The Impact of European Feed-in Tariffs Reform on Photovoltaic R&D

Yu-li Ko* and Kenneth L. Simons**

Version: February 20, 2020

Previous title: The Cross-Border Impact of Demand-Pull Policies on R&D: A Firm-Level Analysis

*Ko: phone (518) 948-2957, email yuli.ko.research@gmail.com . **Simons: Department of Economics, Rensselaer Polytechnic Institute, 110 8th Street, Troy, NY 12180-3590, phone (518) 276-3296, fax (518) 276-2235, email simonk@rpi.edu .

The authors thank Korea Energy Economics Institute personnel, particularly Dr. Dong-Woon Noh and Dr. Chul-Yong Lee, for their assistance with data acquisition and inquiries regarding the dataset, and James D. Adams, David Popp, Susan Walsh Sanderson, and participants at the 2016 Industry Studies Conference for helpful comments. This work was supported in part by the Engineering Research Centers Program of the National Science Foundation under NSF Cooperative Agreement No. EEC-0812056, partially by New York State under NYSTAR contract C090145, and partially by the National Science Foundation under Grant No. SBE-0965310. Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation or New York State.
The Impact of European Feed-in Tariffs Reform on Photovoltaic R&D

Abstract

The recent fall in photovoltaic R&D is investigated through detailed data on Korean photovoltaic firms. An unexpected collapse of European, mainly German and Italian, renewable energy subsidies occurred in 2012. It decreased in 2012, relative to counterfactuals, firms’ R&D investment probability 50 percentage points, R&D investment among performers 83 percent, and R&D employment 59 percent; and by 2013, patent applications per firm 55 percent. Confirming the cause, photovoltaic patent applications from other sources fell in Korea and worldwide, and firms suffered employment reductions and exit. Demand-pull policies induced technological change across borders, creating potential strategic complications in international emissions reduction.

Keywords: induced R&D, demand subsidy, energy policy, renewable energy, solar panel industry, patents, demand-pull, climate change

JEL codes: Q55, O38, Q48
The Impact of European Feed-in Tariffs Reform on Photovoltaic R&D

Patent applications for photovoltaics, the technology used for solar electric panels, rose to a peak in 2011 and dropped off. The drop in photovoltaic and other renewable energy patents has caused concern among economists (Acemoglu et al. 2019, Popp et al. 2019). To correctly evaluate climate and energy policy, it is important to understand the causes of the drop-off.

We investigate the impact of sudden reductions in European subsidies on photovoltaic R&D. Globally, demand subsidies and government procurement for renewable energy spurred 55 percent annual growth in 2004-2010 in new photovoltaic generating capacity (IEA 2016). Installations occurred mainly in European Union countries that adopted as incentives feed-in tariffs (FITs), which are prices paid to renewable electricity producers. Owners of photovoltaic panels were promised constant prices for about 20 years for electricity fed into the grid, with elevated rates subsidized by electric utility customers. The rates promised declined over time as system costs declined, but reductions from late 2010 were deliberately rapid, to reduce fiscal burden given accelerated growth in new installations. Most subsidies came from Germany and Italy, whose combined estimated subsidies fell 74 percent in 2012 and 91 percent (or more) by 2013. This shock to subsidies reduced industry-wide sales in 2012.

The corresponding fall in countries’ photovoltaic patent applications appears in Figure 1. We probe the causality and mechanism of the fall through detailed data for one nation, Korea. An annual Korean photovoltaic manufacturing census provided unique data that allow in-depth investigation. Korean producers are mostly typical but not predominant in the photovoltaic industry. The European shock was largely exogenous to the Korean firms’ decisions.1

A multi-equation model, using the causal shock, instrumental variables, and fixed effects, probes how the FIT shock affected Korean firms’ R&D. The probability of investing in

1 Korean firm and government representatives interviewed did not anticipate the European policy shift. Korea is exempt under the Kyoto protocol from historical responsibility for emissions reduction, and is not a preoccupation of German and Italian policy makers. Korean photovoltaic demand subsidies were negligible compared to Korean photovoltaic exports to Europe, and seventy percent of Korean photovoltaic manufacturers directly exported their products, while more indirectly exported by supplying intermediate goods to export firms.
Figure 1. Photovoltaic Patent Applications by Country and Year, 2004-2014. Notes: Includes all countries with 25 applications in any one year. Photovoltaic technologies are delimited as defined in Online Appendices B.2 and B.3. Source: Authors’ analysis of data in EPO (2017).

Photovoltaic R&D among surviving firms fell 50 percentage points in 2012 and 45 percentage points in 2013, relative to counterfactual non-shock values. R&D investment fell 83 percent and 85 percent in the same two years, among surviving firms with nonzero R&D. Mean photovoltaic R&D employment fell 59 percent in 2012 and 56 percent in 2013. Photovoltaic patent applications per firm fell 31 percent in 2012 and 55 percent in 2013. These patterns match aggregate patent data; after 90 percent per-annum growth in 2003-2010, from 2010 to 2013 Korean firms’ patent applications dropped 58 percent.

We also estimate how much firm expansion, funded by subsidies, translated into greater R&D input and output. We find an elasticity of R&D investment with firm size of 0.8 (statistically indistinguishable from 1), an elasticity of R&D employment of 0.7, and an elasticity of patent applications of 0.5. Our analysis implies that these elasticities contributed directly to the fall in R&D. The low elasticity of patent applications implies that patent applications do not
rise proportionately to subsidies that fuel firm growth—although this should not be construed as necessarily implying less than proportionate development of photovoltaic technology (Schmookler 1966, Dasgupta and Stiglitz 1980, Cohen and Klepper 1996).

To test alternative theories of the patent reduction and better understand results of the shock, we investigate what happened to photovoltaic patent applications outside the manufacturers, and to photovoltaic manufacturers’ employment, exit, and entry. Korean non-manufacturing firms, individuals, universities, and government organizations all halved their photovoltaic patent applications by 2014. Worldwide, countries’ mean patent applications per year fell by half, and 84 percent below a linear time trend, from 2010 to 2014. The simultaneous decline in all types of photovoltaic patent applications, by innovators of prospective future products as well as firms manufacturing established products, suggests that patent applications declined because of conditions that affected contemporaneous as well as future R&D benefits.

After prior growth and entry spurred by subsidies, at the same time as the R&D reductions, mean firm employment for photovoltaics fell 49 percent in 2012 and 50 percent in 2013 relative to counterfactual employment without the shock. Entry in photovoltaics halted, and firms’ mean exit probability per annum rose from 0.005 before 2011 to on average 0.113 during 2011-2013, versus a counterfactual exit probability near zero in 2011-2013 without the shock. One firm that cancelled its investment plans, and exited the industry, was Samsung, which had been a small producer but might have become very major. The sudden shift in industry dynamics shows that the fall in photovoltaic patents was associated with a discontinuous shock that, again, affected the contemporaneous industry not just prospective future sales.

Our analysis shows that one region’s environmental policies can affect firms’ R&D internationally, especially in renewable energy industries. Such cross-border impacts have been considered in a few studies (Lanjouw and Mody 1996, Popp 2006, Popp, Hafner, and Johnstone 2011, Fabrizio, Poczter, and Zelner 2017). Specifically for demand-pull policies, Dechezleprêtre and Glachant (2014) and Peters et al. (2012) found transnational stimulus of wind and photovoltaic energy patents. While most such studies have used national patent counts, with only a few studies at the firm level (Noailly and Smeets 2015), we show how subsidized market growth determines the technological impact through international firms’ entry, exit, growth, and R&D.

The remainder of the paper proceeds as follows. Section I explains the European subsidy shock. Section II explains the identification method. Section III introduces the data. Section IV presents the empirical findings. Section V discusses the results with a focus on generalizability and policy implications.

I. The European Subsidy Shock

European Union (EU) nations, which committed to reduce emissions under the Kyoto protocol, took a leading role in green energy development. Photovoltaics were seen as a promising renewable energy source, but far too expensive to attract much investment without subsidies. EU nations’ subsidy policies in 2004-2012 stimulated the majority, 74% in an average year, of the world’s annual photovoltaic installations. Spain, Germany, and Italy, Figure 2 shows, led in installations. The installations were stimulated mainly by FITs. In mid-2011, however, the subsidy regime in Europe shifted on net from strong and growing subsidies to much weaker subsidies due to large fiscal burden and a recent economic downturn. We focus on FITs in the countries that provided the bulk of subsidies in 2009 to 2011, Germany and Italy.

German and Italian FITs promised generally decreased over time, resulting in the percentage annualized FIT reductions in Figure 3 (for details see Online Appendix A.1). Prices of photovoltaic modules, the final assembled solar panels installed for power generation, fell in 2009 onward, as shown in Figure 4, increasing demand for photovoltaic installations. Germany, responsible for 44 percent of world installations in 2010, cut nominal FITs promised by 26-27 percent in late 2010 and at the start of 2011, 15 percent at the start of 2012, and 34-38 percent throughout the year leading to 2013, compared to prior annual reductions of 5-10 percent in 2005-2010, causing new German installations to flatten in 2011. Italian subsidies caused a sharp
Figure 2. Annual New Photovoltaic Installations by Country, Gigawatts (GW), Years 1993-2015. Source: Data from IEA (2016, p. 68).

Figure 3. Annualized Percent Changes in Real Photovoltaic FITs in Germany and Italy, by System Size and Type, Each January 1. Sources: See Online Appendix A.1.
increase in Italian installations in 2011, yielding continued worldwide market growth. Then Italy cut nominal FITs 32-50 percent over the latter two-thirds year leading to 2012, compared to 5-14 percent in August 2010 and the start of 2011 or 2 percent at the start of 2009. The global market experienced in 2012 its first negative growth since 1995.

Compared to the high growth rates of preceding years, the decrease in Italian installations in 2012 and 2013, and the decrease in worldwide installations in 2012, are in Figure 2 starkly evident. Spurred by a July 2012 Japanese renewable energy bill, and Chinese national procurement decisions that increased 2013 production among Chinese photovoltaic producers, installations but not their growth rate eventually recovered. China is separated from other countries in Figure 2 since its purchases mostly went to Chinese manufacturers (Online Appendix A.3).

FITs are Germany and Italy’s main photovoltaic subsidy. Subsidy costs accrue from FIT payments, which continue for 20 years (plus, in Germany, the rest of the installation year) after a photovoltaic plant’s installation into the electrical grid. The value of electricity generated is excluded, in that only the difference between FITs and an expected wholesale electricity price is counted in the costs. The FIT payments are not inflation-indexed, so they decline at the inflation rate. However, installation of new capacity each year brought growing costs, with the highest cost addition in 2010 for Germany or 2011 for Italy. The 2011 addition in Italy, a record for any country, brought an expected 3.7 billion euros of FIT payments to be paid every year for 20
Table 1. Photovoltaic Subsidies, Germany and Italy, Present Value, Millions of 2013 Euros

<table>
<thead>
<tr>
<th>Year Committed</th>
<th>Germany</th>
<th>Italy</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FITs</td>
<td>Regional Roof-Top Programs</td>
<td>FITs</td>
</tr>
<tr>
<td>2004</td>
<td>5,623</td>
<td>24</td>
<td>0</td>
</tr>
<tr>
<td>2005</td>
<td>8,462</td>
<td>30</td>
<td>0</td>
</tr>
<tr>
<td>2006</td>
<td>6,907</td>
<td>0</td>
<td>64</td>
</tr>
<tr>
<td>2007</td>
<td>9,522</td>
<td>0</td>
<td>570</td>
</tr>
<tr>
<td>2008</td>
<td>13,286</td>
<td>0</td>
<td>2,247</td>
</tr>
<tr>
<td>2009</td>
<td>21,324</td>
<td>0</td>
<td>5,168</td>
</tr>
<tr>
<td>2010</td>
<td>32,154</td>
<td>0</td>
<td>16,039</td>
</tr>
<tr>
<td>2011</td>
<td>21,452</td>
<td>0</td>
<td>50,075</td>
</tr>
<tr>
<td>2012</td>
<td>9,874</td>
<td>0</td>
<td>8,957</td>
</tr>
<tr>
<td>2013</td>
<td>3,134</td>
<td>0</td>
<td>2,620</td>
</tr>
<tr>
<td>2014</td>
<td>1,406</td>
<td>0</td>
<td>202</td>
</tr>
</tbody>
</table>

Notes: 2013 and 2014 italicized values are high estimates. Sources: Authors’ calculations (Online Appendix A.2).

years, according to figures provided to us by Italy’s regulatory organization. The costs are billed to each nation’s electricity customers.

FITs and other subsidies each year can be summarized as present value subsidy costs. In Table 1, present values are reported separately for subsidies committed each calendar year. For Germany, present values for 2004-2012 are from nominal valuations by Frondel, Schmidt, and Vance (2014), and for 2013-2014 we (probably over-) estimate costs by assuming the cost per Watt of capacity increase was the same as in 2012. For Italy, present values in Table 1 include
direct payments in Italy’s Regional Roof-Top Programs through 2005, FIT payments in Italy’s Conto Energia program through July 5, 2013 plus grandfathered projects through 2014, and a high estimate of tax incentives available after the Conto Energia program ended. To compute present values, we discount future costs for expected inflation at 2 percent per annum, as in Frondel, Schmidt, and Vance’s valuations. Higher discount rates would reduce total subsidy valuations almost the same multiple every year, leaving percentage annual changes in subsidy costs almost identical. Detailed calculations and sources are in Online Appendix A.2. Present values for Germany and Italy combined are in the final column of Table 1.

Subsidy commitments paid for the purchase and installation of photovoltaic systems, and therefore directly impacted photovoltaic sales. In total during 2004-2014, the two countries committed 5.0 percent of their 2013 gross domestic product (2.6 percent if a 10 percent discount rate is used) to pay for photovoltaic installations. From 5.6 billion euros in 2004, subsidies rose to 48.2 billion euros in 2010 and 71.5 billion euros in 2011, before falling to 18.8 billion euros in 2012 and then, using probably high estimates, to 6.1 and 2.0 billion euros in 2013 and 2014 respectively. From 2010 when subsidy reductions started becoming apparent, subsidies fell 61 percent in 2012 and (probably more than) 87 percent in 2013. From the peak year of 2011, subsidies fell 74 percent in 2012 and 91 percent in 2013.

In sum, a major shock to European subsidies occurred by 2012, with some policy change as early as 2011. Most of German and Italian subsidies—apparently the bulk of worldwide subsidies—ceased in 2012 and 2013. What effect did this shock to European subsidies have on R&D and patenting?

II. Identification of R&D Impacts

We seek to determine the effect of the European subsidy shock on R&D, in a way that is causally identified and reveals firm outcomes. Estimates must articulate counterfactual outcomes, which would have happened without the subsidy shock, to provide a point of comparison. We analyze the R&D reduction relative to the counterfactual in a way that accounts for how firm growth and prior R&D affect current R&D, and that accounts for a subsidy shock whose ramifications play out over time.

We identify the resulting percentage reduction in R&D or patenting as
\[
\Delta R = \frac{R_c - R_a}{R_c} \times 100,
\]
where \(R_c\) is the counterfactual R&D or patenting that would have happened if German and Italian subsidies had continued, versus the R&D or patenting \(R_a\) with actual subsidy reductions.

When we analyze the national patent counts in Figure 1 by fixed effects regression, with a linear time trend to project a counterfactual outcome and with indicator variables to allow differences from trend given the shock in years 2011, 2012, 2013, and 2014, the estimates imply a dramatic reduction in photovoltaic patenting:

\[
\log \text{Patents}_{it} = \hat{\alpha}_i + 0.27t - 0.29Y11_t - 0.84Y12_t - 1.33Y13_t - 1.82Y14_t + \hat{\varepsilon}_{it}
\]

\((0.04)\ (0.19)\ (0.24)\ (0.29)\ (0.41)\)

Here, \(\hat{\alpha}_i\) is an estimated fixed effect for country \(i\), \(t\) is the linear time trend, \(Y11_t\), \(Y12_t\), \(Y13_t\), and \(Y14_t\) are 0-1 year indicators to capture effects of the shock, and \(\hat{\varepsilon}_{it}\) is the fitted random error (the residual). Robust standard errors are in parentheses. The results imply that relative to a linear time trend, patent applications fell to \(\Delta R = (100 \times (1 - \exp(-1.82)) = 84\) percent below trend by 2014, falling 52 percent from 2010 to 2014. Similar conclusions result using a quadratic time trend.\(^2\)

However, a linear or quadratic projection from previous rates of change may not be appropriate. Nonlinear changes in photovoltaic R&D have been the norm, and there is no guarantee that a quadratic time trend is the right model. Moreover, the patent metrics used are subject to biases including that most firm R&D is not patented and that there may be firm- and time-specific biases in the propensity to patent (Cohen, Nelson, and Walsh 2000, Hall and Ziedonis 2001). Aggregate R&D inputs and outputs depend on the number of an industry’s firms, their sizes, and their prior R&D experience, all factors that aggregate patent counts fail to reveal, but that should largely determine the industry’s R&D output (Doraszelski 2003, Hall, Jaffe, and Trajtenberg 2005, Cohen 2010).

\(^2\) Adding indicators for 2004 through 2009 instead of a trend, there is no counterfactual, and the decrease relative to 2010 R&D is an estimated 35 percent by 2013 \((p=0.061)\) and 47 percent by 2014 \((p=0.051)\).
We therefore move to a deeper analysis, with firms manufacturing photovoltaic products. For analysis, we need a major industrial country, excluding China which uniquely supported its industry during the shock period, with detailed information on individual firms’ photovoltaic R&D and manufacturing efforts. We obtained this information for Korea.

