{it} = 100 * \frac{imp\_CHN_{it}}{prod_{it}+imp_{it}-exp_{it}}$, where imp_CHN_{it} is the value of solar panel imports from China in country i at time t, $prod_{it}$ is country i's production of solar panels at t, and imp_{it} are imports and exp_{it} exports of solar panels from country i at t

Country-level production, overall import and export data for Prodcom code 26112240[5] and 26114070[6] was obtained from Eurostat's Prodcom database and combined with bilateral trade data to construct country-level import penetration measures. Country-level exposure to Chinese import competition at the start of the study period was proxied using trade and production in semi-conductors.[7] The sample includes the 15 countries for which Prodcom data was available from the start of the study period, 1999.[8] Summary statistics are displayed in Table 1.

3.1 Empirical Strategy

Definition of Key Variables

The main dependent variable is each firm's new patent counts. To avoid double-counting the same invention, these counts are constructed at the patent family level, rather than the patent level. A patent family is a group of patents which relate to the same invention, but are filed in multiple patent offices for commercial purposes. Firm-level patent family counts

[5] Photosensitive semi-conductor devices; solar cells, photo-diodes, photo-transistors, etc.

[6] Parts of diodes, transistors and similar semi-conductor devices, photosensitive semi-conductor devices and photovoltaic cells, light-emitting diodes and mounted piezo-electric crystals.

[7] Trade in semi-conductors was identified using HS92 codes 854110, 854121, 854129, 854130, 854140, 854150, 854160, and 854190, while domestic production data from Prodcom is based on Prodcom codes 26112280, 27902050, 26112260, 27115023, 26112240, 26112180, 26112150, 26114070, 26112120, and 26112220.

[8] Austria, Belgium, Luxembourg, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom (the latter having been part of the European Union until 2020, with the so-called transition period following its exit extending to the end of the study period).

are weighted by the size of the patent family. Weighting accounts for the fact that not all patents contain the same amount of innovative novelty – patents which have been filed in a larger number of countries are likely to be more valuable (Lanjouw and Schankerman 1999; Harhoff et al. 2003).

In addition, patent stocks for each firm j were computed as a measure of accumulated past innovation, where $FamStock_{jt} = FamStock_{jt-1} * 0.85 + FamCount_{jt}$, starting from 1980. Following convention (Hall et al. 2005), patents are discounted at an annual rate of 15% to account for the decay in their value over time. The patent stock variable aims to capture firms' heterogeneity in terms of their previously accumulated stock of knowledge. How much a firm has innovated in the past may affect its propensity to further innovate in solar PV and could alter the effects of import competition on the firm's innovative efforts. Theory and empirical evidence tend to suggest that firms which are more productive and/or innovative will be more likely to increase innovation (or at least reduce it to a lesser degree) in response to heightened competition, while the opposite is the case for firms that are further away from the technological frontier. Conversely, firms with a higher a priori patent stock may be more locked into old technological paradigms and therefore less able to innovate in more disruptive technologies.

Import penetration in country i and year t is defined as Chinese imports divided by market absorption:

$$IMP_{it} = 100 * \frac{imp\_CHN_{it}}{prod_{it} + imp_{it} - exp_{it}} \tag{1}$$

where imp_CHN_{it} is the value of solar panel imports from China in country i at time t, $prod_{it}$ is country i's production of solar panels at t, and imp_{it} are imports and exp_{it} exports of solar panels from country i at t. To aid interpretation as a percentage, the fraction is multiplied by 100.[9][10] As an alternative to import penetration, some of the regressions use overall Chinese imports as the variable of interest (while controlling for market size).

The China Shock literature traditionally exploits sectoral variation in import penetration. Because I analyse trade and innovation in only one product, only geographical variation in trade is available. To obtain additional variation, I interact country-level import penetration and overall imports with a firm-level exposure variable based on the similarity of firms' patent portfolios to Chinese firms and inventors. For each sampled firm and each Chinese applicant or inventor associated with a solar patent, I collect all other patents in PATSTAT and their IPC codes. I then construct the share of each IPC class in the knowledge stock (calculated iteratively from 1980 and discounted at 15% per year) of each sampled firm, as well as the share of each IPC class in the knowledge stock of Chinese inventors and applicants overall. Following Jaffe (1986), I use these shares to compute the cosine similarity of each firm's patent portfolio to the patent portfolios of Chinese solar applicants/inventors. This firm-level exposure variable is bounded between 0 and 1, with higher levels indicating higher similarity and therefore exposure to Chinese inventors.

[9] The measure, being a percentage, is robust to price fluctuations which would affect both the numerator and the denominator. The sharp decline in solar panel prices during the period is therefore no cause for concern.

[10] There are a few instances in which market absorption, and thus also import penetration, are smaller than zero. This may happen for a number of reasons related to the construction of Prodcom and external trade statistics by Eurostat. The production data is derived from the PRODCOM survey, while the trade data originally comes from external trade surveys. These surveys differ in a few respects, such as the sampling procedure, the product classification used originally, and the fact that Prodcom accounts for sales, while external trade statistics record the value of goods passing a border and estimate this value if no sale takes place, etc. Furthermore, Prodcom does not identify whether a product sold is consumed, or added to an inventory; for this reason, positive exports may be observed during a year when no production appears to have taken place.

Instrumental Variable Estimation

Any attempt to study the effects of an increase in trade on an economy must contend with endogeneity issues. Import penetration in a given market at a given time is likely to be correlated with numerous factors which could affect, or be affected by, the innovativeness of the local industry – for example, local demand, the ability of the local industry to meet demand, its competitiveness in terms of quality and price, etc. However, import penetration in other, similar countries or overall Chinese export growth are more likely to be externally driven by China, rather than each country's endogenous characteristics and capabilities.

The main regression specification therefore uses exposure-weighted Chinese export growth in solar panels as an instrument for import penetration in each country. The instrumental variable is 3-, 4- and 5-year averages in overall Chinese exports to the rest of the world times a given country's import penetration in semi-conductors at the start of the study period (1999).

Prior research within the China shock literature tends to consider multiple industrial sectors, rather than just one. Because this is a case study focusing on a single technology, the only sources of variation in import competition are time and geography. While other work within the China Shock literature has constructed Bartik-style instruments exploiting the share of a given industry in regional employment, for instance (Autor et al. 2013), this paper therefore uses start-of-period import competition in semi-conductors as a measure of 'exposure'. In addition, I interact import competition with firm-level technological similarity to obtain a more granular measure of exposure. The analysis further accounts for unobserved firm characteristics and time shocks by using year and firm fixed effects.

The validity of the instrumental variable rests on the assumption that it is a) relevant and b) exogenous. Relevance is easily verified using the results of the first stage regression reported in Table 2. The instrument is highly relevant, with a first stage F-statistic of 22.6 for regressions using import penetration and 98,909 when using overall Chinese imports.

The exclusion restriction for Bartik-style instruments requires that the shares used to construct them are uncorrelated with the error term of the main regression, given controls (Goldsmith-Pinkham et al. 2020). The validity of the instrumental variable used here therefore rests on the assumption that the share of Chinese imports in each country's market for semi-conductors in 1999 does not affect innovation in solar panels through any channels other than its implications for import competition in solar panels (given controls, which include firm fixed effects). I argue that this is a reasonable assumption, given that China did not accede to the WTO until 2001 and did not account for a significant share of semi-conductor trade in 1999. In the dataset used in this analysis, the highest level of import penetration in semi-conductors in 1999 was observed in Belgium, amounting to 0.01%. By 2012, semi-conductor import penetration in Belgium had risen more than tenfold to 0.11%, with the highest levels observed in the Netherlands at 0.69%.

