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October 2022

Centre for Climate Change Economics
and Policy Working Paper No. 404
ISSN 2515-5709 (Online)

Grantham Research Institute on
Climate Change and the Environment
Working Paper No. 379
ISSN 2515-5717 (Online)

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Suggested citation:

Andres, P (2022) *Was the trade war justified? Solar PV innovation in Europe and the impact of the 'China shock'*. Centre for Climate Change Economics and Policy Working Paper 404/Grantham Research Institute on Climate Change and the Environment Working Paper 379. London: London School of Economics and Political Science

Was the Trade War Justified? Solar PV Innovation in Europe And the Impact of the ‘China Shock’*

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October 27, 2022

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 2012, 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 4,632 firms in 14 EU countries over the period 1999-2018. I show that firms which were exposed to higher import competition innovated more. Further, I find that during the years following the trade war, firms with a higher existing stock of innovation became less innovative. The results imply that competition from China constituted a positive push for more innovation among European solar innovators, calling into question the rationale behind the trade war.

*My thanks go to Giorgio Presidente, Roger Fouquet, Misato Sato, Simona Iammarino, Ulf Blieske, John Van Reenen, Robin Burgess and Ben Filewood for their thoughtful comments at various stages of the paper’s development, as well as the participants of the seminars and workshops where this paper was presented and discussed. All remaining errors are mine. I also acknowledge administrative support from the Grantham Research Institute, thereby acknowledging its funders: the Grantham Foundation for the Protection of the Environment and the ESRC through the Centre for Climate Change Economics and Policy.

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1 INTRODUCTION

Preventing the worst effects of 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 (cf. 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 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 2011 and the EU-China solar trade war in 2012. 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 (Baldwin et al. 2004; Melitz 2003). A similar effect could exist for innovation, with the most innovative firms escaping competition through innovation (cf. Bloom et al. 2016), or innovating in order to simply keep up with competitors (Aghion et al. 2005; Baldwin 1992). Trade may further unlock benefits from comparative advantage, knowledge spillovers, and increased incentives to innovate due to a larger market (cf. Grossman et al. 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 (cf. 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. They 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 (cf. Bloom et al. 2016; Melitz 2003). This paper finds support for the former hypothesis, showing that firms in countries which faced higher import competition tended to innovate more in solar PV (if only slightly).

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. 2016 estimate the effect of Chinese import competition on US manufacturing innovation and find a significant negative impact, both at the firm- and technology class-level. Meanwhile, Chakravorty et al. 2017, using citation-weighted patent counts, find that Chinese import competition increased innovation among publicly listed US firms, particularly those in low-tech industries – this contradicts other results that show positive effects on innovation to be present and/or most pronounced among the most technologically advanced. Further, Acemoglu et al. 2016b 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 et al. 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 4,632 firms in 14 EU countries between 1999 and 2018. 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. Using import penetration in other countries or world exports as an instru-

ment is a widely used approach in the broader China Shock literature. The results indicate that firms which were exposed to higher import competition tended to innovate more, though the effect is economically small. Moreover, a high a priori technology stock is negatively associated with future innovation. When the period before and after the trade war are analysed separately, I find that the negative relationship between current innovation and the existing firm-level stock of innovation is present only in the years after the 2012 trade war. This would suggest that incumbents with a large existing stock of innovation became ‘lazy’ only after policy committed to protecting them from competition, strengthening support for the hypothesis that China’s entry introduced a healthy dose of competition into the European market for solar photovoltaics and calling into question to what extent it was in fact harmful to the domestic industry. I find no evidence of import competition inducing firm exit among solar innovators; however, these results are unlikely to be representative for solar manufacturers who do not innovate, which are not included in my sample. 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 WAR

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 2020; Calel et al. 2016). However, a broader literature on technological change and the environment argues that this is not enough: 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 (Acemoglu et al. 2012; Acemoglu et al. 2016a; Jaffe 2012; Jaffe et al. 2005; Popp 2010; Popp et al. 2010). 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 elec-

tricity 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 brought forward by governments seeking popular support for pro-climate technology support; this strategy, while possibly effective, has also contributed to trade tensions in the renewable energy space (Lewis 2012, 2014).

Gerarden 2017 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 (as compared to the benefit of short run mitigation alone), 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 2017). 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 photovoltaic 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 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 2017).

Due (at least to a large extent) to these dramatic falls in equipment costs, the levelised cost of electricity (LCOE) has decreased rapidly, making it competitive with fossil fuels in many cases. Figure 1 illustrates the rapid reduction in the LCOE from solar PV, 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.

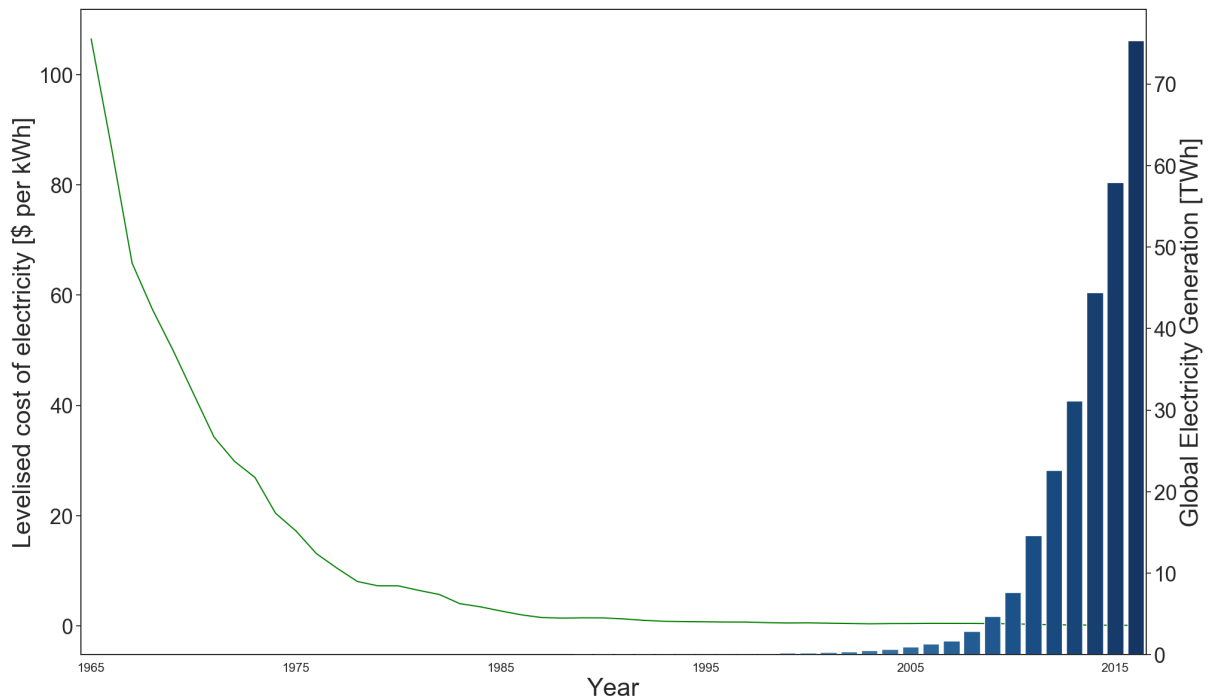


FIGURE 1
Solar PV Cost and Deployment Over Time

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 et al. 2018. First printed in Andres et al. 2021.