Our interviews with Korean government staff dealing with photovoltaic policy, as well as two Korean global photovoltaic company employees, indicated that the subsidy reduction was unexpected. Indeed, Korean manufacturer-sector pairs planning investments circa December annually grew to a high of 57 percent in 2010, and only then fell to 41 percent in 2011 and a low of 7 percent in 2012—a change in investment plans that is statistically significant \(( p = 8.5 \times 10^{-13})\) and robust to controls for manufacturer-sector pair fixed effects (see Online Appendix A.4). Hence Korean firms made decisions under the belief that demand subsidies would continue, and the surprise collapse of European subsidies undermined their market and known sources of market growth for the foreseeable future.

A. Estimation Strategy

We use a system of equations at the firm level to analyze a distributed lag of the shock, firm size, and prior R&D. This system of equations not only provides the counterfactual R&D estimate. It also probes how R&D impacts were determined, thus moving discussions of induced R&D to a next level to better understand what controls the effects of subsidy policies.

The firm equations consistently identify the change in R&D subject to two additional econometric assumptions, beyond the usual generalized method of moments assumptions. First, the distributed lag of the shock—which will be equivalent to year indicators—would be 0 instead of 1 absent the shock. That is, the impact of FIT reductions would have been no better and no worse than the trend in years preceding 2011. Second, the observed residuals would be the same with or without the shock. That is, with or without FIT reductions, each firm in each year would do equally well or badly relative to its expectations, and hence to each other.\(^3\)

\(^3\) The two assumptions support in-sample counterfactuals, not counterfactuals for hypothetical entrants nor for firms that hypothetically might not have exited, as the latter would require more assumptions and vastly more complex estimation. The second assumption is effectively an
The use of the demand subsidy shock for identification helps avoid potential omitted variable bias. It also avoids the endogeneity of newly installed capacity, used for example by Peters et al. (2012) and Dechezleprêtre and Glachant (2014). Capacity is an equilibrium measure determined, as Cohen (2010) points out for any sales measure, by the interaction of supply and demand.

R&D metrics used are not only patents, but also photovoltaic R&D investment and photovoltaic R&D employment. Direct R&D metrics address the concerns about biases in patent metrics, so the R&D input metrics provide a more trustworthy alternative to the usual patent data. R&D measures reveal firm research activity even if it did not yield unique new technologies and even if it was subject to propensity-to-file biases. Moreover, R&D investment and R&D employment are not subject to research, writing, and filing delays, so they provide more accurate timing of when the shock had its effect. Also, relative reductions in R&D investment and employment and patenting help expose how the shock affects firm R&D. Since our R&D metrics are specific to photovoltaic business units, they are not subject to aggregation and avoid conflating non-photovoltaic R&D trends with photovoltaic R&D.

All three R&D input and output metrics, plus firm size measured by photovoltaic business unit employment, and firm exit, each serve as dependent variables in the estimation equations. These are the key variables discussed above as determinants of firm photovoltaic R&D, plus the major firm outcomes for which the Korean data are systematically available. Recursive substitution in fitted equations yields counterfactuals for each actually-producing firm in successive years. Standard errors are computable by bootstrap methods or (with simultaneous-equation generalized method of moments estimation) the delta method, with bootstrap standard errors used here as they generally yield slightly larger standard errors. Delta method standard errors are reported in Online Appendix D.7. Estimates have been verified by multiple methods to ensure accuracy.

Since the estimation equations each include the independent variable photovoltaic employment or lagged photovoltaic employment, and it may be determined endogenously, we use a further identification strategy. Employment is instrumented by a first lag of the approximation, which could be dispensed with by using complex simulation methods if joint probability distributions of all variables were well known.
employment variable, in all equations with evidence of endogeneity (whenever a C test of the null hypothesis of exogeneity is rejected at a significance level $p < 0.25$). The resulting coefficient estimate for employment reveals the elasticity of R&D inputs and output with firm size, which explains how much demand subsidies contribute to R&D measures within firms.\(^4\)

**B. Estimation Equations**

In the equations, dependent variable $j$, denoted $r_{ij}^j$, measures photovoltaic-specific activities of firm $i$ in year $t$: (1) R&D investment participation, equal to 1 if the firm’s R&D budget was nonzero or 0 otherwise; (2) log R&D investment among firms with nonzero R&D; (3) log R&D employment plus one; (4) log patent applications plus one; (5) log employment; and (6) exit from photovoltaic production. R&D investment participation, following convention, is modeled separately from R&D spending if spending is nonzero. R&D employment and patent applications for simplicity are modeled with a single combined equation by including the “plus one” increment inside the logarithms in case of zero R&D employment or zero patent applications.\(^5\) Patent applications $P_{it}$ contribute to a discounted knowledge stock, $S_{it} = \sum_{t=0}^{\infty} (1-\delta)^t P_{i-t}$, using depreciation rate $\delta = 0.1$.\(^6\)

The six equations take the form

\[
 r_{ij}^j = \alpha_i^j + \sum_{t=0}^{2} \beta_i^j d_{i-t} + \beta_j^i \log(1 + Q_{it-\Delta(j)}) + \beta_j^4 \log(1 + S_{it}) + \varepsilon_{it}^j,
\]

\(^4\) Without this further identification strategy, we find, estimates of R&D effects of firm size are biased strongly toward zero.

\(^5\) The offset of one is not arbitrary; it ensures a substantial but not overwhelming difference in $r_{ij}^j$ between firms with zero R&D employment or patent applications and firms with the smallest nonzero values (0.1 or 10 yield unreasonably tiny or large differences). The same is true for $Q_{it-\Delta(j)}$ and $S_{it}$. Alternative offsets yield minor variations in conclusions.

\(^6\) Like Hall and Mairesse (1995), who assume for R&D spending a depreciation rate of 0.15, we confirm that alternative depreciation rates from 0.05 to 0.30 make almost no difference in conclusions (Online Appendix D.8).
where fixed effects $\alpha_{ij}$ and coefficients $\beta_{0j}, \dots, \beta_{4j}$ are to be estimated, $e_{it}$ are firm- and year-specific random variations, and $d_{\ell-t}$, $\log(1+Q_{it-\Delta(j)})$, and $\log(1+S_{it})$ are independent variables. The shock to demand subsidies is analyzed in distributed lag form with lags $\ell = 0$ to 2 after year 2011, when $d_{2011} = 1$ indicates the start of major European subsidy reductions, while $d_t = 0$ for $t \neq 2011$. Variables $d_{t-0}$, $d_{t-1}$, and $d_{t-2}$ are equivalent to year indicators for 2011, 2012, and 2013. Coefficients $\beta_{0j}$, $\beta_{1j}$, and $\beta_{2j}$ capture effects of evolving European policy on each dependent variable as firms reacted to the cut in subsidies. R&D investment participation and exit are modeled using both linear probability and probit formulations, with similar results. Business size, a primary predictor of R&D, is measured as log photovoltaic employment $Q_{it}$ plus one.\(^7\)

Current employment is used to predict the R&D input and output measures, consistently with prior research on firm size and R&D (Cohen 2010), and employment lagged by $\Delta(j) = 1$ year instead of 0 is used to predict year $t$ employment and exit. Thus when the dependent variable is log photovoltaic employment, this models an adjustment process in the size of the firm’s photovoltaic activity. When the dependent variable is exit, lagged employment is necessary since employment data are not available in the year of exit. Lagged photovoltaic employment is recorded as zero before a firm began photovoltaic manufacture.

The fixed effects $\alpha_{ij}$ are firm fixed effects in most equations, but are constrained to be sector effects for R&D investment participation, or sector group effects for exit, as defined in section III. This retains reasonable degrees of freedom in estimation (see Online Appendix C.1). Sector indicators account for differences in entry barriers, market concentration, production methods, and research approaches. Firm fixed effects fully control for sectors, since no firm changed sectors.

C. Interpretation of Firm Size Effects

Impacts of firm size reveal how much demand subsidies that cause firm growth are converted into firm-level R&D inputs and outputs. R&D investment is typically roughly

\(^7\) Employment is the consistently-available photovoltaic business size measure.
proportionate to firm size (Cohen 2010), which is a leading predictor of firms’ ability to capitalize on returns to R&D (Schmookler 1966, Cohen and Klepper 1996), suggesting $\beta^2_3 = 1$. R&D output typically rises less than proportionately with firm size, suggesting $0 < \beta^4_3 < 1$ (Cohen 2010), with $\beta^1_3$ and $\beta^3_3$ calibrating similar trends for R&D investment participation and R&D employment. Normally firm size increases in prior size but the growth rate $\log(E_t / E_{t-1})$ decreases in prior size $\log E_{t-1}$, suggesting $0 < \beta^5_3 < 1$, and exit decreases in firm size, $\beta^6_3 < 0$ (Dunne, Roberts, and Samuelson 1989).

D. Firm Entry Equation

Entry of new firms is modeled as a Poisson process in which entrants arrive at the rate

$$entryrate_t = \alpha^7 + \sum_{i=0}^2 \beta^7_i d_{t-i},$$

with the number of entrants at $t$ having a Poisson distribution with this rate.

E. Competitive Market

Photovoltaic products are highly competitive internationally and within Korea. Largely substitutable using kilowatt-hours of electricity produced per year in ideal sunshine as the measure of quantity, photovoltaic devices sold between nations and inside Korea should have been impacted similarly. Although the materials and manufacturing sector groups had fewer competitors than the rest of the industry, they still appear to have been fairly competitive. We attempted triple-differences models (see Online Appendix D.6), in case firms with higher export shares or in downstream sectors were most affected by the shock, but as anticipated no statistically significant differences arose.

8 Confirming the role of size, in interviews for this research, three industry experts emphasized the import of scaling up to firm outcomes including survival.

9 Inverters, described in section III, are a partial exception because they are used for products beyond photovoltaics and are specific to countries’ power systems.

10 Online Appendix D.5 considers models with an exchange rate control. Estimated subsidy impacts remain strong and statistically significant. The control induces spurious correlation, so
As in related literature such as Popp (2002), the model does not explicitly analyze competition. This treatment seems appropriate given products close to commodities. Moreover, the model’s controls for firm or sector fixed effects largely account not only for competitive conditions, but also for firm and sector traits including differing R&D needs and propensities to patent.

F. Supply Side Conditions

Worldwide, there is little evidence that increased supply preceding the shock was greater than expectations formed from subsidies and from past market growth (Online Appendix A.5). During 1993-2010 the 59 percent annual average installations growth (Figure 2) would soon nullify possible positive expectation errors. In contrast, by 2011 or 2012 the subsidy reductions caused the industry to be left with high capacity relative to demand. Volatility in expectations if anything most affected upstream sectors of wafers and polysilicon, 6.8% of Korean firms analyzed, with substantial price decreases in 2009 preceding the European subsidy shock (Figure 4). Korea’s share of world production installed outside China remained roughly constant, as Figure 5 shows, suggesting that industry impacts in Korea were comparable to impacts in other nations.

The demand subsidy collapse coincided with a policy-driven reduction in China’s supply growth. Chinese policymakers had supported photovoltaic industry growth, but after 2011 actively curtailed production in response to reduced worldwide photovoltaic demand. Chinese producers’ annual changes in share of non-Chinese installations appear in Figure 5. By 2010, Chinese firms’ production had grown to 51.5 percent of all photovoltaic modules, and 47.2 percent of all cells, installed outside China. The figure shows Chinese producers’ annual change in market share among non-Chinese installations. In 2011, growth remained similar to the previous two years, slightly less for modules and more for photovoltaic cells. In 2012, share growth became smaller, 2.9 and 0.5 percentage points in modules and cells respectively, is not part of our preferred specification. Likewise, we do not control directly for time series economic conditions, however, Online Appendix D.3 shows that the Korean photovoltaic firm R&D inputs and output, employment, exit, and entry outcomes are entirely distinct compared to Korean economy-wide outcomes.
Figure 5. Change in Chinese and Korean Producers’ Percentage Share of Photovoltaic Module and Cell Production Installed Outside China, 2004 to 2013. Note: Change from prior year in $100\% \times (Y_i - I)/(1 - I)$, where $Y_i$ is country $i$’s world production share and $I$ is China’s world installations share. Sources: Production from EPI (2015), installations from IEA (2016, p. 68).

compared to 6.2 and 6.3 percentage points in 2008 through 2010. In 2013, Chinese share plummeted, with growth of $-11.2$ and $-11.7$ percentage points respectively, as sales were redirected toward Chinese installations. The shift in Chinese government support therefore decreased the growth of industry competitiveness outside China during 2012 and especially 2013. China’s response seems a natural part of the worldwide response to the shock. Even if it were viewed as an uncontrolled influence, however, the estimated effects of the European demand subsidy shock would be underestimated as a result of China’s government involvement.

III. Data

A government agency, the Korea Energy Economics Institute (KEEI), provided photovoltaic firm data. The longitudinal dataset (KEEI 2013) provides reliable and almost complete documentation of the Korean photovoltaic industry from late infancy in 2004 to fair
maturity in 2013. The dataset has 84 firms. For firms with multiple business units, variables are totals across units. All supply chain sectors are covered, as shown in Table 2.\footnote{More information on the firm dataset is in Online Appendix B.1. The data lack sufficient information to estimate production or cost functions, although cost reduction curves appear typically to stem from innovation (Simons 2019), so analysis of R&D may obliquely address the major source of cost reduction.}

The sectors are best understood through a brief technical overview. Modules are the final assembled product, also called solar (electric) panels. Cells are the solar electricity-generating component. Conventional cells are semiconductor devices built in and on wafers, much like silicon wafers used for computer chips, but made of polycrystalline silicon termed polysilicon. The polysilicon is formed into ingots which are then cut into wafers. Thin-film cells also are usually made with polysilicon, with energy-generating components deposited in much thinner sheets than conventional cells. Glass, film coatings, metal paste, and other components are needed to build the solar modules. Inverters convert direct current from the cells to alternating

\begin{table}
\centering
\caption{Sectors of the Korean Photovoltaic Industry}
\begin{tabular}{llr}
\hline
Sector & Sector Group & Percent of Sample \\
\hline
Conventional Modules & Cells and Modules & 23.9 \\
Conventional Cells & Cells and Modules & 4.4 \\
Thin-Film Cells & Cells and Modules & 0.7 \\
Ingots & Wafers & Materials & 4.2 \\
Polysilicon & Materials & 2.6 \\
Inverters & Components & 10.5 \\
Glass & Components & 1.5 \\
Film Coatings & Components & 4.4 \\
Metal Paste & Components & 5.7 \\
Other Components & Components & 2.4 \\
Manufacturing Equipment & Manufacturing Equipment & 22.6 \\
Multi-Sector Firms & Multi-Sector Firms & 17.1 \\
\hline
\end{tabular}
\end{table}
current for external electrical use. *Manufacturing equipment* built by specialist firms is used by manufacturers of cells, modules, components, and materials.

R&D investment and R&D employment accounting are subject to tax law for firms claiming the Korean Tax Credit for Development of Research and Manpower. A claimant firm must have an officially approved R&D team or independent R&D institute, with researchers who work only on R&D projects (Son, Song, and Park 2012). R&D investment includes researcher wages, research space rent, and research consumables, but excludes government R&D funding and R&D equipment.

We matched the firm data with Korean patent application data (EPO 2017). Patent applications were identified for all photovoltaic manufacturing sectors, through technological classifications and keyword searches described in Online Appendix B.2. All R&D output, not just more successful output, is quantified, by counting applications regardless whether they were eventually granted.\(^\text{12}\) Matching accounted for name variants, typographic errors, and changes in firm name and ownership. Credit is split among applicants excepting individuals also listed as inventors.\(^\text{13}\) Multiple applications stemming from an invention are counted once using a standard metric, the DOCDB family. Data span all Korean patent applications from late 1997, or only granted patents earlier.

All measures pertain only to the photovoltaic industry. R&D investment and employment are specific to business units in the photovoltaic industry. Similarly, entry and exit are specifically of photovoltaic business units. What happened to these photovoltaic businesses when photovoltaic subsidies collapsed?

**IV. The Impacts of Subsidies on R&D**

Estimates of the model equations (1) appear in Tables 3A-3B. Estimates use two-stage least squares (2SLS) or ordinary least squares (OLS), with each equation just identified. OLS is used in columns 4 and 6 since tests fail to reject exogeneity in the corresponding 2SLS models \((p=0.462 \text{ and } 0.877 \text{ respectively})\). The estimates in columns 1 and 6 use linear probability

---

\(^\text{12}\) Use of all applications also avoids bias from patent grant delays.