Estimation Strategy

The system of equations used to estimate the relationship of interest is

$$\begin{cases} \sum_{k=t}^{t+3} FamCount_{j,k} = & \exp(\beta_1 \overline{IMP}_{i,t-4,t-3,t-2,t-1} * \overline{Exposure}_{j,t-4,t-3,t-2,t-1} \\ & + \beta_2 \overline{FamStock}_{j,t-4,t-3,t-2,t-1} + \gamma_j + \delta_t + \varepsilon + u_{FirstStage}) \\ \overline{IMP}_{i,t-4,t-3,t-2,t-1} = & b_1 \overline{CHNExports^{ROW}}_{i,t-4,t-3,t-2,t-1} * IMP_{i,1999}^{semi-conductors} \\ & + b_2 \overline{Exports}_{i,t-4,t-3,t-2,t-1} + b_3 \overline{Absorption}_{i,t-4,t-3,t-2,t-1} \\ & + \gamma_j + \delta_t + u \end{cases} \tag{2}$$

where $\sum_{k=t}^{t+3} FamCount_{j,k}$ is the sum of quality adjusted patent families by firm j during the current year and the following 3 years; $\overline{IMP}_{i,t-4,t-3,t-2,t-1}$ is import penetration in country i (where firm j is based), averaged over the preceeding 4 years; $\overline{Exposure}_{j,t-4,t-3,t-2,t-1}$ is firm-level proximity to the Chinese knowledge stock; $\overline{FamStock}_{j,t-4,t-3,t-2,t-1}$ is firm j's weighted, discounted patent family stock; $\overline{CHNExports^{ROW}}_{i,t-4,t-3,t-2,t-1}$ are Chinese exports to the rest of the world (excluding country i); $\overline{Exports}_{i,t-4,t-3,t-2,t-1}$ are country i's exports; and $\overline{Absorption}_{i,t-4,t-3,t-2,t-1}$ is market absorption in country i, all averaged over the preceeding 4 years. $IMP_{i,1999}^{semi-conductors}$ is import competition in semi-conductors in country i at the start of the period; γ_j are firm fixed effects; δ_t are year dummies; u and ϵ are error terms. Forward looking sums for the dependent variable and backward looking averages for the regressors are used to account for the fact that innovation is a prolonged process and any changes therein are likely to occur over a timespan of several years. Complete patent data from the PATSTAT 2023 edition is available until 2020, implying that 4-year forward looking sums effectively limit the analysis to 2017 and earlier.

Due to the count nature of the dependent variable, the relationship is estimated using a poisson fixed effects model, with the instrumental variable strategy implemented using the control function method. The residuals from the first stage are included in the second stage regression to control for the endogenous part of the main regressor.

Theory suggests that competition is more likely to induce innovation among firms which are at the technological frontier, while discouraging it among those which are lagging behind. To account for the potential heterogeneity of the relationship under investigation, some regressions include interactions of the main regressor with two binary variables indicating whether the firm's historical patent family stock is in the top or bottom 1st, 5th, 10th or 20th percentile of the sample for a given year.

Other variations of the regression model include 3- and 5-year sums and averages, and substituting overall Chinese imports for import penetration.

4 Empirical Results

Trends in Solar PV and Related Patenting

Figure 3a plots the number of new solar PV patent families over time by country of inventor or applicant. Patenting by Chinese inventors shows two peaks: one around 2007 and the other around 2017. In contrast, Figure 3b shows that the number of new patent families filed in the Chinese Patent Office, while stagnant in other authorities, has risen continuously and steeply since the early 2000s. Figure 4a plots new patent families filed anywhere in the world by generation of solar cell over time, showing a clear dominance of 2nd and 3rd generation over 1st generation solar cells since the 1990s. Figure 4b plots new patent families in solar PV and related technologies filed at any patent authority. While there appears to have been a slight dip in patenting in upstream production equipment and inputs, as well as solar cells and solar thermal, following the trade disputes in 2012/13, overall trends for all technologies continue to increase.

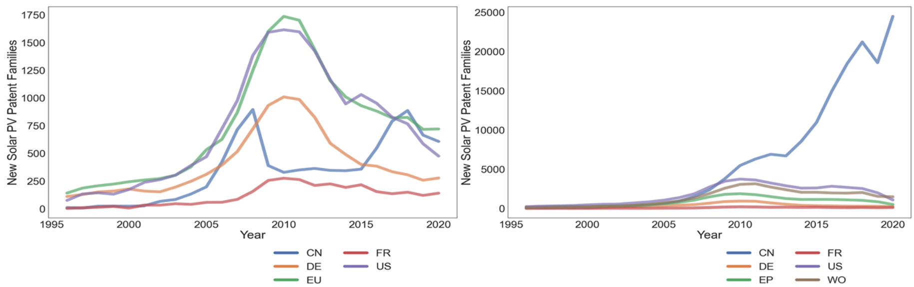
Effect of Import Competition on Firm Innovation

Table 3 reports regression results of overall solar cell innovation on imports, with and without the inclusion of the instrumental variable estimation. While the coefficient on Chinese

Table 2 First stage regression

	(1) Import penetration	(2) Chinese imports
Chinese exports (ROW) × Semiconductor IMP^{1999}	0.086***	0.738***
	(0.010)	(0.080)
Market size (USD 100 M)	−0.000***	0.000***
	(0.000)	(0.000)
Exports (USD 100 M)	0.002***	0.372***
	(0.000)	(0.008)
Constant	0.015	−1.959***
	(0.015)	(0.110)
F Stat	22.62	98909.26
Observations	15,356	15,356

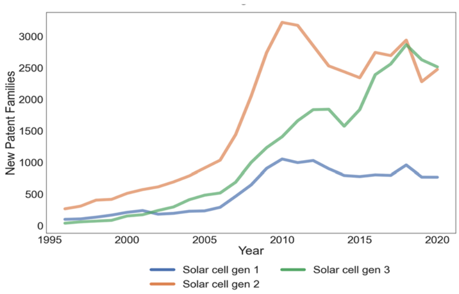
First stage regression on estimation sample.
All variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table shows the results of the first stage regression, using either import penetration or overall Chinese import volume as the endogenous regressor. The first stage includes year and firm fixed effects
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$



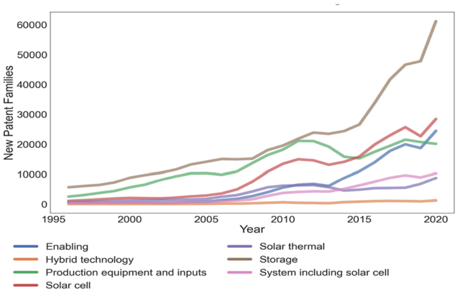
(a) Country of Inventor (b) Patent Office

Fig. 3 Regional trends in solar PV patenting.
Note Figure 3a plots new solar PV patent families by country of inventor, while Figure 3b plots families by patent authority, showing that while relatively few new families were attributed to Chinese inventors between 2007 and 2017, patents filed in the Chinese patent office are on a steep upward trend from around 2005 onwards.

Import Penetration, as well as overall Chinese imports, interacted with firm-level exposure, is negative and significant when no instrumental variable and no other interactions are included (Models (1) and (5)), it becomes insignificant when using an instrumental variable design. The coefficient on import penetration remains insignificant when interaction terms accounting for heterogeneity in firms' existing patent stocks are introduced. However, Models (7) and (8) suggest that overall Chinese imports (controlling for market size) affect solar cell innovation differently for different firms. Firms whose patent stocks are in the bottom 10th percentile (which, as the data is heavily skewed towards 0, make up the majority – about 70% of



(a) New Solar PV Patent Families by Generation



(b) New Solar Related Patent Families

Fig. 4 Global patenting trends in solar cell generations and related technologies.
Note Figure 4 plots new families filed at any patent office by generation of solar cell and for related technologies

observations) increase their quality-adjusted patenting by a factor of $e^{0.109} \approx 1.115$ for each unit of exposure weighted imports (100 M USD times the cosine similarity to Chinese inventors). Firms whose stocks are in the top 10th percentile, conversely, reduce patenting by a factor of $e^{-0.026} \approx 0.974$. The coefficient on the historical stock of patent families is consistently negative and significant (though small in size), indicating that firms with a large historical knowledge stock tend to innovate less in general.