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 world wide. 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 around 2011/2012.

In 2011, the US and China entered into a trade dispute over solar PV subsidies when the US imposed anti-dumping and countervailing duties on Chinese and Taiwanese module manufacturers, following a petition led by a subsidiary of the German firm SolarWorld. In 2012, China filed a WTO dispute against the US, which was partially upheld. Following the US' failure to comply with the ruling, China imposed anti-dumping duties on US (and Korean) polysilicon. Tariffs were supported by a coalition of congress members and manufacturing firms despite

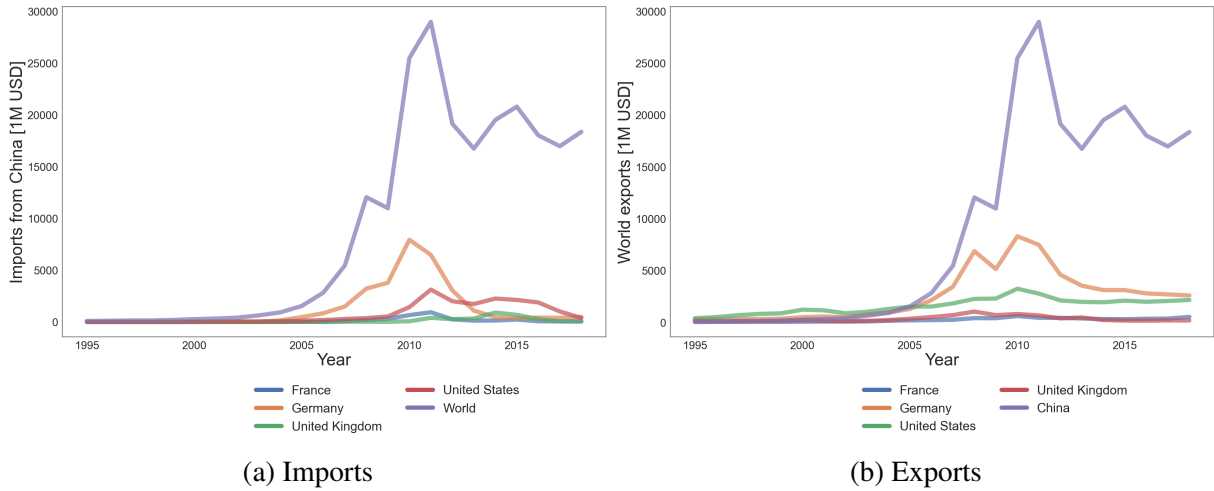


FIGURE 2

Regional and Global Trends in Solar PV Trade

Note: Figure 2a plots Chinese exports of solar panels to 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, which led to the global production glut in 2011/12.

opposition from a majority of US solar firms (Hughes et al. 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 Commission 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 export volumes (Meckling et al. 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 (Crowley et al. 2019; Huang et al. 2016), 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 et al. 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 et al. 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 TFP, employment, exports and investment in R&D over the period 1999-2007, and estimate 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 (Curran 2015; Meckling et al. 2018; Wu et al. 2013). 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

Data Sources This paper combines firm-level patent and financials data with country-level trade and production data. Firm-level financials data was obtained from Bureau van Dijk’s (BvD) Orbis database. Patent data was obtained from the EPO’s PATSTAT Global Database (2021 spring edition) and matched to firms in Orbis, using patent and firm identifiers in Orbis patent data. Firms in the database can be identified by industry classification (NACE, NAICS, US SIC, and BvD’s own classification). However, it is not possible to identify firms engaged in manufacturing a specific product from these higher level classifications. For this reason, firms were selected based on whether they could be identified as having innovated in a relevant technology at some point.

As a first step, relevant patents were selected using a list of technology codes from the Cooperative Patent Classification (see table 5 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 6 (appendix A).¹² Patents were matched to firms listed as their owners, resulting in a list of EU firms in the Orbis database which were associated with a solar photovoltaic related patent at any point. Firms in the sample were then selected using this list. The final sample forms an unbalanced panel of 4,632 firms. For the selected firms, financial data was obtained from Orbis, including data on profit margins and total assets. The patent data was further used to construct two indicators of innovation, as described in more detail in the following section.

Bilateral trade data was acquired from CEPII’s BACI database (Gaulier et al. 2010). The database contains annual bilateral trade values and volumes for all countries at the Harmonised

1. My thanks 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 three; 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.

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 854140³ and 854150⁴. Country-level production, overall import and export data at Prodcom code 26112240⁵ and 26114070⁶ was obtained from Eurostat's Prodcom database and combined with bilateral trade data to construct country-level import penetration measures.

3.1 Empirical Strategy

Definition of Key Variables Import penetration in country i and year t is defined as Chinese imports by market absorption:

$$IMP_{it} = \frac{imp_CHN_{it}}{prod_{it} + imp_{it} - exp_{it}} \quad (1)$$

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 .⁷⁸ The main dependent variable is citation-weighted 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 are weighted by the number of citations they receive within 3 years of priority.⁹ Citation-weighting accounts for the fact that not all patents contain the same amount of innovative novelty – patents which have been cited more frequently are likely to constitute a greater technological advance and be more valuable (cf. Jaffe et al. 2017).

In addition, patent stocks for each firm were computed as a measure of accumulated past innovation, where $Fam_stock_t = Fam_stock_{t-1} * 0.85 + tech_t$, starting from 1980. Following convention (cf. Hall et al. 2005), patents are discounted at an annual rate of 15% to account

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 semiconductor devices n.e.s. in heading no. 8541, including photovoltaic cells, whether or not assembled in modules or made up into panels

5. Photosensitive semiconductor devices; solar cells, photo-diodes, photo-transistors, etc.

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

7. The measure, being in essence 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.

8. 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.

9. A robustness check uses citations received within 5, instead of 3, years of priority.

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 by a lesser amount) 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.

For the purpose of analysing the effect of import penetration on firm survival, Orbis' 'status' variable was used to compute a *survival* variable taking the value of 1 if a firm was still active three years after the time period given, and 0 if it was not. Status information was not available for all firms in the sample, and where the dataset could be matched to the 'status' variable, the latter was often 'Unknown'. For this reason, a firm was defined as still 'Active' if that was its status; following Bloom et al. 2016, if its status was 'Dissolved (merger or take-over)'; or if its status was 'Active (default of payment)' or 'Unknown' *and* the firm was still observed in the dataset in 2018. Moreover, where the variable 'status year' was missing it was imputed as being the last year during which the firm is observed. From this point, two alternative survival indicators were constructed: one in which all firms whose status was still 'Unknown' were dropped, and one in which they were retained and would automatically be assigned as having exited once the status year was less than three years in the future.