\(^\text{13}\) Hence patent application counts per firm and year are often non-integer, so count data statistical models are not used.
### Table 3A. Impacts of Year in Shock, Employment, and Knowledge, Eq. (1)-(4)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R&amp;D\text{ Invest.}_{it}$</td>
<td>log($R&amp;D\text{ Investment}_{it}$)</td>
<td>log($R&amp;D\text{ Employment}_{it}+1$)</td>
<td>log($\text{Patent Apps}_{it}+1$)</td>
</tr>
<tr>
<td><strong>Model:</strong></td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>OLS</td>
</tr>
<tr>
<td>Year 2011&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.0159</td>
<td>0.189</td>
<td>0.0540</td>
<td>0.00573</td>
</tr>
<tr>
<td></td>
<td>(0.0608)</td>
<td>(0.154)</td>
<td>(0.0729)</td>
<td>(0.101)</td>
</tr>
<tr>
<td>Year 2012&lt;sub&gt;t&lt;/sub&gt;</td>
<td>-0.370</td>
<td>-1.167</td>
<td>-0.351</td>
<td>-0.0546</td>
</tr>
<tr>
<td></td>
<td>(0.0687)</td>
<td>(0.466)</td>
<td>(0.135)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>Year 2013&lt;sub&gt;t&lt;/sub&gt;</td>
<td>-0.314</td>
<td>-1.200</td>
<td>-0.263</td>
<td>-0.236</td>
</tr>
<tr>
<td></td>
<td>(0.0744)</td>
<td>(0.424)</td>
<td>(0.122)</td>
<td>(0.140)</td>
</tr>
<tr>
<td>log($\text{Employment}_{it}+1$)</td>
<td>0.200</td>
<td>0.816</td>
<td>0.637</td>
<td>0.335</td>
</tr>
<tr>
<td></td>
<td>(0.0387)</td>
<td>(0.161)</td>
<td>(0.0698)</td>
<td>(0.0524)</td>
</tr>
<tr>
<td>log($\text{Patent App. Stock}_{it-1}+1$)</td>
<td>-0.00959</td>
<td>0.238</td>
<td>0.0909</td>
<td>0.185</td>
</tr>
<tr>
<td></td>
<td>(0.0259)</td>
<td>(0.143)</td>
<td>(0.0527)</td>
<td>(0.0842)</td>
</tr>
<tr>
<td>Sector or Firm Fixed Effects</td>
<td>Sector</td>
<td>Firm</td>
<td>Firm</td>
<td>Firm</td>
</tr>
<tr>
<td>Observations</td>
<td>452</td>
<td>284</td>
<td>452</td>
<td>456</td>
</tr>
<tr>
<td>Firms</td>
<td>84</td>
<td>76</td>
<td>84</td>
<td>84</td>
</tr>
</tbody>
</table>

**Notes:** Standard errors in parentheses are robust and clustered by firm, and include small-sample corrections. In columns labeled 2SLS, log($\text{Employment}_{it}+1$) is instrumented by its lag, log($\text{Employment}_{it-1}+1$). Sample size varies: for log($R&D\text{ Investment}_{it}$), analysis is among firms with positive R&D; for log($\text{Patent Apps}_{it}+1$), four observations lacking instrument at start of sample can be included as no instrument is used; other analyses use full sample.

Models, however, equivalent instrumental variables probit (column 1) and probit (column 6) models were also estimated, and results will be compared when computing R&D impacts.

#### A. R&D Impacts

Korean photovoltaic firms slashed R&D in response to the European fall in subsidies. R&D spending among firms in the sample, plotted in Figure 6, grew exponentially initially, with
Table 3B. Impacts of Year in Shock, Employment, and Knowledge, Eq. (5)-(6)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model:</td>
<td>log(Employment&lt;sub&gt;i&lt;/sub&gt;&lt;sub&gt;t&lt;/sub&gt;)</td>
<td>Exit&lt;sub&gt;i&lt;/sub&gt;&lt;sub&gt;t&lt;/sub&gt;</td>
</tr>
<tr>
<td>Year 2011&lt;sub&gt;t&lt;/sub&gt;</td>
<td>-0.111</td>
<td>0.125</td>
</tr>
<tr>
<td></td>
<td>(0.0982)</td>
<td>(0.0396)</td>
</tr>
<tr>
<td>Year 2012&lt;sub&gt;t&lt;/sub&gt;</td>
<td>-0.631</td>
<td>0.136</td>
</tr>
<tr>
<td></td>
<td>(0.137)</td>
<td>(0.0420)</td>
</tr>
<tr>
<td>Year 2013&lt;sub&gt;t&lt;/sub&gt;</td>
<td>-0.439</td>
<td>0.0755</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.0357)</td>
</tr>
<tr>
<td>log(Employment&lt;sub&gt;i&lt;/sub&gt;&lt;sub&gt;t-1&lt;/sub&gt;+1)</td>
<td>0.351</td>
<td>-0.0153</td>
</tr>
<tr>
<td></td>
<td>(0.0525)</td>
<td>(0.0107)</td>
</tr>
<tr>
<td>log(Patent App. Stock&lt;sub&gt;i&lt;/sub&gt;&lt;sub&gt;t-1&lt;/sub&gt;+1)</td>
<td>0.214</td>
<td>0.00624</td>
</tr>
<tr>
<td></td>
<td>(0.0668)</td>
<td>(0.00888)</td>
</tr>
<tr>
<td>Sector or Firm Fixed Effects</td>
<td>Firm</td>
<td>Sector Group</td>
</tr>
<tr>
<td>Observations</td>
<td>448</td>
<td>397</td>
</tr>
<tr>
<td>Firms</td>
<td>84</td>
<td>84</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses are robust and clustered by firm, and include small-sample corrections. In column labeled 2SLS, log(Employment<sub>i</sub><sub>t-1</sub>+1) is instrumented by its lag, log(Employment<sub>i</sub><sub>t-2</sub>+1). Sample size varies: for Log(Employment<sub>i</sub><sub>t</sub>), instrument is unavailable for four firms at start of sample; for Exit<sub>i</sub><sub>t</sub>, <sub>t</sub>=2004 data lack lagged employment and outcome is unmeasured in final year.

One hundred billion won equaled U.S. $91.3 million at 2013 year-average exchange rates. All won values presented are real 2013 values.
likewise fell by 50.2 percent and patent applications by 48.3 percent in 2012. Firms that exited in 2012 carried out 3.6 percent of 2011 R&D (and exiting firms in 2013 carried out 10.0 percent of 2011 R&D); the collapse came primarily not from exit but from R&D budgets. Of the 64 firms that did not exit in 2012, 29 (with 130 billion won of 2011 R&D) ceased R&D investment and only 4 began R&D investment.

Estimates for the R&D input and output measures are plotted in panels 1-4 of Figure 7. R&D participation rates were an estimated 35.9 percent and 44.1 percent in 2012 and 2013 respectively, compared to counterfactual rates of 86.0 percent and 89.0 percent respectively without the subsidy cuts. The counterfactuals, recall, assume there was no subsidy shock and adjust for the resulting increases in employment and patent application stocks.\(^\text{16}\) The reduction is similar for actual R&D participation rates among Korean photovoltaic manufacturers, shown by small circles in panel 1: 95.8 percent reported R&D investments in 2010, versus 77.0 percent in

\(^{15}\) As a percentage of aggregate reported revenues, aggregate R&D investment was 2.7, 0.8, 1.4, 4.3, 5.3, 11.7, and 6.9 in respective years 2004-2010, then 5.4, 1.3, and 1.4 in 2011-2013.

\(^{16}\) The recursive effects through employment and R&D stocks caused one-sixth to three-quarters of the reduction in the alternative R&D metrics by 2012 and 2013.
Figure 7. Estimated Mean or Geometric Mean R&D Inputs and Output, Employment, and Exit Rate (Solid); Counterfactuals (Dashed); and Sample Means (Circles) or Geometric Means (Diamonds). Note: Active photovoltaic producers each year, and only active R&D investors in panel 2. Geometric means of R&D investment, one plus R&D employment, one plus patent applications, and employment. Panels 1-3 exclude four firms in 2004 with unknown lagged employment. Panel 5 excludes four firms in 2004 and 2005 with unknown second lag of employment. In panels 1 and 6, dotted lines substitute probit formulations. Source: Authors’ analysis.

2011, 35.9 percent in 2012, and 44.1 percent in 2013. Probit estimates and counterfactuals, shown by the finely dotted lines beside the linear model estimates and counterfactuals in panel 1, imply an almost identical dramatic reduction.

---

17 The estimated R&D participation equation is a somewhat weak predictor; adding a time trend yields a more dramatic estimated effect of subsidy reductions.
Among R&D performers, panel 2 of Figure 7 reports estimates for R&D investment. The figure shows dramatic net reductions in R&D relative to the counterfactual of no subsidy reductions, as well as a drop-off in R&D investment sample means. Sample means in panel 2 are geometric means, indicated by small diamonds instead of circles, and corresponding to the model’s use of a logarithmic R&D variable. All numbers are computed only among firms actually investing in R&D each year. R&D investment averaged an estimated 83.5 percent lower than the counterfactual in 2012 (484 instead of 2,931 million won) and 85.0 percent lower in 2013 (484 instead of 3,233 million won).

Drop-offs in 2012 and 2013 also occurred for photovoltaic R&D employment. Panel 3 of Figure 7 shows the net effects on the R&D workforce. The panel again uses geometric means among surviving firms. The estimated annual geometric means track closely the geometric means of actual R&D employment. Comparing estimates to counterfactuals, the estimates imply a 59.3 percent reduction in photovoltaic R&D workforce in 2012, from 13.7 to 5.6 R&D employees on average, and a 56.0 percent reduction in 2013, from 15.5 to 6.8 R&D employees. Taken together, the estimates indicate a major cross-border impact of demand-pull policies on R&D inputs.

Firms’ patent application counts also fell, as shown in panel 4 of Figure 7, by an estimated 31.0 percent in 2012, from a counterfactual value of 1.67 to 1.15 on average, and by 55.1 percent in 2013, from 2.02 to 0.91. Thus, firms’ patenting activity decreased by half what it would be without the shock by two years after the subsidy cuts. The delayed effect on patent filings, compared to R&D inputs, reflects that R&D projects typically take one or several years before reaching fruition.\(^{19}\)

A broader comparison of patent sources allows comparison of largely established-product R&D with largely new-product R&D. Within established photovoltaic manufacturers, R&D

\(^{18}\) Linear probability, probit, and firm fixed effects specifications, all with instrumentation, yield similar fitted models (see Online Appendix D.2).

\(^{19}\) Production function models of R&D output (Pakes and Griliches 1980, Hall, Griliches, and Hausman 1986) yield little additional predictive power, and are restricted to Online Appendix D.1 to keep this analysis concise.
presumably involves largely incremental improvements to existing products and processes. In contrast, for inventors not yet manufacturing photovoltaic products, R&D is more likely to involve new product innovation. Photovoltaic patent application counts are shown annually in Figure 8 for companies, individuals, universities, and government institutions. Applications related to the sample firms, their broader parts, or their chaebols, are excluded to leave only independent organizations.

The drop-off in photovoltaic patent applications occurred in both established photovoltaic product manufacturers and other sectors in Korea. Photovoltaic patent applications by companies not (yet) producing in the photovoltaic sector dropped sharply in 2012 and continued to fall in 2013 and 2014, reaching 53.5 percent of the 2011 total by 2014. For individuals, applications fell simultaneously, by 2014 reaching 50.0 percent of the highest (2011) annual count. For universities and government institutions, the drop-off in patent applications took a
year longer, but by 2014 reached 70.2 percent and 49.5 percent, respectively, of their year-2012 peak totals. Thus, new product research apparently was curtailed at the same time as incremental research on established photovoltaic products.

The mean estimated effects of European subsidy reductions are also listed in Table 4.20 The counterfactual outcome without a subsidy shock is divided by the outcome with the subsidy shock for each firm, and that ratio is averaged across firms. The mean estimated ratio among firms actually manufacturing each year appears in the top Panel of Table 4, along with its standard error. On average, firms’ R&D investment probability was an estimated 54% less by 2012 because of the subsidy shock, R&D investment among investing firms was 82% less, R&D employment was 62% less, and patent applications were 72% less. As the standard errors indicate, these estimated effects are highly statistically significantly different from a neutral ratio of 1.

For probabilities, the changes may also be considered in terms of absolute differences, in the bottom panel of Table 4. The probability of nonzero R&D investment declined on average 44 percentage points by 2012. This estimated effect is highly statistically significant.

B. R&D Elasticity with Firm Size

Firm size, measured by employment, enhances firms’ predicted R&D inputs and output in Table 3A, like in other industries (Cohen 2010). Since the demand subsidy shock decreased firm employment, this yielded an indirect effect of the subsidy reductions on R&D. The biggest firms’ contractions had the biggest impact on aggregate R&D. Over the industry’s history, photovoltaic firm growth increased R&D, such that growing subsidies yielded growing firm R&D.

The size of this effect is estimated to be substantial, with R&D investment having an elasticity near the proportional relationship $\beta_3 = 1$ typical in prior industrial organization research, but with smaller elasticities for R&D employment and patent applications. The

---

20 The estimates in Table 4 use probit formulations for R&D investment probability and exit, and use bootstrap (cluster robust) standard errors. Linear probability models yield slightly larger estimated effects, and delta method (cluster robust) standard errors are generally smaller, although slightly larger for employment (see Online Appendix D.7).
Table 4. Mean Estimated Net Effect of European Subsidy Reductions

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prob. of Nonzero R&amp;D Investment</td>
<td>0.964</td>
<td>0.457</td>
<td>0.533</td>
</tr>
<tr>
<td>(0.073)</td>
<td></td>
<td>(0.067)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>R&amp;D Investment (if &gt; 0)</td>
<td>1.107</td>
<td>0.181</td>
<td>0.165</td>
</tr>
<tr>
<td>(0.182)</td>
<td></td>
<td>(0.102)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>R&amp;D Employment</td>
<td>0.944</td>
<td>0.376</td>
<td>0.420</td>
</tr>
<tr>
<td>(0.104)</td>
<td></td>
<td>(0.090)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>Patent Applications</td>
<td>0.441</td>
<td>0.279</td>
<td>0.196</td>
</tr>
<tr>
<td>(0.096)</td>
<td></td>
<td>(0.074)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>Employment</td>
<td>0.895</td>
<td>0.510</td>
<td>0.494</td>
</tr>
<tr>
<td>(0.088)</td>
<td></td>
<td>(0.082)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Prob. of Exit</td>
<td>26.951</td>
<td>28.794</td>
<td>18.248</td>
</tr>
<tr>
<td>(13.600)</td>
<td></td>
<td>(15.227)</td>
<td>(13.503)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prob. of Nonzero R&amp;D Investment</td>
<td>-0.028</td>
<td>-0.443</td>
<td>-0.391</td>
</tr>
<tr>
<td>(0.058)</td>
<td></td>
<td>(0.063)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Prob. of Exit</td>
<td>0.118</td>
<td>0.134</td>
<td>0.072</td>
</tr>
<tr>
<td>(0.055)</td>
<td></td>
<td>(0.056)</td>
<td>(0.042)</td>
</tr>
</tbody>
</table>

Notes: Mean across firms of each firm’s difference or ratio. Probabilities use probit formulations. Standard errors in parentheses are clustered by firm, bootstrapped with 2,000 replications (1,998 for exit probability in 2013, see Online Appendix C.2).

The probability of conducting photovoltaic R&D increased by an estimated \( (0.200 \times \ln(2) = ) 13.9 \) percentage points with a doubling of photovoltaic employment. Among R&D performers, the elasticity of photovoltaic R&D investment with respect to photovoltaic employment is estimated as 0.82, not statistically distinguishable from 1 \( (p=0.255) \). The elasticities of photovoltaic R&D employment and photovoltaic patent applications with respect to photovoltaic employment are estimated at approximately 0.64 and 0.34 respectively (both less than one at \( p = 2.0 \times 10^{-7} \) and
3.9 \times 10^{-21}); these are approximate elasticities because they tell the estimated percentage increase in one plus photovoltaic R&D employment, or one plus the number of patent applications, that coincide with a 1 percent increase in one plus the firm’s overall photovoltaic employment. Exact elasticities implied by the model, without the “one plus” offsets, on average among observations with nonzero R&D measures, are 0.79 for R&D investment, 0.73 for R&D employment, and 0.47 for patent applications (Online Appendix D.9).

Hence, as subsidies caused firms to grow, firm R&D investment increased nearly proportionately with the number of employees, but R&D employment grew a bit more slowly and patent applications grew most slowly. This finding is consistent with the literature testing the Schumpeterian hypothesis on firm size and R&D, and suggests that larger firms may have hired more expensive high-quality researchers or carried out more difficult R&D projects to refine products and processes as well as the low-cost easy projects that all firms tend to carry out (Cohen and Klepper 1996). Thus, a major indirect impact on R&D resulted when, as shown next, the demand shock reduced firm size.

C. Firm Revenues, Employment, Exit, and Entry

R&D industry-wide depends on firm growth, entry, and exit. Moreover, the downturn in revenues decreased current and presumably expected profit, affecting firm size and composition and triggering the reductions in R&D. Therefore, deeper understanding and a check on the R&D findings come from examining revenues, employment, exit, and entry.

Korean photovoltaic manufacturers’ revenues and employment grew through 2010 or 2011, and then contracted dramatically. Revenues totaled across firms in the industry are plotted annually, using the KEEI data, in Figure 9. Industry total revenue increased from near zero in 2004 to a peak of eight trillion won (about $7 billion) in 2011, driven mainly by exports. The sharp V-shaped reduction and recovery in revenue after 2011 reflects the trends in global installations, seen in Figure 2, which corresponded to a reduction in exports from Korea. Figure 9 also plots the total annual value of (direct) exports reported by the Korean photovoltaic manufacturers. The few domestic installations during 2009-2012 had little impact on the industry. Exports were even closer to total revenues than the figure suggests, because the total revenues double-count materials and components sold between firms and used in later stages of photovoltaic production.
Figure 9. Revenue from Photovoltaic Products, Direct Export Revenue from Photovoltaic Products, and Photovoltaic R&D Investment, Trillions of 2013 Won, 2004-2013. Source: Authors’ analysis of KEEI (2013) data. Note: Industry revenue is total across photovoltaic sectors (value-added is unavailable).

Figure 10 summarizes industry dynamics of the Korean industry, in terms of the annual number of firms, entry, exit, and directly exporting firms. Only four Korean firms produced photovoltaic products before 2004. The number of firms tripled to 12 in 2004, surged to 68 in 2009, and reached a peak of 74 firms in 2011. The majority of firms entered during 2007-2009. Entry decreased after 2009, then fell to zero after the demand shock in 2011. Only one exit occurred before 2011, while exit was substantial during 2011-2013. The exit following the shock confirms that firm survival was closely related to changes in global demand subsidies.