There is some nuance to this result. Table 13 (Appendix) carries out the same analysis, but uses the top and bottom 1st percentile, instead of the 10th percentile, of accumulated patent stocks. Firms in the top 1st percentile make up only 0.8% of observations, while those in the top 10th percentile account for 6.57%.[11] The results in column (8) of Table 13 indicate that firms in the top 1st percentile increase quality-adjusted patenting by a factor of $e^{0.012} \approx 1.01$ for each unit of exposure weighted imports. No significant results are found for the top 5th percentile (Appendix Table 14), which account for 3.88% of observations, while the top 20th percentile (Appendix Table 15, 9.91% of observations) show a similar pattern to the top 10th percentile.

Table 4 reports results separately for different generations of solar cells. While the coefficients on exposure-weighted import penetration and its interactions remain insignificant for patenting in 2nd-generation solar cells, columns (2) and (4) suggest that a larger share of Chinese imports in overall market absorption is associated with higher patenting in generation 1 and 3 technologies for firms in the bottom 10th percentile of historical patenters. Meanwhile, higher levels of overall Chinese imports are associated with an increase in generation 2 patent counts by a factor of $e^{0.166} \approx 1.18$ for firms in the middle 80th percentile range, and a reduction by a factor of $e^{-0.156} \approx 0.86$ for firms in the top 10th percentile. Patenting in generation 1 solar cells increases for the bottom 10th percentile only, while patenting in generation 3 declines by a factor of $e^{-0.019} \approx 0.98$ for the middle 80th percentile but increases by a factor of $e^{0.124} \approx 1.13$ for the bottom 10th percentile of historical patent stocks. These results broadly hold when controlling for market concentration using the Hirschmann-Herfindahl Index (calculated based on firms' shares in overall patent stocks within their countries) – results reported in Table 9 (Appendix).

Results differ slightly when using the ORBIS firm sample (Appendix Table 17): higher levels of import penetration are significantly associated with higher patenting in solar cells

[11] As the distribution is heavily skewed towards 0, the choice of percentile makes little difference as far as the lowest category is concerned (always about 70%).

Table 3 Effects of Chinese imports on solar cell innovation

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	−0.081**	−0.045	−0.122	−0.064				
	(0.032)	(0.060)	(0.126)	(0.141)				
Import penetration × Exposure × Bottom 10%			0.091	0.084				
			(0.174)	(0.181)				
Import penetration × Exposure × Top 10%			0.040	0.019				
			(0.127)	(0.123)				
Chinese imports (USD 100 M) × Exposure					−0.013**	−0.007	0.011	0.020
					(0.005)	(0.006)	(0.013)	(0.013)
Chinese imports (USD 100 M) × Exposure × Bottom 10%							0.108***	0.109***
							(0.023)	(0.024)
Chinese imports (USD 100 M) × Exposure × Top 10%							−0.023**	−0.026**
							(0.012)	(0.012)
Fam stock	−0.001**	−0.001**	−0.001***	−0.001**	−0.002***	−0.002***	−0.001**	−0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market size (USD 100 M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.009***	−0.009***	−0.009***	−0.009***	−0.007**	−0.006*	−0.007**	−0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	15,356	15,356	15,356	15,356	15,356	15,356	15,356	15,356

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 1000 repetitions. Models 2, 4, 6 and 8 use an instrumental variables regression, implemented using the control function method
*p < 0.10, **p < 0.05, ***p < 0.01

overall for the middle 80th percentile and negatively for the top 10th percentile, while no significant effect is observed for individual generations of solar cells. Meanwhile, Chinese imports overall seem to reduce innovation in the middle 80th percentile, while increasing it in the bottom 10th percentile, for generations 1, 3 and overall. As in the PATSTAT sample, a higher historical patent stock is associated with lower levels of future patenting.

Repeating the baseline regression separately for the periods before and after the trade dispute yields interesting effects: until 2012, both import penetration and increases in import volume increase patenting for firms with historical stocks in the bottom 10th, but reduce it for firms with a historical stock within the top 10th percentile. After 2013, all coefficients become insignificant (this can be observed both during the immediate aftermath, as well as the post-trade-war period overall). Results are reported in Appendix Table 10.

I also examine the effects of Chinese imports on patenting in related technologies (results reported in Appendix Tables 11 and 12). Import penetration is negatively and significantly associated with patenting in storage technologies for the top 10th percentile and positively

Table 4 Effects of Chinese imports on solar cell innovation

	(1) Solar cells	(2) Gen 1	(3) Gen 2	(4) Gen 3	(5) Solar cells	(6) Gen 1	(7) Gen 2	(8) Gen 3
Import Penetration × Exposure	−0.064	−0.363	9.714	−0.057				
	(0.134)	(0.221)	(17.086)	(0.161)				
Import penetration × Exposure × Bottom 10%	0.084	0.916***	−9.049	0.275**				
	(0.174)	(0.214)	(17.104)	(0.136)				
Import penetration × Exposure × Top 10%	0.019	0.000	−9.501	0.000				
	(0.119)	(0.000)	(17.088)	(0.000)				
Chinese imports (USD 100 M) × Exposure					0.020	−0.002	0.166*	−0.019**
					(0.013)	(0.014)	(0.092)	(0.010)
Chinese imports (USD 100 M) × Exposure × Bottom 10%					0.109***	0.163***	−0.018	0.124***
					(0.023)	(0.030)	(0.090)	(0.025)
Chinese imports (USD 100 M) × Exposure × Top 10%					−0.026**	0.000	−0.156*	0.000
					(0.011)	(0.000)	(0.090)	(0.000)
Fam stock	−0.001**	−0.002	−0.039***	−0.001	−0.001**	−0.002	−0.038***	−0.001
	(0.001)	(0.003)	(0.005)	(0.001)	(0.001)	(0.002)	(0.005)	(0.001)
Market size (USD 100 M)	0.000	−0.000	0.000***	−0.000	0.000	−0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.009***	−0.011	−0.013***	0.006	−0.006*	−0.007	−0.013***	0.011
	(0.003)	(0.007)	(0.004)	(0.007)	(0.003)	(0.008)	(0.005)	(0.008)
IV regression	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	15,356	2612	5855	3105	15,356	2612	5855	3105

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in different generations of solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among during that year. Standard errors are heteroskedasticity robust and bootstrapped with 1000 repetitions. All regressions use an instrumental variables regression, implemented using the control function method
*p < 0.10, **p < 0.05, ***p < 0.01

for patenting in production equipment for the bottom 10th percentile of historical innovators, while no significant effect is found for any other technologies. The volume of imports, on the other hand, is significantly associated with an increase in patenting for the bottom 10th and/or middle 80th percentiles in solar thermal, production equipment, storage, enabling, and systems related technologies. It is negatively and significantly associated in patenting in solar thermal, production equipment, storage, and enabling technologies for the top 10th percentile of historical patent stocks.