The Orbis database contains firm financials, such as value of assets, turnover, employment, and profit margins¹⁰. Firm financials data was cleaned as per the steps laid out in appendix B.

The full sample comprises 4,632 firms over the period 1999-2018 (this includes specialised solar PV manufacturers such as SolarWorld and Solaris; but also others such as Airbus or Cambridge Consultants Limited). The countries included are Austria, Belgium, Luxembourg, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. Summary statistics are reported in table 1.

10. Profit Margin (%) = (P/L before Tax & Extr. Items / Operating Revenue (Turnover)) * 100

TABLE 1
Summary Statistics

	mean	sd	min	max
Fam Count (Unweighted)	0.07	0.65	0.00	43.00
Fam Count	0.06	0.82	0.00	62.87
Fam Stock (Unweighted)	0.35	2.64	0.00	188.24
Fam Stock	0.33	3.19	0.00	225.95
Total Assets (USD)	1.30e+09	9.34e+09	0.00	3.04e+11
Nbr of Employees	1818.27	10152.26	0.00	323298.00
Operating Revenue/Turnover (USD)	1.11e+09	8.54e+09	-1.06e+06	3.87e+11
Profit Margin	5.02	20.65	-100.00	100.00
Years Since Incorporation	28.80	32.49	0.00	567.00
Import Penetration	0.90	11.90	-14.89	236.85
Country Exports (USD 1,000)	1.63e+06	2.19e+06	72.09	8.44e+06
Chinese World Exports (USD 1,000)	1.37e+07	9.19e+06	152722.03	2.94e+07
Observations	49583			

Note: The table shows the mean, standard deviation and range of key firm- and country-level variables. While the regression uses citation-weighted patent family counts and stocks, the table also includes simple counts as a point of comparison. Import Penetration is defined as $IMP_{it} = \frac{imp_CHN_{it}}{prod_{it} + imp_{it} - exp_{it}}$, 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 .

Estimation Strategy Any attempt to study the effects of an increase in trade on an economy inevitably suffers from 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 country i '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 long differences in overall Chinese exports to the rest of the world times a given country's import penetration at the start of the study period (1999). The validity of this instrument rests on the assumption that overall Chinese export growth is driven by developments in Chinese policy and is exogenous to the relationship under investigation. The analysis additionally accounts for unobserved time shocks by using year fixed effects. Firm and country fixed effects are eliminated by using 5-year differences in all variables, following Bloom et al. 2021.

Choice of Instrument 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 (cf. Autor et al. 2013), this paper therefore uses start-of-period import competition as a measure of 'exposure'.

Based on the strategy followed in Bloom et al. 2021, and to make the analysis consistent with approaches used in the broader China Shock literature, the dependent variable is log-

transformed to facilitate the interpretation of the regression coefficients ($LN(1 + FamCount)$). Firm fixed effects are captured by taking five year differences (value at t minus value at $t-5$) of all variables in the regression (note that this shortens the study period by five years), with the exception of the firm's a priori patent stock of which a 6-year lag is included to ensure it is not intrinsically correlated with the dependent variable. Standard errors are clustered at the firm level.¹¹ The analysis is carried out using the *ivregress 2sls* command. The first stage includes both the simple and cubed version of the instrumental variable, both of which are highly significant (the former with a negative, the latter with a positive sign).¹² The instrument is highly relevant with a first stage F-stat of 87.74 for the baseline regression not including interaction terms.

The system of equations¹³ used to estimate the relationship of interest is

$$\left\{ \begin{array}{l} \Delta_5 LN(1 + FamCount)_{jt} = \beta_1 \Delta_5 \hat{IMP}_{it} + \beta_2 \Delta_5 \hat{IMP}_{it} * LN(1 + FamStock)_{jt-6} \\ \quad + \beta_3 LN(1 + FamStock)_{jt-6} + \beta_4 \Delta_5 X_t + \delta_t + \varepsilon \\ \Delta_5 IMP_{it} = b_1 \Delta_5 Exports_{CHN,t} * IMP_{i,1999} + b_2 (\Delta_5 Exports_{CHN,t} * IMP_{i,1999})^3 \\ \quad + b_3 \Delta_5 Exports_{CHN,t} * IMP_{i,1999} * LN(1 + FamStock)_{jt-6} \\ \quad + b_4 (\Delta_5 Exports_{CHN,t} * IMP_{i,1999})^3 * LN(1 + FamStock)_{jt-6} \\ \quad + b_5 LN(1 + FamStock)_{jt-6} + b_6 \Delta_5 X_t + \delta_t + u \end{array} \right. \quad (2)$$

where IMP_{it} is import penetration in country i (where firm j is based) in year t ; $Exports_{CHN,t}$ are world exports of solar panels from China in year t ; $IMP_{i,1999}$ is import penetration in country i in 1999; $FamCount_{jt}$ is the citation-weighted new patent family count for firm j in year t ; $FamStock_{jt}$ is firm j 's weighted, discounted patent family stock; X_t is a vector of controls¹⁴; δ_t are period dummies; u and ε are error terms. The interaction term between IMP_{it} and $FamStock_{jt}$ is included in order to explore how a high existing stock of innovation and 'innovativeness' more generally affect the firm's response to import competition.

11. Clustering at the country level provides too small a number of clusters to be useful.

12. This function was found most appropriate to approximate the relationship between the endogenous regressor and the instrument.

13. For brevity, I omit the first stage regression on the interaction term including the endogenous regressor. The full system is written in appendix C.

14. Profit margin and total assets (as a proxy for firm size) are included to control for firm characteristics. Country-level solar panel exports are included to control for characteristics of the country's solar panel manufacturing sector.

TABLE 2
Effects of Import Competition on Solar Cell Innovation

	(1) Solar cells	(2)	(3) Gen 1	(4)	(5) Gen 2	(6)	(7) Gen 3	(8)
Δ_5 Import Penetration	0.005*** (0.002)	0.005*** (0.002)	0.002*** (0.001)	0.001** (0.000)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)
Fam Stock (log, t-6)	-0.179*** (0.022)	-0.184*** (0.023)	-0.090** (0.036)	-0.096*** (0.037)	-0.160*** (0.026)	-0.158*** (0.025)	-0.205*** (0.067)	-0.152** (0.077)
Δ_5 Import Penetration X Fam Stock (log, t-6)		-0.016 (0.021)		-0.006 (0.012)		-0.009 (0.015)		0.041 (0.033)
Year FEs	X	X	X	X	X	X	X	X
IV Regression	X	X	X	X	X	X	X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	14565	14565	14565	14565	14565	14565	14565	14565

5-Year Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: The table shows the results of a linear regression of firm-level weighted patent family counts by generation of solar cell and overall. All variables are 5-year-differenced, except the historical stock of patent families which is lagged. Import penetration is instrumented by 5-year-differences in overall Chinese solar PV exports multiplied by country-level import penetration at the start of the period (1999).