Employment and exit estimates appear in Panels 5 and 6 of Figure 7. In 2012 and 2013 the estimated employment was 48.9 percent and 50.4 percent, respectively, below the counterfactual with no subsidy shock. The exit probability rose by 12.5, 13.7, and 8.4 percentage points in 2011, 2012, and 2013 respectively, relative to the counterfactual of no subsidy shock. Thus, the subsidy shock apparently decimated Korean photovoltaic

---

21 Consistent with the statistical analysis, the count excludes firms in the year of exit, when no data are available on employment, R&D, and other measures.
manufacturers in each year from 2011 to 2013. By 2012, Table 4 shows, employment was on average 49% less, and the probability of exit 29 times higher or 13.4 percentage points higher, as a result of the subsidy shock. These effects are highly statistically significant, or marginally significant for the exit ratio.

The drop to zero entry in 2012 and 2013 is statistically significant \( (p = 2.0 \times 10^{-4}) \) in exact Poisson regressions. Exact methods compute \( p \)-values exactly in small samples, in this case 10 annual observations. (An alternative model, the negative binomial model, cannot be estimated because exact methods for negative binomial models do not exist at this writing, while conventional asymptotic negative binomial models cannot estimate standard errors and \( p \)-values when coefficient estimates equal negative infinity.)

**D. Subsidy Cuts versus Alternative Causes of the Fall in R&D**

The dramatic fall in photovoltaic R&D is part of a dramatic worldwide fall in renewable energy patenting, and the European renewable energy subsidy shock investigated here for the photovoltaic industry provides a single apparent cause. Other potential causes may also seem plausible, so we consider their relevance and interactions in explaining both drop-offs. Popp et
al. (2019), in a working paper released after the first version of this paper, consider five explanations of the fall: shale gas, diminishing returns to innovation, success at innovation, a clean energy investment bubble, and weakened regulations. Here we discuss the consistency of these potential causes with our empirical findings on timing, employment, exit, entry, and manufacturer and non-manufacturer patent applications.

Popp et al. (2019) largely rule out shale gas while Acemoglu et al. (2019), in a working paper, argue that shale gas extraction made natural gas a more inexpensive fuel for electricity and caused the fall in renewable energy patenting. Popp et al. (2019) point out that the increase or stability of electricity prices in the European Union, Japan, and the United States make shale gas “at best a partial explanation” (p. 22) of the fall in renewable energy patents. Our results also seem to rule out the shale gas explanation. If shale gas changed expectations for renewable energy need, this likely would have reduced long-term (new product) photovoltaic R&D at about the time shale gas trends became apparent, potentially much earlier than 2012, while reductions in photovoltaic demand and incremental R&D need not be simultaneous and may not be expected at all. Thus the simultaneous changes in incremental and new product R&D, and the timing of employment reduction, exit, and entry cessation, are not obvious fits for the shale gas explanation. In our open-ended interviews with photovoltaic government and industry personnel, the reductions in European FITs were mentioned repeatedly, whereas natural gas was never mentioned. The German and Italian FIT shock apparently was driven by high program cost (in the wake of a 2009 economic downturn) and the small amount of photovoltaic production in-country, not by projected fuel alternatives.

Diminishing returns to innovation and success at photovoltaic innovation might affect R&D and patenting, but again would not harm current production. Popp et al. (2019) rule out diminishing returns to innovation. For photovoltaic technology, at least, this conclusion seems appropriate. Sudden diminishing returns or sudden success, both extremely rare to begin with, would be extremely unlikely to occur simultaneously for both incremental and new product innovation. Yet both types of innovation declined simultaneously. A dramatic research success for a competing energy technology could imply an eventual decrease in photovoltaic demand, but no such breakthrough or replacement product for a competing energy technology has been apparent, and even success of a competing energy technology should have more long-term new product R&D impact than short-term incremental R&D impact.
Regarding a clean energy investment bubble, high policy-induced demand might be expected to cause investment. Indeed, Popp et al. (2019) find an increased share of startup funding for clean energy just when European subsidies were highest, and a decline when subsidies declined. An investment decline however does not explain why demand for photovoltaic products would decline, as we have shown it did. Also, the burst bubble would suggest a potential reduction in new product R&D, but little or no reduction in incremental R&D of established manufacturers, particularly large established manufacturers. In fact, R&D fell across the Korean manufacturing industry, including in the largest manufacturers.

Weakened regulations through European subsidies, the major source of photovoltaic demand in 2009-2011, in contrast should have reduced demand for renewable energy. The weakened regulations signaled a permanent reduction in governmental will to support renewable energy, and so should have reduced investment incentives simultaneously in both incremental and new product R&D. The reduced subsidies yielded a collapse of German and Italian photovoltaic purchases, which previously constituted the bulk of worldwide photovoltaic sales. Given the resulting financial crisis in manufacturers and reduced subsidies going forward, major R&D reductions are an obvious outcome.

V. Conclusion

European photovoltaic subsidies in Germany plus Italy, responsible for 55-64 percent of world photovoltaic sales in 2009-2011, were slashed 74 percent in 2012 and at least 91 percent by 2013. The fall in subsidies dramatically reduced photovoltaic R&D in Korea and worldwide. Effects in Korea seem to have been nearly exogenous. Relative to a counterfactual of no subsidy

---

22 Popp et al. (2019) also consider weakened regulations in the form of the U.S. Trump administration replacing the Obama administration, and the fall of European Union prices for carbon emission allowances. Trump was elected to the U.S. presidency in 2016, and decreases in European carbon prices occurred in 2008 to early 2009 and again in late 2011 and late 2012. The U.S. administrative shift therefore should have had any effects in 2016 and later. The fall in European carbon prices, if they reduced R&D and demand for renewable energy products, would have done so around 2009 as well as in 2012 and 2013, though this might have contributed to decreased demand from utilities in 2012 and 2013.
shock, Korean photovoltaic manufacturers’ probability of investing in photovoltaic R&D fell an estimated 50 percentage points in 2012. Investing firms’ (geometric mean) R&D investment fell 83 percent. R&D employment fell 59 percent, and a year later patent applications had fallen 55 percent. Firm size, driven by subsidies, fueled R&D; a doubling of firm employment corresponded to a 14 percentage point increase in the probability of conducting photovoltaic R&D, and the elasticity with respect to firm employment was 0.8 for R&D investment, 0.7 for R&D employment, and 0.5 for patent applications. The subsidy reductions caused a halving of employment, exit that annually decimated firms (mainly smaller R&D performers), and a cessation of entry. A halving of patent applications also occurred by 2014 among other firms, individuals, government institutions, and universities in Korea, and in countries worldwide.

The findings allow crude estimation of the sensitivity of R&D to subsidies. German and Italian combined subsidies fell at least 91 percent, so the probability of investing in R&D fell at least (50/91=) 0.55 percentage points per 1 percent decrease in German and Italian subsidies, and R&D investment among investing firms, R&D employment, and patenting had an elasticity of at least 0.91, 0.65, and 0.60 respectively with respect to German and Italian subsidies. Worldwide, data on the annual value of photovoltaic subsidies is unavailable, but a reasonable rough approximation may be that worldwide subsidies fell 60 percent. This would imply that the probability of investing in R&D fell 0.8 percentage point per 1 percent decrease in world subsidies, and that R&D investment among investing firms, R&D employment, and patenting had an elasticity of around 1.4, 1.0, and 0.9 respectively with respect to world subsidies. These are rapid, short-term responses over the two years after the subsidy change.

A. Generalizability

The photovoltaic industry outcomes in Korea seem representative of photovoltaic industry outcomes in most countries. Photovoltaic manufacturers exited worldwide, given fierce price competition driven by subsidy cuts. The halving of patent applications around the world seems to correspond to R&D reductions in manufacturers around the world. The same dynamic of subsidy-driven firm growth presumably drove these firms’ rise and then fall in R&D. Chinese manufacturers also faced competitive pressure and exit, although China was an exception with government policies that supported continued growth and R&D.

Generalizability to other environmental and non-environmental technologies, our findings and the photovoltaic industry’s history suggest, depend on accessibility to the
subsidized market. Entry barriers, which differ by country, affect firm growth and hence international R&D inducement. Factors that affect entry barriers, such as established market dominance, firms’ technological expertise, favorable factor supplies, regional technology spillovers, and developmental stage of the industry and technology, may influence impacts. For example, prior crystalline silicon technology experience and R&D, partly with silicon semiconductor chips, aided the entry of most Korean photovoltaic firms. Technological entry barriers are relatively low for crystalline silicon photovoltaics, but higher for a competing technology, thin-film photovoltaics.

Trade barriers would impede export-driven firm growth that, our results show, increases international R&D through market access. Access to European markets was possible for Korean firms because subsidies were given without restrictions on supplier nationality. Tradability of specific goods and services also affect impacts, as demand-pull policies targeted to non-tradable goods and services—environmental goods and services are often non-tradable due to their local nature—may yield no accessible market for foreign firms.

B. Policy

Major photovoltaic firms and innovators are from major emitter countries that are not leaders in greenhouse gas emissions reduction, like the U.S., China, and Korea. With internationalization of production and R&D, a bigger and more diverse pool of international innovators potentially induces more technological change. Thus demand-pull subsidies that were apparently an effect of the Kyoto Protocol may have incentivized freeriding countries and countries with little historical responsibility to increase the global emissions reduction effort through private and public R&D investment. Moreover, cost reduction for renewable energy and direct industrial participation may incentivize these countries to join in international emissions reduction. However, national governments may choose to support domestic demand selectively if not mandated by international treaty, foreseeing that their domestic demand may mostly incentivize foreign competitors’ innovation.
**Strategic Options:** Demand-pull policies can be designed to support industries in which a country has an advantage through entry barriers.\(^{23}\) Entry barriers including economies of scale and comparative advantage create greater rationale for a country to implement demand-pull policies (Porter 1991, Porter and van der Linde 1995, Ambec et al. 2013). Nonetheless, demand-pull policies may eventually incentivize intense cross-border entry, as for Korean photovoltaic firms after government and private R&D investment overcame entry barriers (Lee 2011). Entry barriers may be lower during windows of opportunity, reflecting an evolutionary stage of technology and industry, when a policy maker may target demand-pull policies to promote her country’s firm growth.

A policy maker may choose demand-pull policies to couple with trade strategies. Nontariff barriers or non-tradability can impede foreign firm access to supported demand. For example, Italy eventually implemented 10 percent higher photovoltaic FITs for photovoltaic modules of largely European origin (D’Orsi 2014). Government procurement programs, sometimes protected for national security, may limit access and stimulate technological leadership by domestic firms, as in the United States for early satellite photovoltaic cells (Mowery and Nelson 1999). A preference for domestic firms in government purchases may occur even among participants in the World Trade Organization’s Agreement on Government Procurement (Brülhart and Trionfetti 2004, Shingal 2015). Subsidies may be directed to local goods and services, in industries with little value-added exposed to free trade, as in water power using dams or construction of energy-efficient buildings. Policies can focus on a potentially profitable sector of an industry, with bigger gains from trade aiding the sector’s profitability, as German demand-pull policies may have benefited Germany’s photovoltaic equipment sector.

The Chinese government supported its photovoltaic industry through the tough times in 2012 and 2013, with subsidies and other measures, while firms elsewhere in the world downsized and exited. The Chinese response does not undo our conclusion that the subsidy decreases reduced firm R&D, because as we have shown, Chinese market share gains outside Korea slowed and then actually decreased in 2012-2013. However, government support helped

---

\(^{23}\) Likewise, governments might, or might not, trade off environmental regulation with industry size, enhancing trade competitiveness and keeping production from moving abroad along with pollution (Barrett 1994, Copeland and Taylor 1994, Ulph 1996).
Chinese firms solidify cost advantages and improve quality, ultimately making them more dominant. This may not be a typical effect of a subsidy shock, as it depended on the Chinese government’s decision for heavy support.

**Technology Impacts:** Support also varies by technology. Commercial-stage technology may benefit more from demand subsidies than competing pre-commercial technologies, possibly causing inefficiency (David 1985, Nemet 2009). In the photovoltaic industry, thin-film technology has been a technological laggard that promises potentially much lower costs. Thin film manufacturing, however, is technologically harder to enter and harder to scale up, and most Korean and international firms entered with conventional silicon-based technology. Thus, technological path dependence may solidify mature technologies’ lead as a result of international demand-pull policies.

Indirect policies typically are thought less efficient than direct policies to achieve a policy goal (Atkinson and Stiglitz 1976), however, indirect incentives through foreign demand-pull policies affect the efficiency and extent of country-level direct R&D funding. Indeed, government institution R&D is correlated with foreign demand-pull policies, our patent applicant analysis has shown for Korean government photovoltaic research. One way to understand this correlation is that policy makers directly fund R&D to aid their countries’ firms to profit from subsidized markets.

The efficiency of demand-pull policies itself is hard to quantify, but our results show that little of demand subsidies directly support current manufacturers’ R&D. Korean manufacturers devoted in the average year 4.1 percent of sales to R&D. The total across supply chain sectors is somewhat higher, plus Korean sources other than current photovoltaic manufacturers generated 1.6 times more patent applications than the photovoltaic manufacturers.

Our analysis illustrates that demand subsidies, for photovoltaics and in general, are a policy tool that has strong ramifications for R&D and hence for product and manufacturing improvements, which are essential to a renewable energy transition. Much as for climate change abatement (Nordhaus 2015), demand-pull policy can yield incentives for national governments’ non-coordinated strategic behaviors, a phenomenon that deserves further investigation. Policy goals beget considerable urgency to comprehend these international R&D outcomes.
References


For Online Publication

Online Appendix for
The Cross-Border Impact of Demand-Pull Policies on R&D:
A Firm-Level Analysis

A. The European Subsidy Shock

A.1 Details of the Subsidy Changes

The specific policies that yielded the shock were rather difficult to predict, coming from periodic revisions by national regulatory agencies and lawmakers in Germany and Italy. Both countries promised feed-in tariffs (FITs) for electricity produced by photovoltaic systems, with slightly higher incentives for electricity consumed on-site. FITs were set at the time a system was commissioned, i.e., connected to the grid, and thereafter were to remain constant for 20 years without inflation adjustment, plus for the remainder of the year of installation for German installations. In Germany, the regulatory regime was the Renewable Energy Sources Act. In Italy, the regulatory regime was the Conto Energia, announced in July 2005 and altered through four subsequent phases, before being replaced from July 2013 with tax credits that covered part of the cost of photovoltaic systems.

Germany: German FITs granted to newly commissioned systems are shown in Figure A1, as a function of commissioning date on the bottom axis, and as a function of system type and marginal size in different curves. System types included photovoltaics on buildings or in “free space” (e.g., fields). System size affected FITs for systems on buildings. System marginal size is indicated in the figure’s legend, measured by peak power, which is power output in test conditions with near-optimal lighting. The effect of size on tariffs was marginal in that, for example, a 35 kilowatt (kW) system receives an aggregate tariff equal to 10/35 times the 0-10 kW FIT plus 20/35 times the 10-30 kW FIT plus 5/35 times the 30-40 kW FIT. Curves for systems higher in the legend are printed overtop curves of systems lower in the legend of Figure A1; if a curve is not visible for a given commissioning date, the relevant FIT is given by the first visible higher curve. No tariffs were defined for on-building systems exceeding 750 kW from 2017 onward. Systems installed on building facades receive 5 eurocents per kilowatt-hour (kWh) bonus. Electricity consumed on-site receives an additional bonus given the difference
between a payment for consumption and the consumer price of electricity. FITs were initially constant within years, although later changed more frequently, eventually monthly. Nominal FITs per kWh of electricity fed into the electrical grid were promised to be constant for 20 years after the date when a photovoltaic system was installed (and connected to the grid). No inflation
Figure A2. Percentage Changes to Real German Photovoltaic Feed-In Tariff Granted to Newly Commissioned Systems, by Commissioning Year and by Marginal System Size as of First Day of January in Each Year. Notes: Pertains to electricity fed into the grid from systems installed on buildings (without bonus for facade installations). When a curve is not visible, it is the same as the next higher curve (smaller system size) in the legend. Systems over 750 kW received no tariffs from 2017 onwards. System size is measured by peak power. Source: Authors’ analysis of data in Netztransparenz (2019).

Annual percentage changes in real FITs, as of the date of installation, for each system type and size appear in Figure 3 in the body of the paper, and a color version appears in Figure A2 for added visibility. The figures use FITs as of 1 January each year, making it easy to judge when large decreases in FITs occurred. Aside from a big decrease for giant 1-10 megawatt (MW) systems on buildings at the start of 2009, the largest percentage decreases in FITs
Figure A3. Gigawatts of Peak Power of Photovoltaic Systems Commissioned in Germany by System Size and Year. Notes: System size is measured by peak power. Source data do not distinguish whether systems are installed on buildings or as facades. Source: Authors’ analysis of data in Netztransparenz (2017).

occurred at the start of 2011, at the start of 2012, and then throughout the years leading up to 2013 and 2014.

The total gigawatts of new systems installed each year appears, in Figure A3, broken down by system size. The available data do not distinguish system types, but most small systems were on buildings and most large systems were in open fields. The systems that contributed the most new power during 2010-2013 were 10-30 kW systems and 100 kW – 1 MW and 1-10 MW systems.

Italy: Data on Italian FITs were not available from any one source, so we compiled information from the official government regulations of the five regimes of the Conto Energia, with verification and specific dates of policies from additional sources. All FIT values were double-checked for accuracy using original government documents and additional sources.