4.1 Effect of Import Competition on Firm Survival

Finally, I use the ORBIS sample to estimate the effects of Chinese import penetration and import volume on the probability of firm survival, using a logistic regression reported in Table 5. The instrumental variable regression is once again implemented using the control

Table 5 Effects of Chinese imports on firm survival

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	−0.818*	−1.205**	−1.451	−1.567				
	(0.465)	(0.548)	(2.949)	(2.991)				
Import penetration × Exposure × Bottom 10%			0.974	0.697				
			(3.205)	(3.174)				
Import penetration × Exposure × Top 10%			1.500	1.199				
			(3.049)	(3.067)				
Chinese imports (USD 100 M) × Exposure					−0.107***	−0.105***	−0.092	−0.090
					(0.034)	(0.035)	(0.340)	(0.295)
Chinese imports (USD 100 M) × Exposure × Bottom 10%							0.001	0.001
							(0.345)	(0.303)
Chinese imports (USD 100 M) × Exposure × Top 10%							−0.063	−0.063
							(0.342)	(0.297)
Fam stock	0.120	0.119	0.106	0.108*	0.120	0.120	0.162*	0.162*
	(0.082)	(0.078)	(0.071)	(0.065)	(0.076)	(0.079)	(0.084)	(0.084)
Total assets (USD 100 M)	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Number of employees	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market size (USD 100 M)	0.000	0.000	0.000	0.000	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.023	−0.021	−0.022	−0.021	−0.021	−0.021	−0.021	−0.021
	(0.020)	(0.019)	(0.020)	(0.020)	(0.022)	(0.021)	(0.022)	(0.022)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs								
Observations	25,772	25,772	25,772	25,772	25,772	25,772	25,772	25,772

Poisson pseudo-likelihood estimation.
Dependent variable: firm survival over 3 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a logistic regression of firm survival on Chinese import competition and overall imports. The dependent variable takes the value 1 if a firm is still active within 3 years, and 0 if it is not. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 1000 repetitions. IV regressions are implemented using the control function method

function method. Results suggest that accounting for heterogeneity in firm patent stocks is not appropriate here. Model (2) indicates that a unit increase in exposure-weighted import penetration is associated with an $e^{-1.205} \approx 0.3$ factor reduction in the odds of a firm surviving over the next 3 years. Model (6) suggests that a unit increase in exposure-weighted import volumes reduces the same odds by a factor of $e^{-0.105} \approx 0.9$.

4.2 Robustness and Limitations

The baseline analysis relies on forward-looking sums (for the dependent variable) and backward-looking averages (for the explanatory variables) over 4 years. As a robustness check, I carry out the same analysis using 3- and 5-year sums and averages. Results are reported in Appendix Table 8. Using 3-year sums and averages yields a qualitatively similar result in terms of the coefficient on exposure-weighted Chinese imports for firms whose patent stocks fall within the bottom 10th percentile, while there is no significant effect for the top 10th percentile. Over 5 years, on the other hand, qualitatively similar results are observed as over 4 years; however, there is an additional significant positive effect of imports on innovation for the middle 80th percentile range. All significant coefficients also increase in magnitude. This suggests that changes in innovation in response to competition tend to take place over longer time periods.

I further carry out two placebo tests.

First, I repeat the baseline regressions using randomised exposure variables. Firm-level exposure is randomised using a beta distribution, with the α and β parameters estimated using the real mean and variance of the distribution. Import penetration is randomised using Kernel Density estimation, and import volume is randomised using a log-normal distribution. Results are reported in Appendix Table 18. All coefficients related to import competition are insignificant, lending credence to the validity of the baseline model.

Second, I construct a sample of firms patenting in dentistry prosthetics (IPC Class A61C/13). Dentistry prosthetics were chosen as innovation dynamics therein are arguably unlikely to be correlated with innovation in the solar sector (to the extent that this is ever the case where the evolution of different technologies is concerned). Results are reported in Appendix Table 19. All patent-based variables, as well as exposure to Chinese firms, are constructed in the same way as in the main sample. This time, both the interaction of import volume (in solar PV) with the bottom 10th percentile and that with the top 10th percentile", removing the word "and" after "(in solar PV) of historical patent stocks are positive and significant (recall that in the main analysis, the first tended to be positive, the second negative and significant). This suggests that the effect of historical patenting dynamics may be the main driver of these results.

Results differ somewhat between the PATSTAT and ORBIS samples. No significant effect of import penetration on overall solar PV innovation was found in the PATSTAT sample, while in the ORBIS sample I observe a significant positive effect on firms with knowledge stocks within the middle 80th percentile and a significant negative effect on firms within the top 10th percentile. For overall Chinese imports I observe the same positive significant effect on firms within the bottom 10th percentile as in the PATSTAT sample; however, the coefficient becomes significant (and negative) for the middle 80th percentile, but insignificant for the top 10th percentile. There are some further differences when analysing different generations of solar cells separately, as discussed above.

While these results can be interpreted similarly, it is interesting that ORBIS firms display a similar response to import penetration as PATSTAT firms do to overall imports. The differences observed particularly between different levels of historical knowledge stocks could potentially be due to the characteristics of the ORBIS sample. Only about 31.49% of all patent families identified in PATSTAT could be matched to ORBIS. Moreover, other research has highlighted that larger, more productive firms tend to be overrepresented in ORBIS data (Bajgar et al. 2020). The PATSTAT sample is therefore more likely to be representative of the population of patenting firms. On the other hand, the ORBIS sample does allow for the inclusion of firm-level controls which may increase confidence in the results.

The exclusion of tandem, triple junction, perovskites and quantum dot solar cells from the category of generation 3 solar cells presents an additional limitation of the analysis. Finally, the analysis considers innovation as the only outcome of interest. Employment and market share, including in upstream and downstream sectors, are not taken into account here.

5 Discussion and Conclusion

Transitioning to cleaner energy sources is crucial in the fight against climate change. The expansion of low cost manufacturing of solar panels in China is credited with contributing strongly to the rapid decrease in the cost of producing electricity from solar photovoltaic technology. However, it has not been popular with some Western producers, and led to the imposition of anti-dumping duties against Chinese solar panels by the European Commission in 2013 (following a similar move in the US the previous year). In order to justify trade defence measures under WTO law, the member imposing them must argue convincingly that the other member is harming its industry by flooding its market with an unfairly subsidised or otherwise underpriced product.

This paper provides an investigation of the effect of the ‘China Shock’ on solar PV innovation using a causal inference estimation strategy. I combine patent data from the EPO’s PATSTAT database with country-level trade and production data from UN Comtrade and Eurostat, as well as firm level financials and status information from Bureau van Dijk’s ORBIS database. Innovation is measured using patent family counts, weighted by family size to account for quality, and import competition instrumented using changes in overall Chinese solar PV exports to the rest of the world interacted with start-of-period import competition in semi-conductors. I also interact import penetration and import volumes with a firm-level measure of similarity to Chinese innovators.

I find that an increase in exposure-weighted imports from China is associated with an increase in patenting for firms with a small existing patent stock and a reduction for firms with a relatively high patent stock, where the latter is defined as falling within the top 10th or 20th percentile for a given year. Conversely, firms whose accumulated knowledge stock falls within the top 1st percentile increase their patenting in response to an increase in imports. The effect of import penetration (the share of Chinese imports in overall market absorption) is statistically significant only for innovation in generation 1 and 3 solar cell technology, leading to an increase in patenting among firms with a relatively small historical stock of innovation. Firms with a large existing patent stock generally innovate less, which may be a sign of technological lock-in. Similar findings are obtained using a smaller sample of ORBIS firms with assets and employment as additional control variables.

The theoretical frameworks discussed in section 1 indicate that firms at the technological frontier are likely to innovate more in response to an increase in competition, while laggards are likely to innovate less. The findings in this paper are consistent with this prediction if we consider – somewhat counter-intuitively – firms with a small historical knowledge stock to be among the most innovative firms in the sample. This proposition seems reasonable given the consistently negative relationship between the historical knowledge stock and future patenting observed in this paper. The small minority of firms with an accumulated stock within the top 1st percentile also increased their innovation in response to heightened competition, while the remainder of those within the top 20th percentile reduced patenting.

The empirical literature on the effect of Chinese import competition on innovation overall has yielded mixed results for the US, but broadly positive ones for Europe (Shu and Steinwender 2019). The results presented here are also consistent with Carvalho et al. (2017)'s observation that levels of competition in the solar sector were quite low prior to China's entry.

Given China's manufacturing dominance in primarily crystalline solar PV, we would expect that firms might attempt to compete by moving into 2nd or 3rd generation solar cells. However, when analysing the effects of Chinese imports on innovation within each generation separately I do not observe much of a difference, except that the positive effect of overall imports is observed for the middle 80th percentile range of historical innovators for generation 2 and the bottom 10th percentile for generation 1 and 3. I also find a significant positive effect of import penetration on innovation among firms within the bottom 10th percentile in generation 1 and 3. These dynamics could be a reflection of the technology lifecycle, wherein more established as well as very novel technologies benefit from competition which is particularly driven by newcomers. Firms with a 'medium-sized' knowledge stock seem to have been more important in driving innovation in generation 2 solar technologies in response to import competition.