4 RESULTS & DISCUSSION

Trends in Solar PV and Related Patenting Figure 3a plots the number of new solar PV patent families over time by country of inventor of the priority patent.¹⁵ Patenting by Chinese inventors appears to have peaked earlier than elsewhere. 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 war in 2012, overall trends for all technologies continue to increase.

Effect of Import Competition on Firm Innovation Table 2 reports the main regression results of solar cell innovation on import penetration, using 5-year long differences, and its interaction with the firm's a priori patent stock. For the first specification (overall solar cell patenting), the coefficient on import competition alone is positive and implies that a unit increase in import penetration (which is essentially imports from China as a percentage of market size) increases patenting by about 0.5%¹⁶. Qualitatively similar results are found for patenting in generation 1. The interaction term is not statistically significant. A higher lagged patent stock is negatively and significantly associated with future patenting.

15. The first patent in the family

16. $100 * (e^{0.005} - 1) \%$

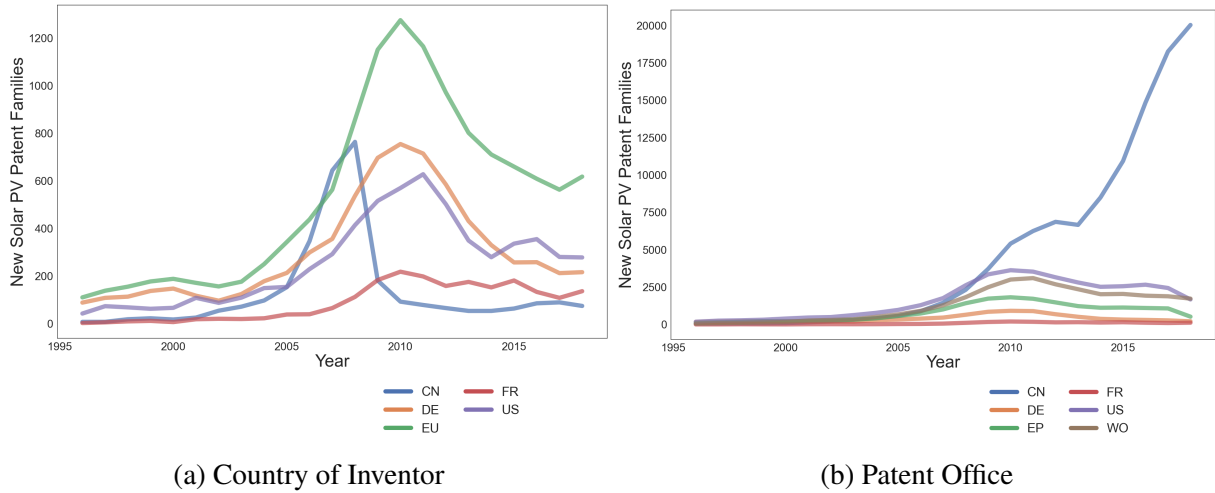


FIGURE 3

Global Patenting Trends in Solar Cell Generations and Related Technologies

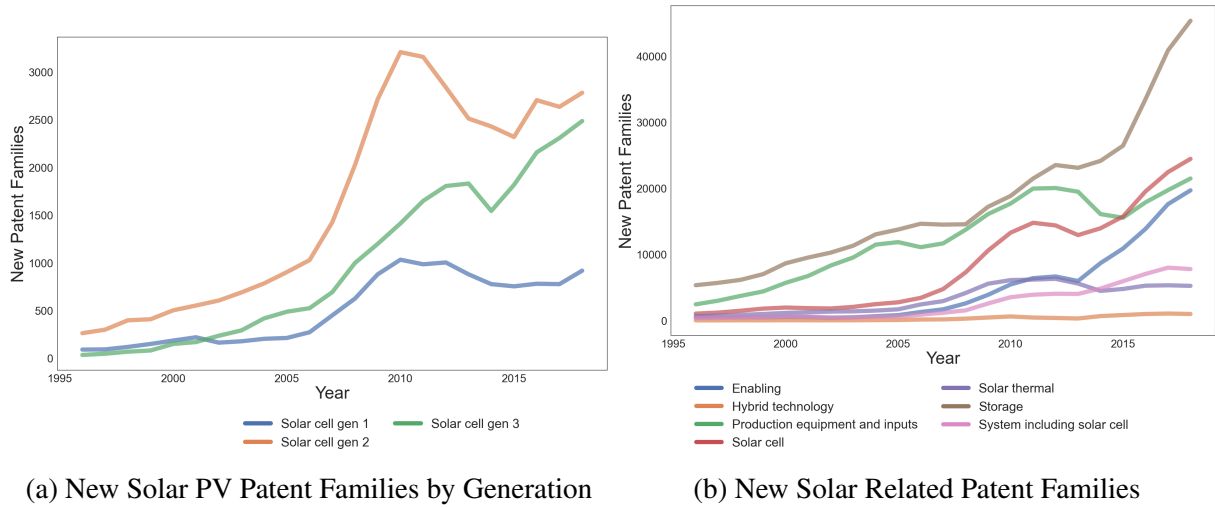


FIGURE 4

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 few new families were attributed to Chinese inventors after a small peak in the early 2000s, patents filed in the Chinese patent office are on a steep upward trend. Figure 3 plots new families filed at any patent office by generation of solar cell and for related technologies.

It is conceivable that trade and competition in solar photovoltaics could affect innovation related technologies, such as energy storage or upstream production equipment. Table 3 therefore reports regression results using firm-level patenting in a range of solar-related technologies as the outcome. Firms in countries with higher import competition appear to have patented more in upstream equipment and inputs (columns 7 and 8), though this effect is reduced and eventually reversed for firms with a higher prior patent stock. The coefficient on the interaction of solar PV import penetration with the lagged patent stock is negative and significant for production equipment and storage technologies (columns 8 and 10). In interpreting these results one might speculate that higher demand for production equipment and storage due to the expansion in cheap solar panel manufacturing reduced the need for innovation by incumbents in such technologies, but increased incentives to enter or catch up for other firms.

No statistically significant impacts of solar PV import competition on patenting in related technologies can otherwise be identified. As is the case for solar cells, a higher existing patent stock *in the technology in question* is associated with lower patenting going forward, but the interaction with import penetration is statistically insignificant in most specifications.