Italian FITs granted to newly commissioned systems are shown in Figure A4, as a function of commissioning date on the bottom axis, and as a function of system type and size in different curves. Again, system types included photovoltaics on buildings or “other systems” (in fields). System size affected FITs for systems on and off buildings. System size is indicated in the figure’s legend, measured by peak power. Curves for systems higher in the legend are printed overtop curves of systems lower in the legend of Figure A4; if a curve is not visible for a given commissioning date, the relevant FIT is given by the first visible higher curve. FITs for systems above 1 MW became available from 1 January 2008. FITs initially increased with system size, but they decreased with system size after 13 April 2007. Systems that were architecturally integrated, replaced asbestos, were installed on public authority buildings or land, in small towns, were involved in energy efficiency upgrades, or meeting certain other conditions allowed increased FITs depending on the commissioning date. Electricity consumed on-site effectively receives an additional bonus, given the difference between a payment made and the cost of electricity. Nominal FITs per kWh of electricity in Italy were promised to be constant for the remainder of the year of installation plus 20 years. In Italy as in Germany, no inflation adjustment was to be made to payments.

Annual percentage changes in real FITs, as of the date of installation, for each system type and size appear in Figure 3 in the body of the paper, and a color version appears in Figure 24.

Beginning in 2011, systems on shelters, pergolas, canopies, greenhouses, and noise barriers were specifically treated and received the algebraic average of on-building and other-system FITs.
Online Appendix

Figure A4. Italian Photovoltaic Feed-In Tariff Granted to Newly Commissioned Systems, by Commissioning Date and by System Size on Buildings (Solid) or for Free Space Installations (Dotted), in Eurocents per Kilowatt-Hour. Notes: Nominal (not inflation-adjusted) values. Pertains to electricity fed into the grid (without bonus for architectural integration, asbestos removal, public authorities, small towns, energy efficiency, or other conditions). When a curve is not visible, it is the same as the next higher curve in the legend, except that before 2008 no feed-in-tariffs were granted for systems over 1 MW. System size is measured by peak power. Date tick marks indicate January first of each year. Source: Author-compiled data from official government documents and other sources (see text).

A5 for added visibility. The figures use FITs as of 1 January each year, making it easy to judge when large decreases in FITs occurred. Decreases at the start of 2008 and in the year leading up to 2011 were most substantial for large systems, but these changes were dwarfed by the percentage decrease in FITs in the years leading up to 2012 and 2013. The decrease in the year leading up to 2012 ranged from 32 percent to 50 percent depending on system type and size.
Figure A5. Percentage Changes to Real Italian Photovoltaic Feed-In Tariff Granted to Newly Commissioned Systems, by Commissioning Year and by System Size, on Buildings (Solid) or for Free Space Installations (Dotted), as of First Day of January in Each Year. Notes: Pertains to electricity fed into the grid from systems installed on buildings (without bonus for architectural integration, asbestos removal, public authorities, small towns, energy efficiency, or other conditions). When a curve is not visible, it is the same as the next higher curve (smaller system size) in the legend, except no tariff changes existed before 2009 for systems over 1 MW. System size is measured by peak power. Source: Authors’ analysis of data compiled from official government documents and other sources (see text).

The total gigawatts of new systems installed each year appears, in Figure A6, broken down by system size. The available data do not distinguish system types, but most small systems were on buildings and most large systems were in open fields. In total, 48.1% of the gigawatts of photovoltaic power systems operating by the end of 2013 were estimated to have been ground-based ordinary photovoltaic systems, with 0.1% in a newer category of concentrating
Online Appendix

Figure A6. Gigawatts of Peak Power of Photovoltaic Systems Commissioned in Italy by System Size and Year. Notes: System size is measured by peak power. Source data do not distinguish system type other than power. Source: Authors’ analysis of data in GSE (2019).

Photovoltaic plants and 51.8% on or integrated into buildings (IEA 2013, p. 71). The systems that contributed the most new power during 2010-2013 were 200 kW – 1 MW systems, followed by 50-200 kW and 1-5 MW systems.

A.2 Photovoltaic Subsidies

Flows of future FIT payments for photovoltaic systems, expected each year over the 20-year (or balance of the year plus 20 years) period following systems’ installation and electrical grid connection, were the main subsidy cost. For Germany, the annual subsidy commitments for future FIT payments, for photovoltaic systems connected each year 2000-2012, are estimated by Frondel, Schmidt, and Vance (2014). We estimated (probably overestimated) 2013 and 2014 values by assuming the cost per MW of German photovoltaic capacity increase (BWE 2019, p. 7) was the same as Frondel, Schmidt, and Vance (2014, p. 9) estimated for 2012. For Italy,
annual subsidy payments anticipated were built into the legal framework of the Conto Energia. The Italian regulatory organization, Gestore dei Servizi Energetici (GSE), compiled subsidy commitment data for the entire Conto Energia program. GSE reported to us the annual flows of FIT payments estimated to result from each year’s installations (GSE, private communication, 11 February 2020), as approved for 2014, and these data are shown in Table A1.

Subsidy commitments in each year were measured by GSE as the flow of future FIT payments, or by Frondel, Schmidt, and Vance as the flow of FIT payments less the wholesale cost, absent further subsidies, of the subsidy-stimulated electricity. For comparability, we subtracted approximate wholesale electricity costs from the GSE figures. We used annual contemporaneous annual average day-ahead national uniform prices from GME (2020) and multiplied by the number of kW of capacity installed in a year\(^\text{25}\) times 1.2 MWh/kW.\(^\text{26,27}\)

\(^{25}\) For purposes of this electricity cost adjustment, capacity installed each year 2006 to 2012 was computed as the change in installed capacity at each year’s end, using GSE (2014, p. 9) for 2008 to 2012 and USEIA (2020) series INTL.116-7-ITA-MK.A (capacity - solar) for 2006 and 2007. Capacity installed was treated as zero in 2005 given zero Conto Energia cost reported for 2005. Capacity installed in 2013 was computed as new capacity through the end of July (GSE 2014, p. 10), and capacity installed in 2014 was treated as zero, so that grandfathered installations after July 2013 are ignored, contributing slight overestimation of subsidies for 2013 and 2014.

\(^{26}\) The figure of 1.2 MWh/kW results by dividing nationwide photovoltaic electricity generated by capacity in 2014, a year when capacity was fairly stable. Data stem from GSE (2014, pp. 9 and 28). Capacity figures are reported at year-end, whereas generation includes photovoltaic plants connected throughout the year, hence the need to use a year with fairly stable capacity. Using data from 2004 and 2005, when capacity was also somewhat stable, yields figures of 0.94 and 0.91 MWh/kW respectively. Data for 2004 and 2005 stem from USEIA (2020), series INTL.116-12-ITA-BKWH.A (generation - solar) and INTL.116-7-ITA-MK.A (capacity - solar). As expected given new installations, intermediate years especially 2007-2010 yield lower figures.

\(^{27}\) Capacity figures in this document always pertain to peak power conditions, under well-defined test conditions with near-optimal sunlight. Figures with units of Watt, kW, or MW are capacities, while figures with units of kWh or MWh are amounts of electricity generated.
Table A1. FIT Payments Granted for Photovoltaic Plants Supported by the Conto Energia Program, as of 2014

<table>
<thead>
<tr>
<th>Year</th>
<th>FIT Payments (Nominal Million Euros)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>0.0</td>
</tr>
<tr>
<td>2006</td>
<td>4.3</td>
</tr>
<tr>
<td>2007</td>
<td>35.8</td>
</tr>
<tr>
<td>2008</td>
<td>159.5</td>
</tr>
<tr>
<td>2009</td>
<td>341.0</td>
</tr>
<tr>
<td>2010</td>
<td>1,082.7</td>
</tr>
<tr>
<td>2011</td>
<td>3,710.1</td>
</tr>
<tr>
<td>2012</td>
<td>891.1</td>
</tr>
<tr>
<td>2013</td>
<td>229.3</td>
</tr>
<tr>
<td>2014</td>
<td>12.3</td>
</tr>
</tbody>
</table>


Future FIT payments were discounted at an assumed inflation rate of 2 percent by Frondel, Schmidt, and Vance (2014). We use the same assumed inflation rate, which is just under the Italian mean inflation rate (2.2%) during 2004-2013. Since Italy granted FITs for 20 years, with FIT payments received throughout the year, we multiplied the annual cost in FIT payments by $\int_0^{20} e^{-rt} \, dt$. Using $r = 0.02$, this means that annual FIT costs are multiplied by 16.484 to arrive at cumulative costs.

Italy provided subsidies through its Regional Roof-Top Programs before the Conto Energia program. The Regional Roof-Top Programs provided 20 million euros of subsidies for rooftop solar installations in 2004 (IEA 2004, p. 63) and 25 million euros in 2005 (IEA 2005, p.
Additional funds for research and demonstration, amounting to 5 million euros in 2004, are excluded here.

Italy also provided subsidies through tax incentives following the 6 July 2013 conclusion of the Conto Energia program. Under the tax incentive program, ten annual tax refunds would reimburse a percentage of photovoltaic system costs. The percentage reimbursed was 50 percent through the end of 2014 (Orioli et al. 2016). Approximate subsidies for these programs are estimated as equivalent to 387 and 380 million euros of nominal value in 2013 and 2014 respectively. These are likely overestimates, because they include the capacity of installations that did not receive tax incentives because they were grandfathered installations under the Conto Energia.

The present values of all subsidy costs are summarized in nominal terms in Table A2. For Italy, the present values in the table include Conto Energia FIT costs, discounted for inflation and net of estimated market electricity costs, as well as Regional Roof-Top Programs subsidies and estimated tax incentives. Values for 2013 and 2014 are likely to be overestimates because Conto Energia costs and tax incentives may recorded for the same installations if they were grandfathered under the Conto Energia program, and because of our assumption above about the cost per MW of German photovoltaic capacity increase in 2013 and 2014. Table 1 reports 2013 real values of each year’s subsidy commitments, discounted using Eurostat’s (2004-2014) harmonized annual consumer prices.

\footnote{Estimates of installed system cost of residential rooftop systems in Italy in 2013 of approximately 3.0 and 2.7 euros per Watt of peak system power are given by Kimura and Zissler (2016, p. 2) and IRENA (2015, p. 88), respectively. (Both estimates are taken from graphs.) Rough estimates of 2-2.4 euros per Watt for residential systems, 1.2-2 euros per Watt for commercial systems, and 1-1.4 euros per Watt for ground-mounted systems in Italy in 2013 are given in IEA (2014, p. 56). From these numbers, we assume an average installed system cost of 2 euros per Watt for systems installed after July 2013. Applying the same 2 percent discount rate for inflation used above, the tax reductions are multiplied by $\sum_{s=1}^{10}(1-r)^s$ which equals 0.896 using $r = 0.02$.}
### Table A2. Photovoltaic Subsidies, Germany and Italy, Present Value, Millions of Nominal Euros, Using 2 Percent Discount Rate

<table>
<thead>
<tr>
<th>Year Committed</th>
<th>Germany FITs</th>
<th>Italy Regional Roof-Top Programs</th>
<th>Italy FITs</th>
<th>Italy Tax Incentives</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>4,779</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>4,799</td>
</tr>
<tr>
<td>2005</td>
<td>7,338</td>
<td>25</td>
<td>0</td>
<td>0</td>
<td>7,363</td>
</tr>
<tr>
<td>2006</td>
<td>6,094</td>
<td>0</td>
<td>55</td>
<td>0</td>
<td>6,149</td>
</tr>
<tr>
<td>2007</td>
<td>8,595</td>
<td>0</td>
<td>499</td>
<td>0</td>
<td>9,094</td>
</tr>
<tr>
<td>2008</td>
<td>12,316</td>
<td>0</td>
<td>2,037</td>
<td>0</td>
<td>14,353</td>
</tr>
<tr>
<td>2009</td>
<td>19,810</td>
<td>0</td>
<td>4,722</td>
<td>0</td>
<td>24,532</td>
</tr>
<tr>
<td>2010</td>
<td>30,230</td>
<td>0</td>
<td>14,897</td>
<td>0</td>
<td>45,127</td>
</tr>
<tr>
<td>2011</td>
<td>20,669</td>
<td>0</td>
<td>47,865</td>
<td>0</td>
<td>68,534</td>
</tr>
<tr>
<td>2012</td>
<td>9,714</td>
<td>0</td>
<td>8,841</td>
<td>0</td>
<td>18,555</td>
</tr>
<tr>
<td>2013</td>
<td>3,134</td>
<td>0</td>
<td>2,620</td>
<td>387</td>
<td>6,141</td>
</tr>
<tr>
<td>2014</td>
<td>1,416</td>
<td>0</td>
<td>203</td>
<td>380</td>
<td>1,999</td>
</tr>
</tbody>
</table>

Notes: 2013 and 2014 italicized values are high estimates. Sources: German FITs committed in 2004-2012 from Frondel, Schmidt, and Vance (2014, p. 9). German FITs in 2013-2014 estimated assuming cost per MW of photovoltaic capacity increase (BWE 2019, p. 7) same as Frondel, Schmidt, and Vance estimated for 2012. Italian Regional Roof-Top Programs payments from IEA (2004, p. 63, 2005, p. 61). Italian FITs committed in all years computed as annual payments in Table A1 minus electricity costs (see text), times $\int_0^{20} e^{-0.02t} dt = 16.484$. Italian tax incentives granted (over)estimated assuming all installations after July 2013 qualified for tax incentives (see text).

If a 10 percent discount rate were used instead of 2 percent when computing present values ($r = 0.10$ instead of $0.02$), the costs reported in Table 1 would change almost proportionately in most cases, yielding the costs indicated in Table A3. German costs would be...
Table A3. Photovoltaic Subsidies, Germany and Italy, Present Value, Millions of Nominal Euros, Using 10 Percent Discount Rate

<table>
<thead>
<tr>
<th>Year Committed</th>
<th>Germany FITs</th>
<th>Italy Regional Roof-Top Programs</th>
<th>Italy FITs</th>
<th>Italy Tax Incentives</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>2,476</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>2,496</td>
</tr>
<tr>
<td>2005</td>
<td>3,802</td>
<td>25</td>
<td>0</td>
<td>0</td>
<td>3,827</td>
</tr>
<tr>
<td>2006</td>
<td>3,157</td>
<td>0</td>
<td>29</td>
<td>0</td>
<td>3,186</td>
</tr>
<tr>
<td>2007</td>
<td>4,453</td>
<td>0</td>
<td>262</td>
<td>0</td>
<td>4,714</td>
</tr>
<tr>
<td>2008</td>
<td>6,381</td>
<td>0</td>
<td>1,069</td>
<td>0</td>
<td>7,449</td>
</tr>
<tr>
<td>2009</td>
<td>10,263</td>
<td>0</td>
<td>2,477</td>
<td>0</td>
<td>12,740</td>
</tr>
<tr>
<td>2010</td>
<td>15,661</td>
<td>0</td>
<td>7,814</td>
<td>0</td>
<td>23,476</td>
</tr>
<tr>
<td>2011</td>
<td>10,708</td>
<td>0</td>
<td>25,108</td>
<td>0</td>
<td>35,816</td>
</tr>
<tr>
<td>2012</td>
<td>5,033</td>
<td>0</td>
<td>4,637</td>
<td>0</td>
<td>9,670</td>
</tr>
<tr>
<td>2013</td>
<td>1,624</td>
<td>0</td>
<td>1,374</td>
<td>253</td>
<td>3,251</td>
</tr>
<tr>
<td>2014</td>
<td>734</td>
<td>0</td>
<td>106</td>
<td>249</td>
<td>1,089</td>
</tr>
</tbody>
</table>

Notes: 2013 and 2014 italicized values are high estimates. Sources: German FIT costs estimated as \( \int_0^{20.5} e^{-0.10t} dt / \int_0^{20.5} e^{-0.02t} dt = 0.518 \) times the values in Table A2. Italian Regional Roof-Top Programs costs unchanged from Table A2. Italian FIT costs computed as \( \int_0^{20} e^{-0.10t} dt / \int_0^{20} e^{-0.02t} dt = 0.525 \) times the values in Table A2. Italian tax incentive costs computed as \( \sum_{s=1}^{10} 0.90^s / \sum_{s=1}^{10} 0.98^s = 0.654 \) times the values in Table A2.

Italian Conto Energia costs would be multiplied by 0.525 in every year. Italian tax incentive costs, the estimated 387 million euros in 2013 and 380 million euros in 2014, would be multiplied by 0.654. Italian costs in 2004 and 2005 would remain at 20

---

29 This treats the present value of a German FIT flow of \( K \) per year as \( \int_0^{20.5} e^{-rt} K dt \), since in Germany FIT payments are made for the remainder of the year of installation, typically about 0.5 year, plus the 20 subsequent years.
and 25 million nominal euros, because Regional Roof-Top Programs expenses were incurred immediately not over time. Therefore total subsidy costs computed would be almost exactly 48% lower in every year.

German and Italian gross domestic product, compared in the main text to subsidy cost, comes from Eurostat (2013).

A.3 China’s Photovoltaic Industry Support

Available trade statistics combine photovoltaics with light emitting diodes and photosensors, impeding a direct analysis of the fraction of photovoltaic materials and device purchases in China that were manufactured by Chinese firms. Nonetheless, trade literature and analyses of Chinese policy strongly suggest that China’s growing photovoltaic purchases in 2012-2015 mostly were provided by Chinese firms. Dominance of Chinese installations by Chinese producers did not extend to the polysilicon sector, however, in which half of supply still had to be imported as of 2012, a problem analyzed by researchers considering China’s photovoltaic industry development strategies (Song, Jiao, and Fan 2015; Zhao, Wan, and Yang 2015). In other sectors, China’s producers were much stronger, as the Chinese photovoltaic industry progressed from using photovoltaic devices in products, to assembling modules, manufacturing chips for modules, creating silicon wafers for chips, and eventually manufacturing the polysilicon for wafers. China produced in 2009 38 percent of the world’s photovoltaic cells but a “negligible” share of polysilicon, while in 2012 it produced 66 percent of the world’s photovoltaic cells but still only 27 percent of polysilicon (Chen 2016, p. 761).