Overall we may infer that competition in the solar PV sector in the European countries studied, prior to China's entry into the sector, was low enough for competition to be conducive to innovation. The firms which responded by innovating more appear to have included relative newcomers to solar PV innovation, as well as very large incumbents with extremely high accumulated knowledge stocks. Other incumbents with large knowledge stocks, which were however not at the very top, seem to have been less able to adapt.

I further study the effects of import competition on innovation in related technologies. Import penetration appears to be negatively associated with patenting in storage technologies for firms with a large existing stock of innovation, while an increase in import volume increases patenting among firms with a low historical knowledge stock and reduces it among firms with a high knowledge stock for solar thermal, production equipment, storage, and enabling technologies. Finally, I use status information from ORBIS to compute a variable indicating firm survival over 3 years, and find that an increase in both import penetration and import volume, weighted by exposure, reduced the odds of firm survival considerably.

Overall, the fact that innovation appeared to be driven mostly by firms with a lower existing patent stock, and that those firms tended to innovate more in response to competition from China, suggests that the overall impact of import competition on innovation pre-trade war was likely positive. Trade defence measures appear to have been mainly in the interest of incumbents which were unable to adapt to a more competitive environment. Future trade policy should more carefully consider the competitive environment and whether more competition could be beneficial in incentivising incumbents to innovate more. Alternative measures for supporting domestic industries, such as R&D support, could also be considered.

However, the role of import competition in driving firm exit has implications for outcomes not explicitly studied here, such as employment or global market share in solar PV. Policymakers may have considered these to be of greater importance than innovation or market dynamism. Further research could explore the effects of Chinese import competition on other outcomes of interest. A focus on solar panel manufacturers more broadly, as well as firms operating in upstream and downstream industries, would be beneficial for this purpose.

Appendix

1. Technology Codes

See Tables 6 and 7.

Table 6 Solar related CPC codes

Technology	CPC codes
Enabling	H02J 2300/22, H02J 2300/24, H02J 2300/26, H02J 3/383, H02J 3/385, H02S 20, H02S 20/10, H02S 20/20, H02S 20/21, H02S 20/22, H02S 20/23, H02S 20/24, H02S 20/25, H02S 20/26, H02S 20/30, H02S 20/32, H02S 30, H02S 30/10, H02S 40, H02S 40/10, H02S 40/12, H02S 40/20, H02S 40/22, H02S 40/30, H02S 40/32, H02S 40/34, H02S 40/345, H02S 40/36, H02S 40/40, H02S 40/42, H02S 40/425, H02S 50, H02S 50/10, H02S 50/15, H02S 99/00, Y02E 10/56, Y04S 10/123
Hybrid technology	H02S 10/12, H02S 40/44, Y02E 10/60
Production equipment and inputs	H01L 31, H01L 51
Solar cell	H01G 9/20, H01L 51/42, H02S 10/30, H02S 30/20, Y02E 10/50, Y02E 10/52, Y02E 10/541, Y02E 10/542, Y02E 10/543, Y02E 10/544, Y02E 10/545, Y02E 10/546, Y02E 10/547, Y02E 10/548, Y02E 10/549
Solar thermal	Y02E 10/40
Storage	H01M 10, H01M 12, H01M 14, H01M 16, H01M 2200, H01M 2250/40, H01M 2300, H01M 4, H01M 50, H01M 8, H02J 15, H02S 40/38, Y04S 10/14
System including solar cell	F03G 6/0001, H02J 2300/24, H02J 2300/26, H02J 3/383, H02J 3/385, H02S 10, H02S 10/10, H02S 10/40, Y02B 10/10
System including solar cell; Storage	H02S 10/20

The table lists the technology codes from the Cooperative Patent Classification (CPC) used to identify Solar PV and related patents. For maximum coverage I also search for the equivalent codes from the International Patent Classification (IPC). I identify a patent family as belonging to a given category if it has at least one patent with a relevant technology code

Table 7 Generations of solar cells

Generation	CPC code	Description
Any	Y02E 10/50	Photovoltaic [PV] energy
1	Y02E 10/544	Solar cells from Group III-V materials
	Y02E 10/545	Microcrystalline silicon PV cells
	Y02E 10/546	Polycrystalline silicon PV cells
	Y02E 10/547	Monocrystalline silicon PV cells
2	H01G 9/20	Electrolytic light sensitive devices, e.g. dye sensitized solar cells
	H02S 10/30	Thermophotovoltaic systems
	H02S 30/20	Collapsible or foldable PV modules
	Y02E 10/52	PV systems with concentrators
	Y02E 10/541	CuInSe2 material PV cells
	Y02E 10/542	Dye sensitized solar cells
	Y02E 10/543	Solar cells from Group II-VI materials
	Y02E 10/548	Amorphous silicon PV cells
3	H01L 51/42	Solid state devices using organic materials as the active part, or using a combination of organic materials with other materials as the active part;specially adapted for sensing infra-red radiation, light, electro-magnetic radiation of shorter wavelength or corpuscular radiation and adapted for the conversion of the energy of such radiation into electrical energy or for the control of electrical energy by such radiation
	Y02E 10/549	Organic PV cells

The table lists the technology codes from the Cooperative Patent Classification (CPC) used to identify Solar PV patents, classified into ‘generations’

2. Additional Regression Tables

2.1 PATSTAT Firm Dataset

See Tables 8, 9, 10, 11, 12, 13, 14 and 15.

Table 8 Effects of Chinese imports on solar cell innovation

	(1) 3 years	(2) 4 years	(3) 5 years	(4) 3 years	(5) 4 years	(6) 5 years
Import Penetration × Exposure	−0.009	−0.064	−0.133			
	(0.121)	(0.148)	(0.181)			
Import Penetration × Exposure × Bottom 10%	−0.105	0.084	0.234			
	(0.217)	(0.170)	(0.175)			
Import Penetration × Exposure × Top 10%	−0.009	0.019	0.001			
	(0.107)	(0.130)	(0.156)			
Chinese Imports (USD 100 M) × Exposure				0.012	0.020	0.032**
				(0.012)	(0.013)	(0.014)
Chinese Imports (USD 100 M) × Exposure × Bottom 10%				0.072***	0.109***	0.158***
				(0.017)	(0.022)	(0.041)
Chinese Imports (USD 100 M) × Exposure × Top 10%				−0.017	−0.026**	−0.038***
				(0.011)	(0.011)	(0.012)
Fam Stock	−0.001**	−0.001***	−0.002**	−0.001**	−0.001**	−0.002**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Market Size (USD 100 M)	0.000**	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.009***	−0.009***	−0.008**	−0.007**	−0.006*	−0.005
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
IV regression	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Observations	19,283	15,356	12,077	19,283	15,356	12,077

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 3, 4 or 5 years.
Independent variables are averaged over the preceeding 3, 4 or 5 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 3, 4 and 5 years in the future. All independent variables are averaged over the preceeding 3, 4 and 5 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 3, 4 or 5 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method