I now turn to the effects of import penetration on an alternative outcome of interest: firm survival. Much of the literature suggests that trade increases productivity by forcing uncompetitive firms to exit and redistributing market share towards the most productive (cf. Melitz 2003). Table 4 therefore reports the results of a logit regression of firm survival over 3 years on import penetration and lagged patent stock. The instrumental variable analysis is implemented using the control function method (cf. Wooldridge 2015), with the second stage regression including the endogenous regressors and the residuals from the first stage as control variables. The first stage uses *reg*, the second stage *logit*. Standard errors are bootstrapped, using 1000 repetitions. Results suggest no statistically significant effect of import competition on firm survival when controlling for other firm-level characteristics, such as assets and profit margins. The coefficient on the interaction between import penetration and lagged patent stock is positive and significant in two specifications (columns 2 and 6); however, it becomes negative and insignificant in the instrumental variables estimation. Overall, I find no conclusive evidence suggesting that import competition affected the probability of survival during the study period. However, recall that firms were selected into the sample using solar-related patent data. These results may not be representative of solar manufacturers which do not patent.

Appendix D shows complete versions of all tables included above¹⁷ and reports the results of several robustness checks. Table 10 reports baseline results using 4- and 5-year long differences and compares results with and without the use of an instrumental variable. Results are qualitatively similar, but the coefficient on import penetration is insignificant in most OLS specifications and its size increases in the IV estimation, suggesting that a basic OLS would underestimate its effects and significance. Tables 11 and 12 report results using only the periods before and after the trade war. While the coefficient on import penetration itself does not

17. Inclusive of coefficients not discussed in the text

TABLE 3
Effects of Import Competition on Solar-Related Innovation

	(1) Solar cells	(2)	(3) Hybrid	(4)	(5) Solar thermal	(6)	(7) Production	(8)	(9) Storage	(10)	(11) Enabling	(12)	(13) Systems	(14)
Δ_5 Import Penetration	0.005*** (0.002)	0.005*** (0.002)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.002)	-0.001 (0.002)	0.005*** (0.002)	0.007*** (0.002)	-0.004 (0.004)	0.015 (0.010)	0.002 (0.002)	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)
Fam Stock (log, t-6)	-0.179*** (0.022)	-0.184*** (0.023)	-0.058** (0.029)	-0.054* (0.029)	-0.155*** (0.026)	-0.154*** (0.027)	-0.165*** (0.015)	-0.163*** (0.015)	-0.103*** (0.012)	-0.067*** (0.033)	-0.216*** (0.046)	-0.141 (0.108)	-0.209*** (0.058)	-0.143 (0.097)
Δ_5 Import Penetration X Fam Stock (log, t-6)		-0.016 (0.021)		-0.007 (0.005)		0.002 (0.005)		-0.017*** (0.006)		-0.156* (0.087)		0.056 (0.085)		0.028 (0.046)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IV Regression	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Observations	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565

5-Year Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: The table shows the results of a linear regression of firm-level weighted patent family counts for solar cells and related technologies. All variables are 5-year-differenced, except the historical stock of patent families which is lagged. Import penetration is instrumented by 5-year-differences in overall Chinese solar PV exports multiplied by country-level import penetration at the start of the period (1999).

TABLE 4
Effects of Import Competition on Firm Survival

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_5 Import Penetration	0.002 (0.002)	-0.001 (0.001)	0.128 (0.124)	0.113 (0.114)	0.002 (0.002)	0.000 (0.001)	0.068 (0.140)	0.058 (0.133)
Fam Stock (log, t-6)	0.490 (0.351)	0.548 (0.373)	0.504 (0.405)	0.468 (0.384)	0.531 (0.339)	0.556 (0.342)	0.538 (0.388)	0.501 (0.378)
Δ_5 Import Penetration X Fam Stock (log, t-6)		0.007** (0.003)		-0.267 (0.268)		0.006** (0.002)		-0.175 (0.314)
Year FEs	X	X	X	X	X	X	X	X
IV Regression			X	X			X	X
Imputed Values					X	X	X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	10947	10947	10947	10947	11029	11029	11029	11029

Logistic Regression

Firm Long Differences.

Dependent Variable: Firm Survival Over 3 Years.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered/Bootstrapped Standard Errors in Parentheses.

Note: The table shows the results of a logit regression of firm survival over 3 years on import penetration. The outcome variable is binary. Independent variables are 5-year-differenced, except the historical stock of patent families which is lagged. Where indicated, import penetration is instrumented by 5-year-differences in overall Chinese solar PV exports multiplied by country-level import penetration at the start of the period (1999). The IV estimation is implemented using the control function method. Where imputed values are indicated, firms with status ‘Unknown’ in Orbis were retained and assigned as having exited if the status year was less than three years in the future.

change much, the coefficients on the lagged patent stock and its interaction with import competition become insignificant for the pre-2012 period. The lagged patent stock is negative and significant post-2012, and the interaction term positive and significant for the IV regression using 5-year differences and positive, but insignificant, when using 4-year differences. This suggests that incumbents with a large existing stock of innovation became ‘lazy’ only after policy committed to protecting them from competition. Finally, table 13 reports results using patent family counts which are weighted by citations received within 5, instead of 3, years, showing that this does not affect results in any meaningful way.

Limitations The main limitation of the results presented in this paper is that any causal interpretation of these results rests on the assumption that overall Chinese exports interacted with import competition in 1999 is a valid instrument for local import competition. While the instrument is highly relevant, the exclusion restriction cannot be tested. The analysis assumes that import competition in 1999 is a valid exposure metric. This is in line with similar literature using start-of-period industry employment shares (cf. Autor et al. 2013). I argue it is a reasonable assumption, given that figure 2 shows Chinese export growth taking off only in the early 2000s. Using this instrument during a period which was marked by two trade wars likely affecting Chinese export growth may be a further cause for concern. I address this by analysing the periods before and after the trade wars separately, and find the same results regarding the effect of import competition.

The interaction term between import competition and the firm’s lagged patent stock is instrumented for using the main instrumental variable interacted with the patent stock. Unfor-

unately, while the individual instrument is highly relevant for import competition itself, the interacted version is essentially irrelevant as an IV for the interaction term. It is therefore not possible to draw a clear conclusion on how the effects of import penetration differ depending on the firm's prior patent stock.

5 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 at the end of 2012 (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 and firm-level financial data from Bureau van Dijk's Orbis database with country-level trade and production data from UN Comtrade and Eurostat. Innovation is measured using citation-weighted patent family counts, 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.

The results provide support for the hypothesis that import competition increased innovation among European firms. They also suggest that in the sample and time-frame considered, firms with a large ex ante stock of innovation tended to innovate less, all else being equal. Taken together, these results are consistent with the prediction from Schumpeterian growth theory that due to low initial levels of competition, an increase in the latter stimulated innovation. Considering these results together with the dramatic falls in deployment costs that are generally thought to be at least partly attributable to Chinese manufacturing expansion, the latter seems to have had a positive effect on the solar sector and its real and potential future contributions to enabling the low carbon energy transition.