Chinese local and national government policies that kept the Chinese photovoltaic industry strong in 2012 and 2013 are emphasized in trade literature (He 2012) and noted in academic research (Corwin and Johnson 2019, Shubbak 2019). National policy is addressed in part by Sun et al. (2014), Gang (2015), Chen (2016), and Xiong and Yang (2016). Local government policies, not only national policies, were important, as explained by Gang (2015),

---

30 The strength and development of the Chinese photovoltaic industry are discussed further by, among others, Sun et al. (2014), Zhang et al. (2016), Chen et al. (2017), Luo, Lovely, and Popp (2017), Binz and Anadon (2018), Lacasa and Shubbak (2018), and Crowley, Meng, and Song (2019).
Online Appendix

Table A4. Percentage of Korean Manufacturer-Sector Pairs Planning Investments, by Year

<table>
<thead>
<tr>
<th>Year</th>
<th>Percent Planning Investment</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>9.09</td>
<td>11</td>
</tr>
<tr>
<td>2005</td>
<td>28.57</td>
<td>14</td>
</tr>
<tr>
<td>2006</td>
<td>21.05</td>
<td>19</td>
</tr>
<tr>
<td>2007</td>
<td>20.69</td>
<td>29</td>
</tr>
<tr>
<td>2008</td>
<td>47.17</td>
<td>53</td>
</tr>
<tr>
<td>2009</td>
<td>45.45</td>
<td>77</td>
</tr>
<tr>
<td>2010</td>
<td>57.14</td>
<td>91</td>
</tr>
<tr>
<td>2011</td>
<td>40.82</td>
<td>98</td>
</tr>
<tr>
<td>2012</td>
<td>7.41</td>
<td>81</td>
</tr>
<tr>
<td>2013</td>
<td>8.11</td>
<td>74</td>
</tr>
</tbody>
</table>


Chen (2016), and Corwin and Johnson (2019). Local governments provided subsidies, and they funded rescues of failing firms in 2012 and 2013.

A.4 Planned Investments Rose in 2008-2010, Fell in 2011, Dropped in 2012

The KEEI (2013) data described in section III of the paper track planned investments annually in each Korean photovoltaic manufacturer-sector pair. Data reports were collected in approximately November of each year. The planned investment data therefore can be used to compare manufacturers’ investment intentions late in each year as European subsidies changed.

The percentage of firm-sector pairs planning investments, as well as the sample size, are shown for each year in Table A4. From 21 to 29 percent in 2005-2007, the percentage of firm-sector pairs planning investments grew to 47 and 45 percent in 2008 and 2009 respectively, and climbed to 57 percent in 2010. After late 2010, however, investment plans fell. In late 2011, 41 percent of firm-sector pairs planned investments. By late 2012 and 2013 however, the percentage had fallen to 7 to 8 percent, lower numbers than ever arose during 2004-2011.

The statistical significance of year-to-year changes in percentages can be assessed using Fisher’s exact test. The test yields a statistical significance of $p = 0.029$ for 2010 versus 2011, $p = 1.5\times10^{-7}$ for 2011 versus 2012, and $p = 8.5\times10^{-13}$ for 2010 versus 2012. These tests are two-sided.
Table A5. Planned Investment Regressed on Year Indicators in Conditional Fixed Effects Logistic Regression

<table>
<thead>
<tr>
<th>Year</th>
<th>Estimate</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>-3.285</td>
<td>7.250</td>
</tr>
<tr>
<td>2005</td>
<td>-1.826</td>
<td>2.081</td>
</tr>
<tr>
<td>2006</td>
<td>-2.226</td>
<td>2.146</td>
</tr>
<tr>
<td>2007</td>
<td>-2.266</td>
<td>0.753</td>
</tr>
<tr>
<td>2008</td>
<td>-0.591</td>
<td>0.365</td>
</tr>
<tr>
<td>2009</td>
<td>-0.476</td>
<td>0.417</td>
</tr>
<tr>
<td>2011</td>
<td>-0.846</td>
<td>0.393</td>
</tr>
<tr>
<td>2012</td>
<td>-3.596</td>
<td>1.282</td>
</tr>
<tr>
<td>2013</td>
<td>-3.527</td>
<td>1.309</td>
</tr>
<tr>
<td>2011 – 2012</td>
<td>2.750</td>
<td>1.197</td>
</tr>
</tbody>
</table>

Notes: Observations are manufacturer-sector-year combinations. Omitted group is year 2010. All regressors are 1 in the year indicated, 0 otherwise. Coefficient estimates and standard errors (in parentheses) are reported. Standard errors are cluster-robust bootstrap estimates, clustered by manufacturer-sector pair, with 2000 replications, less 1 replication in which estimation did not converge. At bottom of table is difference between year 2011 and year 2012 coefficient estimates, and its standard error. N is number of observations.

Controls for the fixed effects of manufacturer-sector pairs are possible using conditional fixed effects logistic regression. Regression results in Table A5 relate whether a manufacturer-sector pair planned investments (1 if true or 0 if not), to year-specific indicators. Comparisons are to the year with the most planned investments, 2010, by making 2010 the omitted year. Again, the drop-offs from 2010 to 2011 and especially 2012 are substantial and statistically significant. At the bottom of the table, the estimated difference between coefficients for 2011 and 2012 appears, and again is particularly large and statistically significant.
Figure A7. Annual Percentage Changes in Production Capacity and Production of Photovoltaic Modules, and Production Capacity Utilization (Percent), Worldwide, 1997 to 2015. Note: May double-count outsourced production, increasingly over time. Source: Based on data from IEA (2016, pp. 51 and 68).

A.5 Market Growth Expectations Largely Reflected Subsidy-Driven Demand

Worldwide, strong subsidy-driven demand for photovoltaic cells and modules fueled rapid industry growth through 2010 and into 2011. Demand growth expectations might be modeled as a moving average of recent growth rates, which imply very high expectations for 2011 and 2012; annual growth rates in world output were 74, 161, 21, 111, and 81 percent in years 2007 through 2011. Of course, those expectations were undercut by the subsidy reductions. Trade literature discussed overcapacity in 2011-2013, and Chung (2013, p. 4) actually suggested in hindsight that overcapacity began in 2010. The term overcapacity was also used in trade literature in some previous years.

Annual growth rates in production capacity and actual production of photovoltaic modules are compared, worldwide, in Figure A7. The data suggest slightly higher 2010 investment in production capacity, but lower investments in 2009 and 2011, relative to expectations that might be formed from recent growth rates. Overall, the data do not seem to suggest that unusual overcapacity or undercapacity came online at the same time as the subsidy reductions. That said, price declines and limited data make capacity investments difficult to
interpret, so errors shortly before the shock remain a potential source of unmeasured estimation error.

**B. Data**

**B.1 Firms**

Data for employment, revenue, revenue from export, and R&D investment are directly available from the dataset, and variables such as entry, exit, and sector are coded or calculated from information in the dataset. Entry is coded based on the explicit entry date in the KEEI data, despite that a few entries indicate positive capacity and zero production quantity in a firm’s early years. Exit is also coded based on the explicit exit date in the KEEI data. Data for other variables are generally not available in the year of exit. For integrated firms, entry is recorded as the first entry of any business unit into any sector, and exit is recorded as exit of the last business unit from the firm’s last sector. In some cases, entry and exit dates were ambiguous in the original data, and were inferred from variables in the data and cross-checked against news sources by the authors to ensure validity.

Dataset integrity and consistency were ensured by the authors using news articles and company websites. One firm’s observations are omitted because of accounting fraud. R&D classification approvals under tax law are commonly carried out by the Korea Industrial Technology Association.

Monetary values are 2013 values, adjusted using the Bank of Korea consumer price index (reflecting employment’s key role in firm inputs including R&D investment).

**B.2 Korean Patent Applications**

Patent applications through the Korean Patent Office were identified using the European Patent Office’s EPO Worldwide Patent Statistical Database, Spring 2017 edition, which contains bibliographic patent data from patent offices worldwide. Before 1999, only granted patents are in the data for South Korea, and therefore patents applied for but not granted are excluded. The data cover the period from the inception of photovoltaic research in Korea. Applications likely pertinent to photovoltaics and photovoltaic materials were identified based on whether English
Online Appendix

translations of titles contained particular keywords, or international patent classification codes included particular categories.\footnote{Five point three percent of patents applied for at the Korean Patent Office before 2014 (5.5 percent before 2015) lacked English translations of titles, but had titles available in Korean language. Therefore Korean language search terms similar to the English search terms were used, as well as terms to identify irrelevant applications as described below, to identify all such photovoltaic patent applications. See the section on Worldwide Patent Applications below.}

Keywords used to identify relevant applications with high certainty are: photo-\textit{voltaic}; photovoltaic-cell; solar-\textit{cells}; solar-batter*; solar pv; dssc; solar thin-film; solar arrays*; solar modules*; solar electric panels*; tabber-stringers*; electroluminescence test*; el test*; solar panel simulators*; tandem cells*; solar\&inverters*. Keywords used to identify additional patents likely to be relevant are: solar panels*; poly-\textit{silicon}; poly-\textit{crysta?ll?ine silicon}; poly-\textit{si}; multi-\textit{crysta?ll?ine silicon}; multi-\textit{si}; amorphous silicon; a\textit{si}; solar silicon; solar (mono)\textit{crystall?ine silicon}; cuinse?2; copper indium gallium selenide; cigs; cadmium telluride; cdte; copper-tin-sulfide; cu2sns3; copper-zinc-tin-sulfide; copper-zinc-tin-sulfur; copper-zinc-tin-sulphur; cztse; cztse. A hyphen indicates a hyphen \textit{or} a space, ? indicates that the preceding character or term in parentheses is optional, \& indicates that terms before and after must exist anywhere in the title, and * indicates any zero or more letters. Keywords were required to match whole words in the title, and searches were not case sensitive. Typos considered reflect errors that appear in the source data. The terms include photovoltaic manufacturing equipment and materials, plus newer types of photovoltaic products, such as tabber-stringer machines, the material CuInSe\textsubscript{2}, and dye-sensitized solar cells. Classification codes used to identify relevant patents with high certainty are: H01L 31/042-058. Classification codes used to identify additional patents likely to be relevant are: H01L 31/04-041, H01L 27/142, H02N 6, and E4D 13/18.

By comparison, prior studies sometimes used simpler keyword searches or only used classification codes. For example, one classification used in prior studies, H01L 25, almost entirely yields patent applications that involve multi-element non-solar semiconductor chips, and therefore should not be used. Use of the likely-to-be-relevant classification codes given above, although common, is dangerous because they are not unique to photovoltaics, and span
applications including photographic image sensors, computer memory devices, X-ray and infrared detectors, optical waveguides, certain light emitters, lasers, and more. Use only of the narrower classifications H01L 31/042-058 misses many relevant patent applications. Much more complete identification of relevant applications, without inclusion of large numbers of irrelevant applications, therefore requires combined use of keywords and classification codes coupled with a follow-up process to weed out irrelevant applications.

Irrelevant applications were dropped from the data, and the remainder were grouped into applications relevant with high certainty versus possibly relevant, using several procedures. First, applications identified only by having “solar panels?” in the title or by classification code E4D 13/18 were checked for possible removal if their titles or abstracts contained “heat*” or “thermal*” since these often pertained to passive solar heat collectors such as hot water heaters. A close reading of the titles and abstracts of these applications was used to identify applications to keep in the sample, if they dealt with thermal properties of photovoltaic panels or thermal characteristics in solar cell manufacture, versus to remove because they pertained to non-photovoltaic solar energy absorbers.\(^{32}\)

Second, keywords of irrelevant applications were identified based on a reading of titles, with abstracts and full documents consulted as necessary to understand the underlying technology. The following keywords in titles identified irrelevant applications: light emitting; lighting emitting; LED lamps?; image sens*; image devices?; imaging devices?; imaging

---

\(^{32}\) No title was available for 2 of the sample’s 18,977 Korean patent applications (before dropping irrelevant applications), both pertaining to firms in the data and identified by classification codes. These were checked manually using the original Korean-language publications, and were found to be relevant. No abstract was available for 2,755 Korean applications through year 2015 including 308 involving firms in the sample, and these were not checked for the terms “heat*” and “thermal*”. Korean-language abstracts only were available for 834 Korean applications through year 2015 including 22 involving firms in the sample, and these were checked by using the Espacenet online search system to identify equivalent applications in English or if needed to carry out machine translations to English, then manually reading the English language abstracts—and where ambiguity arose the broader patent application documents—to ascertain whether the applications were relevant to photovoltaics.
apparatus; image pick-ups?; photo-detectors?; optical modules?; optical waveguides?; photo resists?; RAMs?; DRAMs?; SRAMs?; memory; memories; FRAMs?; EEPROMs?; display devices?; display devices?; LCDs?; liquid-crystal displays?; flat-panel displays?; radiation detectors?; holographic; transistors?; tft; resistors?; capacitors?; optical modulators?; optical diodes?; infrared detector*; infrared sensors?; optical fibers?; optical antennas?; x-ray. However, not ruled as irrelevant on the basis of the term x-ray are applications whose titles include “using x-ray”, which occurred for photovoltaic manufacturing applications. If these keywords appeared for applications initially identified as relevant with high certainty, the applications were reclassified as possibly relevant, but otherwise the applications were dropped from the sample. In every case of an application that would be reclassified from relevant with high certainty to possibly relevant, titles and where necessary abstracts and more were read to check appropriate treatment, and for twelve applications this procedure resulted in the application being dropped. Third, applications with the word “transistor” in their abstracts were checked manually. As a result, nine applications were dropped from the sample. These applications pertained to materials preparation for making transistors.

Fourth, for applications identified as possibly relevant, titles and where necessary abstracts and more were read. As a result, selected applications were dropped from the sample, as they pertained to x-ray or infrared detectors, triboelectric or solar heat generators, or other non-photovoltaic topics. Conversely, where relevant, applications previously considered possibly relevant to photovoltaics were classified as definitely relevant to photovoltaics. Materials preparation applications usually could not be classified as relevant with high certainty, because it was difficult to discern which were developed for photovoltaic uses versus other electronics uses.

Patent applications are treated as stemming from a single invention if they fall within a single DOCDB family as defined by the European Patent Office. In most cases, these are applications that share the same set of prior applications as priorities. Credit is divided evenly

---

33 The DOCDB family metric is named for the EPO’s master documentation database, where it is used. A DOCDB family in most cases is the group of applications having identical sets of priorities in terms of first filings (Paris convention foreign applications), provisional first filings, and equivalents to first filings, ignoring continuations and divisions of existing applications.
Online Appendix

among applications within the family, which in total is counted as one application. Only patent of invention applications are considered.

Matching of patent applicants to firms accounted for name variations, division of R&D labor across multiple companies, and Korean norms of sometimes listing inventors as applicants. Patent applicant names that were potential matches, based on main parts of current and past firm names and of the names of subsidiary organizations, were examined manually to allow for typographic errors, changes in name, diversifying entries, mergers, and acquisitions. If multiple companies were involved in the same application, credit for the research was divided equally among the corporate applicants. Annual application counts are therefore non-integer in 12 percent of observations. Inventors working in a company frequently were listed as applicants in Korean patent practice, but credit was given only to companies, since the whole of a company’s R&D was carried out inside the company regardless whether inventors from the company are named as applicants.

Patent applicants in most cases were categorized in the source data by nation of residence and by sector (simplified here to company, individual, university, or government). A tiny fraction of applicants lacked this information, and it was looked up from patent documents pertaining to the same applicant and from other public sources. For 40 applicants the sector could not be determined, and these applicants (all outside the main sample) are excluded from the annual counts of Korean patent applications by applicant type.

For Figure 8, the index of all non-photovoltaic Korean patents by Korean applicants excludes all applications considered in the searches above, even the few eventually excluded because they are not relevant to photovoltaics. Constructing the index required identification of which applications involved Korean applicants, but the source data sometimes failed to identify the applicants or did not indicate the applicants’ countries. Therefore frequent applicants with missing country data had their nationalities coded by hand when no ambiguities arose, and in all other cases with missing data, the applicant for a particular DOCDB family was classified as Korean if the earliest application in that DOCDB family was filed at the Korean Patent Office, or as non-Korean if the earliest application was filed in a national or regional patent office outside Korea.
Online Appendix

B.3 Worldwide Patent Applications

International patent applications data stem from the same source, the EPO Worldwide Patent Statistical Database (Spring 2017), as used above for Korean patent applications data. Although most applications in the Database have had their titles, and usually abstracts, translated into English, some titles and abstracts are available only in the languages of specific patent authorities. Therefore, for completeness, search terms were translated to cover all major languages that appear in titles and abstracts in the Database (English, Korean, Chinese, German, Japanese, French, Spanish, Portuguese, Italian, Dutch, Russian, Danish, Swedish, Norwegian, Turkish, Finnish, Arabic, and Ukrainian), to allow identification of relevant patent applications and removal of irrelevant applications.

Both singular and plural versions of nouns and adjectives were identified and used in searches, and common terminology was checked using actual text in each language to identify relevant terminology. Select keywords were not used in some languages because no specialized term could be identified for a given language (e.g., for the search term “tabber-stringers?”), other languages did not seem to have a common non-English term used in patent applications), or because other keywords already provided a match for the same term (a subset of words in the search string was a preexisting search string that already identified the relevant patent applications). Actual relevant terminology was identified based on Internet sources as well as documents identified in a given language in the patent database, since simple translations of English keywords would not necessarily yield the keywords used in practice in each language.