Table 9 Effects of Chinese imports on solar cell innovation

	(1) Solar cells	(2) Gen 1	(3) Gen 2	(4) Gen 3	(5) Solar cells	(6) Gen 1	(7) Gen 2	(8) Gen 3
Import penetration × Exposure	−0.106	−0.363*	8.620	−0.057				
	(0.156)	(0.211)	(18.472)	(0.164)				
Import penetration × Exposure × Bottom 10%	0.083	0.907***	−7.933	0.275*				
	(0.168)	(0.208)	(18.464)	(0.150)				
Import penetration × Exposure × Top 10%	0.046	0.000	−8.402	0.000				
	(0.133)	(0.000)	(18.478)	(0.000)				
Chinese imports (USD 100 M) × Exposure					0.022*	−0.002	0.164*	−0.019**
					(0.013)	(0.015)	(0.084)	(0.009)
Chinese imports (USD 100 M) × Exposure × Bottom 10%					0.103***	0.163***	−0.016	0.124***
					(0.024)	(0.029)	(0.081)	(0.025)
Chinese imports (USD 100 M) × Exposure × Top 10%					−0.026**	0.000	−0.154*	0.000
					(0.011)	(0.000)	(0.082)	(0.000)
Fam Stock	−0.001**	−0.002	−0.040***	−0.001	−0.001**	−0.001	−0.039***	−0.001
	(0.001)	(0.003)	(0.005)	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)
Hirschman–Herfindahl index	−0.626*	−1.076	1.021**	−0.458	−0.738**	−2.546**	1.206***	−0.412
	(0.360)	(1.418)	(0.477)	(0.649)	(0.343)	(1.136)	(0.466)	(0.587)
Market size (USD 100 M)	0.000	−0.000	0.000***	−0.000	0.000	−0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.008**	−0.008	−0.014***	0.005	−0.005	−0.002	−0.015***	0.010
	(0.003)	(0.008)	(0.004)	(0.008)	(0.003)	(0.008)	(0.005)	(0.007)
IV regression	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	14,602	2612	5854	3097	14,602	2612	5854	3097

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
Like Table 4, with the additional inclusion of the Hirschmann–Herfindahl Index (HHI) as an indicator overall market competitiveness. The HHI is calculated based on each firm's historical patent stock's share in the sum of knowledge stocks within the sample, by country and year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions

Table 10 Effects of Chinese imports on solar cell innovation

	(1) 2000–2012	(2) 2014–2015	(3) 2014–2017	(4) 2000–2012	(5) 2014–2015	(6) 2014–2017
Import penetration × Exposure	0.077	10.602	0.953			
	(0.114)	(15.820)	(4.118)			
Import penetration × Exposure × Bottom 10%	0.316***	28.097	15.860			
	(0.120)	(28.238)	(11.677)			
Import penetration × Exposure × Top 10%	−0.242**	1.069	0.777			
	(0.099)	(12.908)	(3.280)			
Chinese imports (USD 100 M) × Exposure				0.053***	−0.015	−0.018
				(0.019)	(0.047)	(0.028)
Chinese imports (USD 100 M) × Exposure × Bottom 10%				0.217***	0.022	0.012
				(0.044)	(0.058)	(0.029)
Chinese imports (USD 100 M) × Exposure × Top 10%				−0.059***	0.015	0.020
				(0.017)	(0.040)	(0.022)
Fam stock	−0.002	−0.007	−0.008**	−0.001	−0.007	−0.008***
	(0.001)	(0.014)	(0.003)	(0.001)	(0.015)	(0.003)
Market size (USD 100 M)	0.000	−0.000	−0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.006	0.005	0.003	−0.005	0.007	0.005
	(0.005)	(0.014)	(0.007)	(0.005)	(0.017)	(0.008)
IV regression	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Observations	9320	908	2044	9320	908	2044

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in different generations of solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method

Table 11 Effects of Chinese imports on solar cell and related innovation

	(1) Solar cells	(2) Hybrid	(3) Solar thermal	(4) Production	(5) Storage	(6) Enabling	(7) Systems
Import penetration × Exposure	−0.064	−0.657	0.351	−0.036	0.080	−0.139	0.165
	(0.139)	(0.408)	(0.409)	(0.208)	(0.125)	(0.571)	(0.795)
Import penetration × Exposure × Bottom 10%	0.084	0.200	0.655	0.428*	0.097	0.162	−0.182
	(0.187)	(0.442)	(0.788)	(0.249)	(0.244)	(0.566)	(0.778)
Import penetration × Exposure × Top 10%	0.019	0.000	−0.294	−0.024	−0.252**	0.143	−0.184
	(0.123)	(0.000)	(0.410)	(0.176)	(0.114)	(0.566)	(0.780)
Fam stock	−0.001**	−0.336***	−0.015***	0.001	0.000	−0.002***	−0.002***
	(0.001)	(0.104)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Market size (USD 100 M)	0.000	−0.000**	−0.000	0.000	−0.000***	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.009***	0.011	−0.002	−0.003	0.019***	−0.009***	−0.002
	(0.003)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓
Observations	15,356	1648	9604	14,766	20,256	11,297	8876

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells and related technologies on Chinese import penetration. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method

Table 12 Effects of Chinese imports on solar cell and related innovation

	(1) Solar cells	(2) Hybrid	(3) Solar thermal	(4) Production	(5) Storage	(6) Enabling	(7) Systems
Chinese imports (USD 100 M) × Exposure	0.012	0.022	0.078***	−0.010	0.032***	0.038**	0.036*
	(0.012)	(0.021)	(0.022)	(0.011)	(0.009)	(0.016)	(0.019)
Chinese imports (USD 100 M) × Exposure × Bottom 10%	0.108***	0.059	0.123**	0.117***	−0.057	0.070***	0.076***
	(0.023)	(0.039)	(0.054)	(0.021)	(0.059)	(0.018)	(0.021)
Chinese imports (USD 100 M) × Exposure × Top 10%	−0.024**	0.000	−0.060***	−0.019**	−0.017*	−0.029**	−0.023
	(0.011)	(0.000)	(0.020)	(0.009)	(0.009)	(0.014)	(0.018)
Fam stock	−0.001**	−0.319***	−0.016***	0.000	0.000	−0.002***	−0.003***
	(0.001)	(0.103)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Market size (USD 100 M)	0.000	−0.000**	−0.000	0.000*	−0.000***	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.007**	0.006	−0.004	0.002	0.016***	−0.010***	−0.004
	(0.004)	(0.009)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
IV regression	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓
Observations	15,356	1648	9604	14,766	20,256	11,297	8876

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells and related technologies on overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method

Table 13 Effects of Chinese imports on solar cell innovation

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	−0.081***	−0.045	−0.084**	−0.042				
	(0.030)	(0.057)	(0.038)	(0.070)				
Import penetration × Exposure × Bottom 1%			0.056	0.065				
			(0.138)	(0.136)				
Import penetration × Exposure × Top 1%			0.002	−0.004				
			(0.059)	(0.059)				
Chinese imports (USD 100 M) × Exposure					−0.013**	−0.007	−0.026***	−0.017**
					(0.006)	(0.007)	(0.008)	(0.008)
Chinese imports (USD 100 M) × Exposure × Bottom 1%							0.131***	0.131***
							(0.021)	(0.023)
Chinese imports (USD 100 M) × Exposure × Top 1%							0.015**	0.012*
							(0.007)	(0.007)
Fam stock	−0.001**	−0.001***	−0.001**	−0.001**	−0.002***	−0.002***	−0.002***	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market size (USD 100 M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.009***	−0.009***	−0.009***	−0.009***	−0.007*	−0.006*	−0.007**	−0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	15,356	15,356	15,356	15,356	15,356	15,356	15,356	15,356

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
Like Table 3, but using the 1st and 99th percentile of accumulated patent family stocks. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions

Table 14 Effects of Chinese imports on solar cell innovation

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	−0.081**	−0.045	−0.038	0.023				
	(0.034)	(0.058)	(0.069)	(0.083)				
Import penetration × Exposure × Bottom 5%			0.015	0.016				
			(0.154)	(0.152)				
Import penetration × Exposure × Top 5%			−0.050	−0.067				
			(0.075)	(0.076)				
Chinese imports (USD 100 M) × Exposure					−0.013**	−0.007	−0.017	−0.007
					(0.006)	(0.005)	(0.011)	(0.011)
Chinese imports (USD 100 M) × Exposure × Bottom 5%							0.128***	0.128***
							(0.025)	(0.020)
Chinese imports (USD 100 M) × Exposure × Top 5%							0.005	0.001
							(0.010)	(0.009)
Fam stock	−0.001**	−0.001**	−0.001**	−0.001***	−0.002***	−0.002**	−0.002**	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market size (USD 100 M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.009***	−0.009***	−0.009***	−0.009***	−0.007**	−0.006*	−0.007**	−0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	15,356	15,356	15,356	15,356	15,356	15,356	15,356	15,356