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Appendix

A TECHNOLOGY CODES

TABLE 5
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

Note: 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 6
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	CuInSe ₂ 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

Note: The table lists the technology codes from the Cooperative Patent Classification (CPC) used to identify Solar PV patents, classified into “generations”.

B DATA CLEANING PROCEDURE FOR BVD ORBIS

Following Kalemli-Ozcan et al. (2015), observations were assigned to the reporting year if the financial data was reported during or after June 1st (as indicated by the variable “closing date”), and the previous year if the report was made before June. When constructing the dataset, some firms appeared more than once during a given year; often with different values for some variables. Sometimes this is due to a firm reporting both a consolidated and an unconsolidated account; as a first step, all observations with consolidation code C2 (consolidated account, when there is an unconsolidated companion) were dropped. Where duplicates remained, the following procedure was used:

1. To capture as much information as possible, and based on the procedure suggested in Kalemli-Ozcan et al. (2015), data from five editions of Orbis historical available through the LSE datalibrary was used (2017-09, 2018-12, 2019-12, 2020-12, 2021-06) – in case of duplicates, only the most recent edition was retained.
2. Where duplicates remained, but consolidation codes differed, reports with consolidation code LF (Limited number of financial item) were dropped; then those with code C1 (Consolidated account, when there is no recorded unconsolidated companion); and finally U2 (Unconsolidated account, when there is a recorded consolidated companion). In all these cases, all observations of the firm with that consolidation code were dropped, to ensure each firm’s reporting type is consistent throughout the study period.
3. For remaining duplicates, only the most recently reported observations were retained in cases where multiple values of the variable “closing date” were present.
4. Where duplicates were still present, the average of the competing values was taken.

To address quality issues, and again based on the procedure followed in Kalemli-Ozcan et al. (2015), observations were dropped if total assets, operating revenue, sales and employment were simultaneously missing. Furthermore, the whole company was dropped if

- employment was negative in any year;
- sales, total assets or tangible fixed assets were negative in any year;
- the ratio of employment/sales was larger than the 99.9th percentile in any year and vice versa;
- employment/total assets was larger than 99.9 pct in any year and vice versa;
- employment/revenue larger was larger than 99.9 pct in any year and vice versa;
- the value of sales to total assets was larger than 99.9 pct in any year.

To deal with sudden jumps, observations were set to missing if assets or employment changed by more than 100% upwards or 50% downwards one year and the reverse the following year.

Following this cleaning procedure, financials data and patenting indicators were matched. Where a particular firm was missing in Orbis during a period lying between the year it was first and last observed, a firm-year observation was created, but all control variables derived from Orbis missing. Patent-based innovation counts were set to 0 when no patent was associated with the firm during a particular period.

C FULL SYSTEM OF EQUATIONS

The full system of equations, inclusive of the first stage on the interaction term between import competition and the lagged patent stock, is

$$\begin{cases}
 \Delta_5 \ln(1 + FamCount)_{jt} = & \beta_1 \Delta_5 \hat{IMP}_{it} + \beta_2 \Delta_5 \hat{IMP}_{it} * \ln(1 + FamStock)_{jt-6} \\
 & + \beta_3 \ln(1 + FamStock)_{jt-6} + \beta_4 \Delta_5 X_t + \delta_t + \varepsilon \\
 \Delta_5 IMP_{it} = & b_1 \Delta_5 Exports_{CHN,t} * IMP_{i,1999} + b_2 (\Delta_5 Exports_{CHN,t} * IMP_{i,1999})^3 \\
 & + b_3 \Delta_5 Exports_{CHN,t} * IMP_{i,1999} * \ln(1 + FamStock)_{jt-6} \\
 & + b_4 (\Delta_5 Exports_{CHN,t} * IMP_{i,1999})^3 * \ln(1 + FamStock)_{jt-6} \\
 & + b_5 \ln(1 + FamStock)_{jt-6} + b_6 \Delta_5 X_t + \delta_t + u \\
 \Delta_5 IMP_{it} * \ln(1 + FamStock)_{jt-6} = & b_1 \Delta_5 Exports_{CHN,t} * IMP_{i,1999} + b_2 (\Delta_5 Exports_{CHN,t} * IMP_{i,1999})^3 \\
 & + b_3 \Delta_5 Exports_{CHN,t} * IMP_{i,1999} * \ln(1 + FamStock)_{jt-6} \\
 & + b_4 (\Delta_5 Exports_{CHN,t} * IMP_{i,1999})^3 * \ln(1 + FamStock)_{jt-6} \\
 & + b_5 \ln(1 + FamStock)_{jt-6} + b_6 \Delta_5 X_t + \delta_t + u
 \end{cases} \quad (3)$$

D ADDITIONAL REGRESSION TABLES

TABLE 7
Effects of Import Competition on Solar Cell Innovation

	(1) Solar cells	(2)	(3) Gen 1	(4)	(5) Gen 2	(6)	(7) Gen 3	(8)
Δ_5 Import Penetration	0.005*** (0.002)	0.005*** (0.002)	0.002*** (0.001)	0.001** (0.000)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)
Fam Stock (log, t-6)	-0.179*** (0.022)	-0.184*** (0.023)	-0.090** (0.036)	-0.096*** (0.037)	-0.160*** (0.026)	-0.158*** (0.025)	-0.205*** (0.067)	-0.152** (0.077)
Δ_5 Total Assets (log)	0.013 (0.008)	-0.025 (0.056)	0.003 (0.003)	-0.002 (0.010)	0.004 (0.004)	-0.013 (0.028)	0.002 (0.002)	0.014 (0.016)
Δ_5 Profit Margin	-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)
Δ_5 Country Exports (log)	0.002 (0.004)	-0.000 (0.005)	0.001 (0.001)	-0.000 (0.001)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)	0.004 (0.004)
Δ_5 Import Penetration X Fam Stock (log, t-6)		-0.016 (0.021)		-0.006 (0.012)		-0.009 (0.015)		0.041 (0.033)
Constant	0.001 (0.008)	0.022 (0.031)	-0.005* (0.003)	-0.001 (0.006)	-0.001 (0.005)	0.008 (0.015)	-0.002 (0.003)	-0.009 (0.010)
Year FEs	X	X	X	X	X	X	X	X
IV Regression	X	X	X	X	X	X	X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	14565	14565	14565	14565	14565	14565	14565	14565

5-Year Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: Like table 2, but including coefficients for all control variables.