Keywords used to identify irrelevant applications were not always translated for those languages that appear especially rarely in the Database, and instead, titles and other information about the patent applications were examined manually to determine whether particular applications were irrelevant. In many cases, translation for this purpose used automated translation services (notably Google Translate), which usually appeared to yield reasonable understanding of the main purpose of an application given that technical terms apparently rarely had ambiguous translations. In a few cases, neither abstracts nor images of the original patent documents could be obtained, and in these cases decisions had to be made on the basis of titles alone. Since nations whose patent applications were more difficult to classify in these regards also had very few photovoltaic-related patent applications, and these nations were excluded in
Online Appendix

the cross-national empirical analysis reported in the paper, these issues do not seem to impact any conclusions of the paper.

The full list of keywords used is available from the authors as a Stata format dataset.

B.4 External Control Statistics

Statistics on R&D and manufacturers throughout the Korean economy are drawn from established Korean government and international sources. R&D statistics were compiled by Korea’s Ministry of Science, ICT and Future Planning (MSIP). Workforce, numbers of firms and establishments, and data on firm and establishment exit and entry are from Statistics Korea, which conducts the country’s economic censuses. Patent application counts are from the World Intellectual Property Organization (WIPO).

Table A6 lists the specific data series used and their sources. R&D investment and employment data for control comparisons (Figure A8 below), were computed by dividing nationwide manufacturing R&D spending or R&D employment by the number of manufacturing establishments or the number of active manufacturing enterprises in the same year. Employment control data (for Figure A9 below) were likewise computed by dividing nationwide manufacturing employment by the number of manufacturing establishments or active manufacturing enterprises. Exit rate control data (for Figure A9) were computed as 100 minus the percentage survival rate of manufacturing enterprises in their first year, or as the number of manufacturing enterprise deaths divided by the number of active manufacturing enterprises in the same year.

These data were obtained via the Internet. Data from MSIP were obtained from data search web resources at http://sts.ntis.go.kr/ntisStats.jsp. Data from Statistics Korea were obtained from the Korean Statistical Information Service at http://kosis.kr/index/index.do (an English version is available). Data from WIPO were obtained from their IP Statistics Data Center at https://www3.wipo.int/ipstats/index.htm.

C. Estimation

C.1 Firm and Sector Fixed Effects

The fixed effects term $\alpha_i$ represents firm fixed effects, except in equations with binary dependent variables, where sector or sector group effects are used instead. R&D investment
### Table A6. Data Sources for External Control Comparisons

<table>
<thead>
<tr>
<th>Series</th>
<th>Note</th>
<th>Years</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private R&amp;D spending in manufacturing</td>
<td></td>
<td>2004-13</td>
<td>MSIP</td>
</tr>
<tr>
<td>Private R&amp;D employment in manufacturing</td>
<td></td>
<td>2004-13</td>
<td>MSIP</td>
</tr>
<tr>
<td>Resident applications per million population</td>
<td>patent applications by Korean residents</td>
<td>2004-13</td>
<td>WIPO</td>
</tr>
<tr>
<td>Number of workers in manufacturing (table DT_1F1607)</td>
<td>in establishments with 10 or more workers</td>
<td>2004-13</td>
<td>Statistics Korea</td>
</tr>
<tr>
<td>One year survival rate, from Average survival rate of newly born enterprises, in manufacturing (table DT_2BD0001)</td>
<td>in new manufacturing businesses with 2 or more employees</td>
<td>2008-13</td>
<td>Statistics Korea</td>
</tr>
<tr>
<td>Manufacturing enterprise deaths (table DT_1BD0001)</td>
<td></td>
<td>2011-13</td>
<td>Statistics Korea</td>
</tr>
<tr>
<td>Births, from Number of enterprises by industry (Active/Births/Deaths) (table DT_1BD0001)</td>
<td>total across all industries</td>
<td>2007-13</td>
<td>Statistics Korea</td>
</tr>
<tr>
<td>Births, from Number of enterprises by industry (Active/Births/Deaths), in manufacturing (table DT_1BD0001)</td>
<td></td>
<td>2011-13</td>
<td>Statistics Korea</td>
</tr>
<tr>
<td>Number of establishments in manufacturing (table DT_1F1607)</td>
<td>establishments with 10 or more workers</td>
<td>2004-13</td>
<td>Statistics Korea</td>
</tr>
<tr>
<td>Active manufacturing enterprises (table DT_1BD0001)</td>
<td></td>
<td>2011-13</td>
<td>Statistics Korea</td>
</tr>
</tbody>
</table>

Participation changed between 0 and 1 for only 58 of 84 photovoltaic manufacturers, and exit occurred for only 25 of 84. Firm fixed effects estimates therefore would rely primarily on independent variable variation in linear probability models, straining model specification when analyzing binary dependent variables. In probit models, 26 and 59 firms respectively are effectively excluded from analysis because their fixed effects coefficient estimates equal negative or positive infinity.
R&D investment participation varied within each sector, while exit occurred within each sector group but not within all sectors, suggesting the use of sector and sector group controls respectively. Therefore $\alpha_i^j$ denotes sector effects in the R&D investment participation equation or sector group effects in the exit equation. Formally, $\alpha_i^1$ and $\alpha_i^6$ are constrained such that $\alpha_i^1 = \alpha_{s(i)}$ and $\alpha_i^6 = \alpha_{g(i)}$, where $s(i)$ and $g(i)$ index the first firm in each sector or group. These constraint indices exist exactly, since no firm changed sectors.

C.2 Counterfactual Means and Standard Errors

Write each formula needed to compute a variable, based on equation $j$ for firm $i$ in year $t$, as $f_j^i(\theta, x_i)$, where $\theta$ is a vector of model parameters and $x_i$ is a vector of data pertaining to firm $i$ in years 2011 to 2013. $f_j^i(\theta, x_i)$ may represent the probability of R&D investment, R&D investment among firms with nonzero investment, R&D employment, patent application count, employment, or the probability of exit; the dependent variable in the equation for each of these variables; the difference of a firm’s estimated outcome with subsidy shock minus estimated outcome without shock; or the ratio of a firm’s estimated outcome with subsidy shock over estimated outcome without shock. The mean value of this variable across all firms actually producing in year $t$ is $\frac{1}{\# F_t} \sum_{i \in F_t} f_j^i(\theta, x_i)$, where $F_t$ is the set of firms actually producing in year $t$ and $\# F_t$ is the number of these firms.

Standard errors for means of counterfactual dependent variables in year $t$ may be computed by bootstrap methods or by the delta method. In the bootstrap method (Efron, 1979, Efron and Tibshirani, 1993, Davison and Hinkley, 1997), firms in the sample are randomly selected with replacement to form a bootstrap sample of the same size as the original sample of firms. Estimates, including for mean ratios and differences, are then computed. The random selection and estimation are repeated many times, yielding a large number of bootstrap samples.

---

34 The ratio is not inverted because the estimated outcome without subsidy shock is sometimes exactly zero.
The variance of the estimates across the bootstrap samples consistently estimates the true variance of a parameter estimate, yielding the standard errors in Tables 4 and A9.\textsuperscript{35}

The delta method is first applied separately for each firm \( i \) in year \( t \). For firm \( i \), the variance-covariance matrix can be estimated for the 18-element vector \( f(\theta, x_i) \) consisting of all the functions \( f_i'(\theta, x_i) \) for the six equations’ dependent variables in the three years \( t = 2011, 2012, \) and \( 2013 \). The delta method yields the estimated variance-covariance matrix of \( f(\theta, x) \),

\[
A(\theta_0, x_i) \text{Var}(\theta_0) A(\theta_0, x_i)^T,
\]

where \( \theta_0 \) is the vector of model parameter estimates, \( A(\theta_0, x_i) \) is the \( 18 \times K \) matrix of first derivatives of \( f(\theta, x_i) \) with respect to \( \theta \) evaluated at \( \theta_0 \), \( K \) is the number of model parameters, \( \text{Var}(\theta_0) \) is the estimated parameter variance matrix from the GMM estimation, and the superscript \( T \) is the transpose operator.

Using the delta method, the vector of means \( \frac{1}{\#F_t} \sum_{i \in F_t} f_i'(\theta, x_i) \) has estimated variance matrix

\[
\frac{1}{\#F_t} i' A(\theta_0, x_i) \text{Var}(\theta_0) A(\theta_0, x_i)^T i \frac{1}{\#F_t},
\]

where \( i \) is a vector of \( \#F_t \) ones.

Formulas for counterfactuals were computed automatically by recursive substitution using the model equations, including the equations of Tables 3A-3B plus equations defining dependent and independent variables including the knowledge stock. The underlying equations, the program developed to automate recursive substitution, and the resulting formulas were scrutinized and tested to ensure against errors.

Some formulas for counterfactuals exceeded an expression size limit in Stata 15, which was used to compute model and counterfactual estimates. Therefore, all formulas were

\textsuperscript{35} In our bootstraps, two replications yielded probit exit models unable to yield estimates for some firms, because one or more year indicators perfectly predicted the exit outcome, causing observations to be dropped from estimation. These two replications are excluded when computing exit-related standard errors in Table 4.
simplified in Mathematica 11.3. The simplification also enhances numerical accuracy. When non-simplified formulae did not exceed the expression size limit, they were found to yield identical results to within tiny numerical allowances.

For the delta method, to avoid occasional convergence problems in computing numerical derivatives, analytic derivative formulas were also computed in Mathematica, and were used in Stata to provide consistently accurate derivatives. In early tests, results with analytical derivatives agreed, within a tiny numerical error, with available results using Stata’s built-in delta-method commands with numerical derivatives. Given the verifications carried out, the authors are confident in the veracity of formula construction and computation.

For safety, counterfactuals were also determined by an independent method, not requiring recursive substitution and not requiring Mathematica, and the point estimates were found to agree with those from our main method, within a small allowance for numerical error. (Relative differences never exceeded $10^{-9}$, in our main analyses excluding bootstrap standard error estimation, in the following sense. For alternative estimates $c_{it}$ and $d_{it}$ of a counterfactual, $|c_{it} - d_{it}| \leq 10^{-9} \min(|c_{it}|, |d_{it}|)$ or $|c_{it} - d_{it}| \leq 10^{-9} \text{mean}_{it}(\min(|c_{it}|, |d_{it}|))$, where the mean function $\text{mean}_{it}(\cdot)$ is the mean across $i$ within observations at time $t$.)

D. Data Analyses

Variables used are defined in Table A7 along with their numbers of observations, means, and standard deviations. This section reports sensitivity analyses and robustness checks. The section shows that: production function models of R&D output yield similar results; findings are quite robust to alternative modeling assumptions for binary dependent variables; impacts on Korean photovoltaic firms did not occur in general among Korean firms; findings change little with a broader patent metric; and all firms were roughly evenly exposed to the export demand shock.

D.1 Production Function Models of R&D Output

We estimated more traditional patent production function models (Pakes and Griliches 1980). These variants to column 4 of Table 3A added one or both of R&D investment and R&D employment, along with or in lieu of the firm’s total photovoltaic employment. Specifically, $R&D\text{ Investment Binary}_{it}$ together with $\log(R&D\text{ Investment}_{it})$ were used as R&D investment
## Table A7. Variable Definitions and Summary Statistics

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Definition</th>
<th>Obs</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year 2011&lt;sub&gt;t&lt;/sub&gt;</td>
<td>1 if &lt;i&gt;t&lt;/i&gt; is 2011, 0 otherwise</td>
<td>456</td>
<td>0.162</td>
<td>0.369</td>
</tr>
<tr>
<td>Year 2012&lt;sub&gt;t&lt;/sub&gt;</td>
<td>1 if &lt;i&gt;t&lt;/i&gt; is 2012, 0 otherwise</td>
<td>456</td>
<td>0.140</td>
<td>0.348</td>
</tr>
<tr>
<td>Year 2013&lt;sub&gt;t&lt;/sub&gt;</td>
<td>1 if &lt;i&gt;t&lt;/i&gt; is 2013, 0 otherwise</td>
<td>456</td>
<td>0.129</td>
<td>0.336</td>
</tr>
<tr>
<td>Exit&lt;sub&gt;it&lt;/sub&gt;</td>
<td>1 if firm &lt;i&gt;i&lt;/i&gt; exited from photovoltaic manufacturing in year &lt;i&gt;t&lt;/i&gt;, 0 otherwise</td>
<td>397</td>
<td>0.063</td>
<td>0.243</td>
</tr>
<tr>
<td>Employment&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Employment of the photovoltaic business units of firm &lt;i&gt;i&lt;/i&gt; in year &lt;i&gt;t&lt;/i&gt;</td>
<td>456</td>
<td>99.1</td>
<td>212.2</td>
</tr>
<tr>
<td>log(Employment&lt;sub&gt;it&lt;/sub&gt;)</td>
<td>Logarithm of Employment&lt;sub&gt;it&lt;/sub&gt;</td>
<td>456</td>
<td>3.714</td>
<td>1.228</td>
</tr>
<tr>
<td>log(Employment&lt;sub&gt;it&lt;/sub&gt;+1)</td>
<td>Logarithm of (Employment&lt;sub&gt;it&lt;/sub&gt; + 1)</td>
<td>456</td>
<td>3.758</td>
<td>1.186</td>
</tr>
<tr>
<td>log(Employment&lt;sub&gt;it-1&lt;/sub&gt;+1)</td>
<td>Logarithm of (Employment&lt;sub&gt;it-1&lt;/sub&gt; + 1), for previous year &lt;i&gt;t&lt;/i&gt;–1</td>
<td>452</td>
<td>3.076</td>
<td>1.786</td>
</tr>
<tr>
<td>log(Employment&lt;sub&gt;it-2&lt;/sub&gt;+1)</td>
<td>Logarithm of (Employment&lt;sub&gt;it-2&lt;/sub&gt; + 1), for year &lt;i&gt;t&lt;/i&gt;–2</td>
<td>448</td>
<td>2.413</td>
<td>2.002</td>
</tr>
<tr>
<td>R&amp;D Investment&lt;sub&gt;it&lt;/sub&gt; Binary&lt;sub&gt;it&lt;/sub&gt;</td>
<td>1 if firm &lt;i&gt;i&lt;/i&gt; conducted photovoltaic R&amp;D in year &lt;i&gt;t&lt;/i&gt;, 0 otherwise</td>
<td>456</td>
<td>0.627</td>
<td>0.484</td>
</tr>
<tr>
<td>R&amp;D Investment&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Firm &lt;i&gt;i&lt;/i&gt;’s real photovoltaic R&amp;D investment in year &lt;i&gt;t&lt;/i&gt;, 2013 million won</td>
<td>454</td>
<td>3034</td>
<td>11882</td>
</tr>
<tr>
<td>log(R&amp;D Investment&lt;sub&gt;it&lt;/sub&gt;)</td>
<td>Logarithm of R&amp;D Investment&lt;sub&gt;it&lt;/sub&gt;, calculated only for firms with positive investment</td>
<td>284</td>
<td>6.831</td>
<td>1.747</td>
</tr>
<tr>
<td>log(R&amp;D Employment&lt;sub&gt;it&lt;/sub&gt;+1)</td>
<td>Logarithm of (R&amp;D Employment&lt;sub&gt;it&lt;/sub&gt; + 1) in year &lt;i&gt;t&lt;/i&gt;, counting photovoltaic R&amp;D employees only</td>
<td>456</td>
<td>2.105</td>
<td>1.104</td>
</tr>
<tr>
<td>log(Patent Apps&lt;sub&gt;it&lt;/sub&gt;+1)</td>
<td>Logarithm of 1 + number of patent applications in year &lt;i&gt;t&lt;/i&gt;</td>
<td>456</td>
<td>0.684</td>
<td>1.119</td>
</tr>
<tr>
<td>Patent App Stock&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Discounted sum of number of photovoltaic patent applications, including before entry, discounted 10 percent per annum</td>
<td>456</td>
<td>21.4</td>
<td>115.0</td>
</tr>
</tbody>
</table>
Online Appendix

measures, and \( \log(R&D \text{ Employment}_{it}+1) \) was used.\(^{36}\) These models yield little additional predictive power. Excluding two observations that lack R&D investment data, the (within) \( R^2 \) increases only from 0.250 in the equivalent of column 4 to 0.283 with all variables, or to 0.263 without \( \log(\text{Employment}_{it}+1) \). We replicated prior findings that the lag structure of R&D investment affecting patent output is difficult to identify well, with strong firm fixed effects (Hall, Griliches, and Hausman 1986). The firm fixed effects here are captured by \( \alpha_i \). The model of column 4 therefore has reasonable predictive power and facilitates comparisons of firm size effects on R&D inputs and output. The alternate models also imply a drop-off in patent applications, occurring substantially through the channels of reduced R&D inputs and reduced firm size.

\[ \text{D.2 Modeling Probabilities} \]

The linear probability models in Tables 3A-3B have been shown, in Figure 7 panels 1 and 6, to yield mean estimates and counterfactuals very similar to those from probit models. The probit model results appear as finely dotted lines very close to the linear results. Table A8 compares the 2SLS and OLS linear probability models of Tables 3A-3B, for \( R&D \text{ Investment Binary}_{it} \) and \( Exit_{it} \), with the equivalent instrumental variables probit and probit models.