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
Like Table 3, but using the 5th and 95th percentile of accumulated patent family stocks. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions

Table 15 Effects of Chinese imports on solar cell innovation

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	−0.081**	−0.045	−0.084	0.026				
	(0.031)	(0.060)	(1.825)	(1.721)				
Import penetration × Exposure × Bottom 20%			0.056	−0.004				
			(1.836)	(1.728)				
Import penetration × Exposure × Top 20%			0.001	−0.071				
			(1.821)	(1.718)				
Chinese imports (USD 100 M) × Exposure					−0.013**	−0.007	0.018	0.029
					(0.006)	(0.006)	(0.018)	(0.019)
Chinese imports (USD 100 M) × Exposure × Bottom 20%							0.096***	0.094***
							(0.025)	(0.024)
Chinese imports (USD 100 M) × Exposure × Top 20%							−0.030*	−0.035**
							(0.017)	(0.017)
Fam stock	−0.001***	−0.001***	−0.001**	−0.001***	−0.002**	−0.002***	−0.001***	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market size (USD 100 M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	−0.009***	−0.009***	−0.009***	−0.009***	−0.007**	−0.006*	−0.007*	−0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	15,356	15,356	15,356	15,356	15,356	15,356	15,356	15,356

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
Like Table 3, but using the 20th and 80th percentile of accumulated patent family stocks. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions

2.2 ORBIS Firm Dataset

See Tables 16 and 17.

Table 16 Effects of Chinese imports on solar cell innovation

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	−0.080	−0.002	0.869**	1.252*				
	(0.145)	(0.181)	(0.379)	(0.649)				
Import penetration × Exposure × Bottom 10%			−0.797	−0.994				
			(0.548)	(0.842)				
Import penetration × Exposure × Top 10%			−0.955*	−1.231**				
			(0.518)	(0.591)				
Chinese imports (USD 100 M) × Exposure					−0.050***	−0.056***	−0.034	−0.041*
					(0.014)	(0.015)	(0.021)	(0.023)
Chinese imports (USD 100 M) × Exposure × Bottom 10%							0.129***	0.130***
							(0.037)	(0.038)
Chinese imports (USD 100 M) × Exposure × Top 10%							−0.023	−0.022
							(0.020)	(0.020)
Fam stock	−0.007***	−0.007**	−0.007**	−0.007**	−0.008***	−0.008***	−0.008***	−0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total assets (USD 100 M)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of employees	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market size (USD 100 M)	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	0.003	0.003	0.003	0.003	0.009*	0.009*	0.011**	0.011*
	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5617	5617	5617	5617	5617	5617	5617	5617

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells on Chinese import penetration and overall Chinese imports, using the sample of firms from ORBIS. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. Models 2, 4, 6 and 8 use an instrumental variables regression, implemented using the control function method

Table 17 Effects of Chinese imports on solar cell innovation

	(1) Solar cells	(2) Gen 1	(3) Gen 2	(4) Gen 3	(5) Solar cells	(6) Gen 1	(7) Gen 2	(8) Gen 3
Import penetration × Exposure	1.252**	−0.402	0.105	−0.117				
	(0.596)	(1.725)	(1.454)	(2.233)				
Import penetration × Exposure × Bottom 10%	−0.994	0.730	0.542	32.281				
	(1.024)	(5.107)	(43.788)	(25.680)				
Import penetration × Exposure × Top 10%	−1.231**	0.000	0.000	0.000				
	(0.568)	(0.000)	(0.000)	(0.000)				
Chinese imports (USD 100 M) × Exposure					−0.041*	−0.084***	−0.017	−0.124***
					(0.022)	(0.031)	(0.024)	(0.027)
Chinese imports (USD 100 M) × Exposure × Bottom 10%					0.130***	0.155***	0.073	0.140**
					(0.033)	(0.049)	(0.123)	(0.067)
Chinese imports (USD 100 M) × Exposure × Top 10%					−0.022	0.000	0.000	0.000
					(0.019)	(0.000)	(0.000)	(0.000)
Fam stock	−0.007**	−0.040*	−0.064***	−0.026***	−0.008***	−0.041	−0.064***	−0.027***
	(0.003)	(0.021)	(0.013)	(0.005)	(0.003)	(0.027)	(0.011)	(0.004)
Total assets (USD 100 M)	0.002***	0.002	0.005***	0.002***	0.002***	0.001	0.005***	0.002*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Number of employees	0.000	−0.000	−0.000	0.000	0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market size (USD 100 M)	−0.000	−0.000	−0.000**	−0.000	−0.000	0.000	−0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	0.003	−0.021*	0.002	0.026***	0.011**	−0.009	0.005	0.033***
	(0.006)	(0.011)	(0.008)	(0.010)	(0.005)	(0.012)	(0.009)	(0.011)
IV regression	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5617	944	1929	989	5617	944	1929	989

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in different generations of solar cells on Chinese import penetration and overall Chinese imports, using the sample of firms from ORBIS. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method

2.3 Placebo Regressions

See Tables 18 and 19.

Table 18 Placebo test: randomised exposure

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	0.388	−0.061	−2.597	−3.350				
	(2.383)	(2.966)	(2.770)	(3.039)				
Import penetration × Exposure × Bottom 10%			6.153	6.150				
			(4.237)	(3.879)				
Import penetration × Exposure × Top 10%			3.613	3.913				
			(4.681)	(4.693)				
Chinese imports (USD 100 M) × Exposure					0.034	0.042	−0.086	−0.080
					(0.108)	(0.125)	(0.516)	(0.551)
Chinese imports (USD 100 M) × Exposure × Bottom 10%							0.183	0.179
							(0.548)	(0.579)
Chinese imports (USD 100 M) × Exposure × Top 10%							0.017	0.021
							(0.517)	(0.562)
Fam stock	0.030**	0.031**	0.030**	0.031**	0.032**	0.033**	0.029**	0.030*
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Market size (USD 100 M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	0.011	0.010	0.013	0.012	0.010	0.009	0.011	0.011
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.017)	(0.018)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	581	581	581	581	581	581	581	581

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
Like Table 3, but using randomised exposure variables. Firm-level exposure is randomised using a beta distribution, with the α and β parameters estimated using the real mean and variance of the distribution. Import penetration is randomised using Kernel Density estimation, and import volume is randomised using a log-normal distribution

Table 19 Placebo: innovation in dental prosthetics

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import penetration × Exposure	−0.162	0.192	−0.126	0.056				
	(0.165)	(0.259)	(0.145)	(0.368)				
Import penetration × Exposure × Bottom 10%			−3.537	−2.660				
			(2.834)	(2.934)				
Import penetration × Exposure × Top 10%			−0.517	−0.573				
			(1.728)	(1.831)				
Chinese imports (USD 100 M) × Exposure					−0.017	−0.013	−0.023	−0.021
					(0.014)	(0.014)	(0.015)	(0.015)
Chinese imports (USD 100 M) × Exposure × Bottom 10%							0.277***	0.278***
							(0.056)	(0.059)
Chinese imports (USD 100 M) × Exposure × Top 10%							0.023**	0.025**
							(0.011)	(0.011)
Fam stock	−0.013*	−0.013*	−0.013*	−0.013*	−0.013*	−0.011	−0.013*	−0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Market size (USD 100 M)	−0.000*	−0.000*	−0.000*	−0.000*	−0.000	−0.000	−0.000	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100 M)	0.019***	0.019***	0.019**	0.018***	0.019***	0.018***	0.019***	0.018***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
IV regression		✓		✓		✓		✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2804	2804	2804	2804	2804	2804	2804	2804