TABLE 8
Effects of Import Competition on Solar-Related Innovation

	(1) Solar cells	(2)	(3) Hybrid	(4)	(5) Solar thermal	(6)	(7) Production	(8)	(9) Storage	(10)	(11) Enabling	(12)	(13) Systems	(14)
Δ_5 Import Penetration	0.005*** (0.002)	0.005*** (0.002)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.002)	-0.001 (0.002)	0.005*** (0.002)	0.007*** (0.002)	-0.004 (0.004)	0.015 (0.010)	0.002 (0.002)	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)
Fam Stock (log, t-6)	-0.179*** (0.022)	-0.184*** (0.023)	-0.058** (0.029)	-0.054* (0.029)	-0.155*** (0.026)	-0.154*** (0.027)	-0.165*** (0.015)	-0.163*** (0.015)	-0.103*** (0.012)	-0.067** (0.033)	-0.216*** (0.046)	-0.141 (0.108)	-0.209*** (0.058)	-0.143 (0.097)
Δ_5 Total Assets (log)	0.013 (0.008)	-0.025 (0.056)	0.001 (0.001)	-0.002 (0.003)	0.003 (0.005)	0.003 (0.004)	0.015* (0.009)	-0.019 (0.025)	0.004 (0.008)	-0.222 (0.246)	0.006 (0.004)	0.031 (0.046)	0.005 (0.003)	0.019 (0.027)
Δ_5 Profit Margin	-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)	0.000** (0.000)	0.001 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Δ_5 Country Exports (log)	0.002 (0.004)	-0.000 (0.005)	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.003)	-0.001 (0.003)	0.003 (0.004)	-0.001 (0.004)	-0.004 (0.006)	-0.026 (0.024)	-0.003 (0.003)	0.004 (0.010)	-0.003 (0.002)	-0.000 (0.005)
Δ_5 Import Penetration X Fam Stock (log, t-6)		-0.016 (0.021)		-0.007 (0.005)		0.002 (0.005)		-0.017*** (0.006)		-0.156* (0.087)		0.056 (0.085)		0.028 (0.046)
Constant	0.001 (0.008)	0.022 (0.031)	0.000 (0.001)	0.002 (0.002)	0.010** (0.005)	0.010** (0.005)	-0.000 (0.009)	0.019 (0.015)	0.008 (0.014)	0.136 (0.130)	0.007* (0.004)	-0.012 (0.030)	0.006 (0.004)	-0.004 (0.017)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IV Regression	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Observations	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565	14565

5-Year Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: Like table 3, but including coefficients for all control variables.

TABLE 9
Effects of Import Competition on Firm Survival

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_5 Import Penetration	0.002 (0.002)	-0.001 (0.001)	0.128 (0.124)	0.113 (0.114)	0.002 (0.002)	0.000 (0.001)	0.068 (0.140)	0.058 (0.133)
Fam Stock (log, t-6)	0.490 (0.351)	0.548 (0.373)	0.504 (0.405)	0.468 (0.384)	0.531 (0.339)	0.556 (0.342)	0.538 (0.388)	0.501 (0.378)
Δ_5 Total Assets (log)	0.296** (0.146)	0.336*** (0.110)	0.529* (0.287)	-0.244 (0.796)	0.244** (0.105)	0.281*** (0.099)	0.364 (0.288)	-0.131 (0.912)
Δ_5 Profit Margin	0.014*** (0.004)	0.014*** (0.004)	0.013*** (0.004)	0.013*** (0.004)	0.010** (0.004)	0.010** (0.004)	0.010** (0.004)	0.010** (0.004)
Δ_5 Country Exports (log)	-0.251* (0.149)	-0.253* (0.149)	-0.118 (0.197)	-0.196 (0.194)	-0.073 (0.130)	-0.075 (0.131)	-0.006 (0.192)	-0.056 (0.181)
Δ_5 Import Penetration X Fam Stock (log, t-6)		0.007** (0.003)		-0.267 (0.268)		0.006** (0.002)		-0.175 (0.314)
Constant	3.747*** (0.293)	3.734*** (0.291)	3.508*** (0.378)	3.961*** (0.543)	3.110*** (0.236)	3.097*** (0.235)	2.988*** (0.346)	3.278*** (0.573)
Year FEs	X	X	X	X	X	X	X	X
IV Regression			X	X			X	X
Imputed Values					X	X	X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	10947	10947	10947	10947	11029	11029	11029	11029

Logistic Regression

Firm Long Differences.

Dependent Variable: Firm Survival Over 3 Years.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered/Bootstrapped Standard Errors in Parentheses.

Note: Like table 4, but including coefficients for all control variables.

TABLE 10
Baseline Regression

	(1) Δ_4	(2) Δ_4	(3) Δ_4	(4) Δ_4	(5) Δ_5	(6) Δ_5	(7) Δ_5	(8) Δ_5
Δ_4 Import Penetration	0.001 (0.000)	0.001 (0.000)	0.006*** (0.001)	0.006** (0.002)				
Fam Stock (log, t-5)	-0.160*** (0.017)	-0.160*** (0.017)	-0.159*** (0.017)	-0.174*** (0.030)				
Δ_4 Total Assets (log)	0.002 (0.003)	0.002 (0.003)	0.011 (0.008)	-0.113 (0.177)				
Δ_4 Profit Margin	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)				
Δ_4 Country Exports (log)	-0.000 (0.003)	-0.000 (0.003)	0.006 (0.004)	-0.008 (0.020)				
Δ_4 Import Penetration X Fam Stock (log, t-5)		-0.000 (0.000)		-0.048 (0.060)				
Δ_5 Import Penetration					0.001* (0.000)	0.001 (0.000)	0.005*** (0.002)	0.005*** (0.002)
Fam Stock (log, t-6)					-0.179*** (0.022)	-0.179*** (0.022)	-0.179*** (0.022)	-0.184*** (0.023)
Δ_5 Total Assets (log)					0.007* (0.004)	0.008** (0.004)	0.013 (0.008)	-0.025 (0.056)
Δ_5 Profit Margin					-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Δ_5 Country Exports (log)					-0.001 (0.004)	-0.001 (0.004)	0.002 (0.004)	-0.000 (0.005)
Δ_5 Import Penetration X Fam Stock (log, t-6)						0.001* (0.000)		-0.016 (0.021)
Constant	0.010* (0.006)	0.010* (0.006)	0.002 (0.007)	0.076 (0.104)	0.007 (0.007)	0.007 (0.007)	0.001 (0.008)	0.022 (0.031)
Year FEs	X	X	X	X	X	X	X	X
IV Regression			X	X			X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	16251	16251	16251	16251	14565	14565	14565	14565

Firm Long Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: The table shows the baseline regression specification for both 4-year and 5-year long differences, with and without the use of an instrumental variable. There are a few differences between the specifications, other than that the size and significance of the coefficient on import penetration increases in the IV regression compared to a simple OLS.

TABLE 11
Baseline Regression, Pre-2012 Period

	(1) Δ_4	(2) Δ_4	(3) Δ_4	(4) Δ_4	(5) Δ_5	(6) Δ_5	(7) Δ_5	(8) Δ_5
Δ_4 Import Penetration	0.000 (0.000)	0.001 (0.000)	0.003*** (0.001)	0.004* (0.002)				
Fam Stock (log, t-5)	0.044 (0.068)	0.046 (0.069)	0.039 (0.067)	-0.130 (0.095)				
Δ_4 Total Assets (log)	0.009** (0.004)	0.007* (0.004)	0.013** (0.006)	0.120 (0.110)				
Δ_4 Profit Margin	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000 (0.000)				
Δ_4 Country Exports (log)	0.004 (0.005)	0.004 (0.005)	0.003 (0.006)	-0.001 (0.010)				
Δ_4 Import Penetration X Fam Stock (log, t-5)		-0.001 (0.000)		0.037 (0.038)				
Δ_5 Import Penetration					0.001 (0.000)	0.001 (0.000)	0.004*** (0.001)	0.005** (0.002)
Fam Stock (log, t-6)					0.094 (0.092)	0.093 (0.093)	0.087 (0.091)	-0.056 (0.081)
Δ_5 Total Assets (log)					0.020*** (0.006)	0.021*** (0.006)	0.026*** (0.009)	0.090 (0.070)
Δ_5 Profit Margin					0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Δ_5 Country Exports (log)					-0.005 (0.007)	-0.005 (0.007)	-0.006 (0.007)	-0.009 (0.010)
Δ_5 Import Penetration X Fam Stock (log, t-6)						0.000 (0.001)		0.022 (0.021)
Constant	-0.002 (0.006)	-0.002 (0.006)	-0.004 (0.006)	-0.052 (0.054)	-0.005 (0.008)	-0.005 (0.008)	-0.006 (0.009)	-0.030 (0.030)
Year FEs	X	X	X	X	X	X	X	X
IV Regression			X	X			X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	7664	7664	7664	7664	6256	6256	6256	6256

Firm Long Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: The table shows the baseline regression specification for both 4-year and 5-year long differences for the period before 2012 only.

TABLE 12
Baseline Regression, Post-2012 Period

	(1) Δ_4	(2) Δ_4	(3) Δ_4	(4) Δ_4	(5) Δ_5	(6) Δ_5	(7) Δ_5	(8) Δ_5
Δ_4 Import Penetration	0.001 (0.001)	-0.000 (0.001)	0.004** (0.002)	0.003** (0.001)				
Fam Stock (log, t-5)	-0.240*** (0.032)	-0.239*** (0.031)	-0.240*** (0.032)	-0.240*** (0.031)				
Δ_4 Total Assets (log)	-0.004 (0.005)	-0.004 (0.005)	-0.005 (0.005)	-0.005 (0.005)				
Δ_4 Profit Margin	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)				
Δ_4 Country Exports (log)	-0.004 (0.003)	-0.004 (0.003)	-0.003 (0.003)	-0.003 (0.003)				
Δ_4 Import Penetration X Fam Stock (log, t-5)		0.010 (0.011)		0.003 (0.009)				
Δ_5 Import Penetration					0.001 (0.000)	0.001* (0.000)	0.007*** (0.002)	0.007*** (0.002)
Fam Stock (log, t-6)					-0.270*** (0.040)	-0.271*** (0.040)	-0.264*** (0.040)	-0.244*** (0.038)
Δ_5 Total Assets (log)					-0.002 (0.005)	-0.003 (0.005)	0.007 (0.013)	0.025 (0.029)
Δ_5 Profit Margin					-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Δ_5 Country Exports (log)					-0.002 (0.003)	-0.002 (0.003)	0.008 (0.005)	0.012* (0.007)
Δ_5 Import Penetration X Fam Stock (log, t-6)						-0.001 (0.000)		0.008* (0.005)
Constant	0.024*** (0.008)	0.024*** (0.008)	0.023*** (0.008)	0.023*** (0.008)	0.025*** (0.009)	0.026*** (0.009)	0.053*** (0.016)	0.064*** (0.021)
Year FEs	X	X	X	X	X	X	X	X
IV Regression			X	X			X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	7346	7346	7346	7346	7135	7135	7135	7135

Firm Long Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: The table shows the baseline regression specification for both 4-year and 5-year long differences for the period after 2012 only.

TABLE 13
Baseline Regression With Counts Weighted by Citations within 5 Years

	(1) Δ_4	(2) Δ_4	(3) Δ_4	(4) Δ_4	(5) Δ_5	(6) Δ_5	(7) Δ_5	(8) Δ_5
Δ_4 Import Penetration	0.000 (0.000)	0.001 (0.000)	0.006*** (0.001)	0.006*** (0.002)				
Fam Stock (log, t-5)	-0.160*** (0.017)	-0.160*** (0.017)	-0.160*** (0.017)	-0.177*** (0.033)				
Δ_4 Total Assets (log)	0.002 (0.003)	0.002 (0.003)	0.011 (0.008)	-0.106 (0.162)				
Δ_4 Profit Margin	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)				
Δ_4 Country Exports (log)	-0.000 (0.003)	-0.000 (0.003)	0.006 (0.004)	-0.006 (0.017)				
Δ_4 Import Penetration X Fam Stock (log, t-5)		-0.000 (0.000)		-0.042 (0.051)				
Δ_5 Import Penetration					0.001* (0.000)	0.001 (0.000)	0.005** (0.002)	0.005*** (0.002)
Fam Stock (log, t-6)					-0.180*** (0.021)	-0.180*** (0.021)	-0.179*** (0.021)	-0.186*** (0.023)
Δ_5 Total Assets (log)					0.008* (0.004)	0.009** (0.004)	0.014 (0.010)	-0.019 (0.042)
Δ_5 Profit Margin					-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Δ_5 Country Exports (log)					-0.001 (0.004)	-0.001 (0.004)	0.002 (0.004)	0.000 (0.005)
Δ_5 Import Penetration X Fam Stock (log, t-6)						0.000 (0.000)		-0.013 (0.015)
Constant	0.010 (0.006)	0.010 (0.007)	0.001 (0.008)	0.071 (0.095)	0.006 (0.008)	0.005 (0.008)	-0.001 (0.009)	0.017 (0.023)
Year FEs	X	X	X	X	X	X	X	X
IV Regression			X	X			X	X
Firm- and Country-level Controls	X	X	X	X	X	X	X	X
Observations	16251	16251	16251	16251	14565	14565	14565	14565

Firm Long Differences.

Dependent Variable: Change in Firm-Level Patenting.

Controls Include Long Differences in Total Assets (log), Profit Margin and Country-Level Solar Panel Exports (log).

Clustered Standard Errors in Parentheses.

Note: Like table 10, but using firm-level family counts and stocks weighted by citations received within 5, instead of 3, years of priority. Results do not change in any meaningful way.