Poisson pseudo-likelihood estimation.
Dependent variable: firm-level patenting over 4 years.
Independent variables are averaged over the preceeding 4 years.
Robust standard errors in parentheses.
Like Table 3, but using a sample of firms patenting in dentistry prosthetics (IPC Class A61C/13), with all patent-based variables constructed using patent families from IPC Class A61C/13

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References

Acemoglu D, Aghion P, Bursztyn L, Hemous D (2012) The environment and directed technical change. Am Econ Rev 102(1):131–66
Acemoglu D, Akcigit U, Hanley D, Kerr W (2016) Transition to clean technology. J Polit Econ 124(1):52–104
Acemoglu D, Autor D, Dorn D, Hanson GH, Price B (2016) Import competition and the great us employment sag of the 2000s. J Law Econ 34(S1):S141-s198
Aghion P, Bloom N, Blundell R, Griffith R, Howitt P (2005) Competition and innovation: an inverted-u relationship. Q J Econ 120(2):701–728
Aghion P, Blundell R, Griffith R, Howitt P, Prantl S (2009) The effects of entry on incumbent innovation and productivity. Rev Econ Stat 91(1):20–32
Aghion P, Akcigit U, Howitt P (2014). Handbook of Economic Growth, What do we learn from Schumpeterian growth theory? Elsevier, pp 515–563
Autor D, Dorn D, Hanson GH (2013) The China syndrome: local labor market effects of import competition in the united states. Am Econ Rev 103(6):2121–68
Autor D, Dorn D, Hanson GH, Pisano G, Shu P (2020) Foreign competition and domestic innovation: evidence from us patents. Am Econ Rev: Insights 2(3):357–374
Bajgar M, Berlingieri G, Calligaris S, Criscuolo C, Timmis J (2020) Coverage and representativeness of orbis data. OECD Working Paper 2020/06
Baldwin RE (1992) On the growth effects of import competition. NBER Working Paper 4045
Baldwin JR, Gu W (2004) Trade liberalization: export-market participation, productivity growth, and innovation. Oxf Rev Econ Policy 20(3):372–392
Bloom N, Draca M, Van Reenen J (2016) Trade induced technical change? the impact of chinese imports on innovation, it and productivity. Rev Econ Stud 83(1):87–117
Calel R (2020) Adopt or innovate: understanding technological responses to cap-and-trade. Am Econ J Econ Pol 12(3):170–201
Calel R, Dechezleprêtre A (2016) Environmental policy and directed technological change: evidence from the European carbon market. Rev Econ Stat 98(1):173–191
Carvalho M, Dechezleprêtre A, Glachant M (2017) Understanding the dynamics of global value chains for solar photovoltaic technologies. WIPO Economic Research Working Paper No 40
Chakravorty U, Liu R, Tang R, Zhao L (2023) Firm innovation under import competition from low-wage countries. The World Economy
Crowley MA, Meng N, Song H (2019) Policy shocks and stock market returns: evidence from Chinese solar panels. J Jpn Int Econ 51:148–169
Curran L (2015) The impact of trade policy on global production networks: the solar panel case. Rev Int Politi Econ 22(5):1025–1054
Dechezleprêtre A, Martin R, Mohnen M (2017) Knowledge spillovers from clean and dirty technologies. Grantham Research Institute on Climate Change and the Environment Working Paper No 135
Dent CM (2018) Clean energy trade governance: reconciling trade liberalism and climate interventionism? New Politi Econ 23(6):728–747
Dudley B, Others, (2018) Bp statistical review of world energy. BP Statistical Review, London, 6, 2018
Gaulier G, Zignago S (2010) Baci: International trade database at the product-level (the 1994–2007 version)
Gerarden TD (2023) Demanding innovation: the impact of consumer subsidies on solar panel production costs. Manage Sci 69(12):7799–7820
Gielen D, Boshell F, Saygin D, Bazilian MD, Wagner N, Gorini R (2019) The role of renewable energy in the global energy transformation. Energ Strat Rev 24:38–50
Goldsmith-Pinkham P, Sorkin I, Swift H (2020) Bartik instruments: What, when, why, and how. Am Econ Rev 110(8):2586–2624
Goron C (2018) Fighting against climate change and for fair trade: finding the Eu's interest in the solar panels dispute with China. China-Eu's Law J 6(1–2):103–125
Grossman GM, Helpman E (1990) Trade, innovation, and growth. Am Econ Rev 80(2):86–91
Hall BH, Jaffe A, Trajtenberg M (2005) Market value and patent citations. Rand J Econ 36:16–38
Harhoff D, Scherer FM, Vopel K (2003) Citations, family size, opposition and the value of patent rights. Res Policy 32(8):1343–1363
Hepburn C, O'Callaghan B, Stern N, Stiglitz J, Zenghelis D (2020) Will Covid-19 fiscal recovery packages accelerate or retard progress on climate change? Oxford Rev Econ Policy 36:S359–S381
Houde S, Wang W (2022) The incidence of the US–China solar trade war. Economics Working Paper Series No 22/372

Huang X, An H, Fang W, Gao X, Wang L, Sun X (2016) Impact assessment of international anti-dumping events on synchronization and co movement of the Chinese photovoltaic stocks. Renew Sustain Energy Rev 59:459–469

Hughes L, Meckling J (2017) The politics of renewable energy trade: the US–China solar dispute. Energy Policy 105:256–262

Jabbour L, Tao Z, Vanino E, Zhang Y (2019) The good, the bad and the ugly: Chinese imports, European union anti-dumping measures and firm performance. J Int Econ 117:1–20

Jaffe A (1986) Technological opportunity and spillovers of r &d: evidence from firms, patents, profits and market value. Am Econ Rev 76:984–1001

Jaffe A (2012) Technology policy and climate change. Clim Change Econ 3(04):1250025

Jaffe A, Newell RG, Stavins RN (2005) A tale of two market failures: technology and environmental policy. Ecol Econ 54(2–3):164–174

Konings J, Vandenbussche H (2008) Heterogeneous responses of firms to trade protection. J Int Econ 76(2):371–383

Lanjouw J, Schankerman M (1999) The quality of ideas: measuring innovation with multiple indicators. NBER Working Paper 7345

Lewis JI (2012) Emerging conflicts in renewable energy policy and international trade law. In: proceedings of the world renewable energy forum

Lewis JI (2014) The rise of renewable energy protectionism: emerging trade conflicts and implications for low carbon development. Global Environ Politi 14(4):10–35

Mccarthy KJ (2016) On the influence of the European trade barrier on the Chinese pv industry: Is the solution to the solar-dispute “successful”? Energy Policy 99:154–157

Meckling J, Hughes L (2018) Protecting solar: global supply chains and business power. New Politi Econ 23(1):88–104

Melitz MJ (2003) The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71(6):1695–1725

Nemet GF (2006) Beyond the learning curve: factors influencing cost reductions in photovoltaics. Energy Policy 34(17):3218–3232

Neuhoff K (2005) Large-scale deployment of renewables for electricity generation. Oxf Rev Econ Policy 21(1):88–110

Popp D (2010) Innovation and climate policy. Annu Rev Resour Econ 2:275–98

Popp D, Newell RG, Jaffe A (2010) Energy, the environment, and technological change. Handbook of the Economics of Innovation, Elsevier, 2, 873–937

Shu P, Steinwender C (2019) The impact of trade liberalization on firm productivity and innovation. Innov Policy Econ 19(1):39–68

Stemler A, Shackelford S, Richards E (2016) Paris, panels, and protectionism: matching us rhetoric with reality to save the planet. Vand. J. Ent. & Tech. L. 19:545

Way R, Ives MC, Mealy P, Farmer JD (2022) Empirically grounded technology forecasts and the energy transition. Joule 6(9):2057–2082

Wu M, Salzman J (2013) The next generation of trade and environment conflicts: the rise of green industrial policy. Northwest Univ Law Rev 108(2):401