For the probit specifications, the table shows implied mean (across firms in the sample each year) probabilities of R&D participation and exit and their change with employment. The implied means and their standard errors are similar in columns A1 versus A2 and B1 versus B2, indicating that the linear and probit specifications yield similar conclusions. The marginal effects of employment are, on average, also estimated rather similarly, except that the R&D participation rate is estimated to rise 44 percent less steeply with \( \log(\text{Employment}_{it-1}+1) \) (on average at the margin) in the instrumental variables probit model. Overall, the linear probability models used in Tables 3A-3B and the equivalent probit specifications yield similar interpretations of the effects of the demand subsidy shock.

The linear probability models for \( R&D \text{ Investment Binary}_{it} \) and \( Exit_{it} \) can also be compared to full firm fixed effects models, not used in Tables 3A-3B because of concerns about

\[^{36}\text{When } R&D \text{ Investment Binary}_{it} \text{ was 0, } \log(R&D \text{ Investment}_{it}) \text{ was set to 0, allowing the coefficient of } R&D \text{ Investment Binary}_{it} \text{ to parameterize the investor-noninvestor difference.}\]
Table A8. R&D Participation and Exit: Linear Probability, Probit, and Fixed Effects Models

A. R&D Participation

<table>
<thead>
<tr>
<th>Model</th>
<th>(A1) 2SLS Linear Probability</th>
<th>(A2) Instrumental Variables Probit</th>
<th>(A3) 2SLS Linear Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Implied Mean Prob[R&amp;D Investment Binary&lt;sub&gt;i,t&lt;/sub&gt;=1]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pre-Shock</td>
<td>0.729 (0.0385)</td>
<td>0.740 (0.0357)</td>
<td>0.771 (0.0263)</td>
</tr>
<tr>
<td>in 2011</td>
<td>0.713 (0.0511)</td>
<td>0.723 (0.0540)</td>
<td>0.647 (0.0494)</td>
</tr>
<tr>
<td>in 2012</td>
<td>0.359 (0.0585)</td>
<td>0.321 (0.0554)</td>
<td>0.327 (0.0579)</td>
</tr>
<tr>
<td>in 2013</td>
<td>0.414 (0.0641)</td>
<td>0.387 (0.0615)</td>
<td>0.348 (0.0618)</td>
</tr>
<tr>
<td>dPr[R&amp;D Investment Binary&lt;sub&gt;i,t&lt;/sub&gt;=1]/dLog(Employment&lt;sub&gt;i,t-1&lt;/sub&gt;+1)</td>
<td>0.200 (0.0387)</td>
<td>0.112 (0.0344)</td>
<td>0.283 (0.0646)</td>
</tr>
</tbody>
</table>

B. Exit

<table>
<thead>
<tr>
<th>Model</th>
<th>(B1) OLS Linear Probability</th>
<th>(B2) Probit</th>
<th>(B3) Linear Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Implied Mean Prob[Exit&lt;sub&gt;i,t&lt;/sub&gt;=1]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pre-Shock</td>
<td>0.00276 (0.00799)</td>
<td>0.00516 (0.00502)</td>
<td>-0.0194 (0.0188)</td>
</tr>
<tr>
<td>in 2011</td>
<td>0.128 (0.0383)</td>
<td>0.129 (0.0370)</td>
<td>0.104 (0.0286)</td>
</tr>
<tr>
<td>in 2012</td>
<td>0.139 (0.0404)</td>
<td>0.142 (0.0414)</td>
<td>0.156 (0.0322)</td>
</tr>
<tr>
<td>in 2013</td>
<td>0.0783 (0.0331)</td>
<td>0.0752 (0.0308)</td>
<td>0.150 (0.0307)</td>
</tr>
<tr>
<td>dPr[Exit&lt;sub&gt;i,t&lt;/sub&gt;]/dLog(Employment&lt;sub&gt;i,t-1&lt;/sub&gt;+1)</td>
<td>-0.0153 (0.0107)</td>
<td>-0.0159 (0.0122)</td>
<td>-0.0176 (0.0202)</td>
</tr>
</tbody>
</table>

Notes: Table presents average marginal effects, i.e., in Panel A, average among observations in the sample of Prob[R&D Investment Binary<sub>i,t</sub>=1] if the year in shock indicators are changed to pre-shock, 2011, 2012, or 2013 values respectively, or average of dPr[R&D Investment Binary<sub>i,t</sub>=1]/dLog(Employment<sub>i,t-1</sub>+1), at the employment and other characteristics in each observation (panel B is analogous). p-values for years pertain to differences not from zero but from pre-Shock estimates. Standard errors in parentheses are robust and clustered by firm. Columns A1 and B1 are the same as columns 1 and 6 of Tables 3A-3B. Columns A2 and B2 present maximum-likelihood estimates of instrumental variables probit (A2) and probit (B2) regression models. Columns A3 and B3 are fixed effects models, identical to those in A1 and B1 respectively except with firm fixed effects instead of sector or sector group effects.
Online Appendix

fit. Models with firm fixed effects, instead of sector group or sector effects, appear in columns A3 and B3. The results are fairly similar to those for the models without firm fixed effects, although the negative estimate for the mean probability of exit before the demand shock adds to concerns about the use of firm fixed effects in this model. Overall, the models with firm fixed effects confirm the main conclusions if not the exact point estimates regarding how the demand shock and employment affected R&D participation and exit.

D.3 Control Comparisons

Although firm-specific line-of-business data outside photovoltaics are not available to provide a control group within the sample, nonetheless, control comparisons are possible using aggregate data on the Korean economy. Figure A8 compares the fitted estimates to the most comparable available control statistics. The dashed lines are the control statistics. In the first two panels, indexes of real R&D investment or R&D employment per Korean manufacturing establishment, or per firm in available years, come from government statistics. In the third panel, Korean patent applications with Korean applicants are measured by an index, per person in Korea, using World Intellectual Property Office data. The solid lines show the fitted estimates for photovoltaic manufacturers. For direct comparability, algebraic mean estimates are computed, as well as overall R&D investment (the estimated probability of each firm making nonzero R&D investment times its estimated investment conditional on nonzero R&D).

In the manufacturing sector in general, or in the whole Korean economy for patent applications, R&D inputs and outputs grew gradually from 2004 through 2013. Manufacturing-wide R&D employment per establishment had downturns, growing little in 2007 and 2010 and falling slightly in 2013, but these are blips compared to changes in photovoltaic manufacturing. The photovoltaic estimates imply that arithmetic mean R&D investment per firm fell 83.5 percent from its peak in 2011 to 2012, photovoltaic R&D employment per firm fell 41.3 percent in 2012, and patent applications per firm fell 28.9 percent by 2013. Thus, the reduction of Korean photovoltaic R&D inputs and outputs in response to reduced demand subsidies did not reflect nationwide trends.

The patterns in employment per firm, probability of exit, and number of entrants per year are compared in Figure A9 to control statistics. The dashed lines are indexes of the number of employees per Korean manufacturing establishment or manufacturing firm in the top panel, the
Figure A8. Fitted Estimates Compared to External Control Statistics, using Arithmetic Means, for R&D Inputs and Outputs. Control sources: Korea Statistical Information Service; Ministry of Science, ICT and Future Planning; and World Intellectual Property Office (see Online Appendix B.4). Note: Control statistics for all Korean manufacturers, all Korean industry, or all Korean applicants for Korean patents of invention, as indicated, in available years, normalized to have same mean as fitted estimates.
Figure A9. Fitted Estimates Compared to External Control Statistics (Arithmetic Means), for Firm Employment, Exit, and Entry. Control sources: Korea Statistical Information Service; Ministry of Science, ICT and Future Planning. Note: Control statistics for all Korean manufacturers, all new (first year) Korean manufacturers, or all Korean industry, in available years, normalized to have same mean as fitted estimates.

rate of exit among new Korean manufacturers or all Korean manufacturers in the middle panel, and the number of entering Korean firms in all industry or all manufacturing in the bottom panel,
each in the available years during 2004-2013. While the number of employees per manufacturing establishment experienced occasional downturns of as much as 4 percent during 2001 and 2007, and while annual firm entry experienced declines as much as 5 percent in 2009 and 2012, these are small changes compared to the changes among photovoltaic manufacturers. Contrary to the economy-wide patterns, arithmetic mean photovoltaic employment per firm fell an estimated 29.6 percent from 2011 to 2012, the estimated photovoltaic exit rate grew from 0.2 percent in 2010 to 13.5 percent in 2012, and photovoltaic entry fell to zero in 2012 and 2013.

D.4 Alternate Patent Application Metrics

Patent applications related to photovoltaics were identified in two sets: a first set definitely developed for photovoltaics, and a second set for which it was unclear whether they pertained to photovoltaics versus closely related semiconductor or semiconductor materials technologies (see Online Appendix B.2). The analyses in Tables 3A-3B use only patent applications definitely developed for photovoltaics, to ensure a clean although incomplete measure of firms’ photovoltaic activity. Including the second set of applications as well covers more patent applications, including for raw material innovations, but is likely to overcount applications from large firms such as Samsung and LG that carried out related non-photovoltaic activities.

Using the first and second sets of patent applications combined, the estimates imply slightly more impact than has been reported here. However, the point estimates reported in columns 1-3 and 5-6 of Tables 3A-3B change by at most 0.023, and the standard errors by at most 0.010. When the dependent variable and the patent stock control variable are changed in column 4, the point estimates differ by at most 0.073, and the standard errors by at most 0.004. The conclusions are thus quite robust to this shift in patent application metrics.

D.5 Additional Control Variables

We experimented with controlling for exchange rates using the logarithm of the euros per Korean won year-average exchange rate, to allow for any resultant export demand shifts. The estimated impacts of the European demand subsidy shock as shown in Figure A10 remain similar, more muted but still very large, and highly statistically significant. Near identical results arise with lagged, untransformed, or lagged untransformed exchange rates. We chose not to include this control in our preferred specification because it creates spurious correlation,
Figure A10. Results with Log Exchange Rate Control: Estimated Mean or Geometric Mean R&D Inputs and Output (Solid), Counterfactuals (Dashed), and Sample Means (Circles) or Geometric Means (Diamonds). Note: Active photovoltaic producers each year, and only active R&D investors in panel 2. Geometric means of R&D investment, one plus R&D employment, one plus patent applications, or employment. Panels 1-3 exclude four firms in 2004 with unknown lagged employment. Panel 5 excludes four firms in 2004 and 2005 with unknown second lag of employment. In panels 1 and 6, dotted lines substitute probit formulations.

apparently biasing the estimates much more than it helps. In the exit equation, in fact, there is insufficient information to estimate the exchange rate effect appropriately, yielding a nonsensical negative coefficient estimate because the only year with nonzero exit and without year indicators is the year when the won was least expensive.

Including a time trend in the R&D investment participation allows a much better fit in that equation, and the time trend might reflect some real trend that was occurring over time. Fitted and counterfactual estimates change from Figure 7 only for R&D investment participation. Figure A11 shows the changed results.
Figure A11. Results for R&D Investment Participation with a Time Trend in the R&D Investment Participation Equation: Estimated Mean or Geometric Mean R&D Inputs and Output (Solid), Counterfactuals (Dashed), and Sample Means (Circles). Note: Active photovoltaic producers each year. Excludes four firms in 2004 with unknown lagged employment. Dotted lines substitute probit formulations. Other dependent variable outcomes remain identical to Figure 7.

We experimented with a control for the logarithm of firm age in photovoltaics. Age is defined as one in the year (possibly preceding 2004) when a firm first produced photovoltaic products, and increases by one in each subsequent year. Including age in the model yields estimated positive, although usually statistically insignificant, effects, opposite the effects normally found in industrial organization economics research (Dunne, Roberts, and Samuelson 1989), apparently because years since entry into photovoltaic manufacturing is correlated problematically with rising expectations for dependent variables. With no way to estimate true effects of age, age is excluded in the model.
**Online Appendix**

**D.6 Comparable Effects Across Sectors and for Exporters versus Non-Exporters**

Firms with high export intensity, or in particular sectors, might be thought most vulnerable to demand subsidy reductions, but this is not necessarily true for two reasons. First, non-exporters including firms in upstream sectors sold their products to exporting firms. Second, photovoltaic products are fairly close to commodities with similarly fierce within-country and international competition.

Econometric models were nonetheless used to probe possible interaction effects between the demand subsidy shock and each firm’s fraction of revenues from exports averaged over years through 2010. The analyses found some evidence that exporters may have expanded R&D employment and patent applications more than non-exporters in 2011, but in 2012 and 2013 no interaction effects were statistically significant at conventional levels in models of R&D inputs and output. The highly-competitive modules sector experienced less R&D employment reduction but about typical patent application reduction in 2012-2013, less employment reduction, and typical exit increase, compared to other sectors. The cells sector experienced relatively high reduction in R&D probability and R&D employment, but less reduction in patent applications, in 2012-2013. Materials sectors experienced relatively high reduction in R&D probability and particularly in R&D employment, but no substantial difference in patent applications, in 2012-2013. Overall, the demand subsidy shock apparently had industry-wide impact regardless of firms’ export intensities and sectors.

**D.7 Mean Estimated Net Effect: Linear Probabilities and Delta Method**

Mean estimated net impacts of the subsidies were also computed using linear probabilities, as shown in Table A9. Only mean differences are reported, because mean ratios (of outcome with subsidy shock over outcome without shock) would not be meaningful since some linear probability estimates are negative. The estimates are slightly larger in Table A9 than in Table 4, with comparably small standard errors relative to the estimates.

Standard errors computed by the delta method appear in Table A10. These are robust standard errors clustered by firm, allowing for heteroskedasticity and for correlation across observations within each firm. These standard errors are typically smaller than the standard errors computed by the bootstrap method, except for slightly larger values for employment in 2012 and 2013. We therefore use the bootstrap standard errors in Table 4 to be cautious.
Table A9. Mean Estimated Net Effect of European Subsidy Reductions using Linear Probability Models

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prob. of Nonzero R&amp;D Investment</strong></td>
<td>-0.037</td>
<td>-0.500</td>
<td>-0.450</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.077)</td>
<td>(0.090)</td>
</tr>
<tr>
<td><strong>Prob. of Exit</strong></td>
<td>0.125</td>
<td>0.137</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.042)</td>
<td>(0.039)</td>
</tr>
</tbody>
</table>

*Notes:* Mean across firms of each firm’s difference or ratio. Standard errors in parentheses computed by the bootstrap method clustered by firm, with 2,000 resampling repetitions. Counterfactuals computed by recursive substitution in estimated equations, standard errors by the delta method.

Table A10. Standard Errors by Delta Method, Robust and Clustered by Firm

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>R&amp;D Investment (if &gt; 0)</strong></td>
<td>0.177</td>
<td>0.087</td>
<td>0.076</td>
</tr>
<tr>
<td><strong>R&amp;D Employment</strong></td>
<td>0.097</td>
<td>0.079</td>
<td>0.096</td>
</tr>
<tr>
<td><strong>Patent Applications</strong></td>
<td>0.062</td>
<td>0.051</td>
<td>0.047</td>
</tr>
<tr>
<td><strong>Employment</strong></td>
<td>0.087</td>
<td>0.083</td>
<td>0.097</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prob. of Nonzero R&amp;D Investment</strong></td>
<td>0.063</td>
<td>0.075</td>
<td>0.089</td>
</tr>
<tr>
<td><strong>Prob. of Exit</strong></td>
<td>0.039</td>
<td>0.041</td>
<td>0.039</td>
</tr>
</tbody>
</table>

*Notes:* Compare to standard errors in Tables 4 and A9. Delta method standard errors are unavailable for probabilities with probit formulations.

D.8 Alternative Depreciation Rates and Mean Estimated Net Effect

Alternative depreciation rates for the patent application stock have little impact on the mean estimated net effect of the subsidy reductions. The estimates in Table A11 are computed using depreciation rates of 5, 10, 15, 20, 25, and 30 percent per annum. These estimates use
Table A11. Mean Estimated Net Effect of European Subsidy Reductions with Alternative Patent Application Depreciation Rates (Linear Probability Models, Delta-Method Standard Errors)

<table>
<thead>
<tr>
<th>Depreciation Rate</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year 2011</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prob. of Nonzero R&amp;D Investment, Difference</td>
<td>-0.037</td>
<td>-0.037</td>
<td>-0.038</td>
<td>-0.038</td>
<td>-0.038</td>
<td>-0.038</td>
</tr>
<tr>
<td>Probability of Nonzero R&amp;D</td>
<td>0.063</td>
<td>0.063</td>
<td>0.063</td>
<td>0.063</td>
<td>0.063</td>
<td>0.063</td>
</tr>
<tr>
<td>R&amp;D Investment (if &gt; 0),</td>
<td>1.105</td>
<td>1.107</td>
<td>1.110</td>
<td>1.114</td>
<td>1.119</td>
<td>1.124</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.178</td>
<td>0.177</td>
<td>0.177</td>
<td>0.176</td>
<td>0.176</td>
<td>0.176</td>
</tr>
<tr>
<td>R&amp;D Employment,</td>
<td>0.949</td>
<td>0.944</td>
<td>0.941</td>
<td>0.939</td>
<td>0.938</td>
<td>0.939</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.099</td>
<td>0.097</td>
<td>0.095</td>
<td>0.094</td>
<td>0.094</td>
<td>0.094</td>
</tr>
<tr>
<td>Patent Applications,</td>
<td>0.443</td>
<td>0.441</td>
<td>0.439</td>
<td>0.439</td>
<td>0.438</td>
<td>0.438</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.062</td>
<td>0.062</td>
<td>0.061</td>
<td>0.061</td>
<td>0.060</td>
<td>0.060</td>
</tr>
<tr>
<td>Employment,</td>
<td>0.896</td>
<td>0.895</td>
<td>0.894</td>
<td>0.894</td>
<td>0.895</td>
<td>0.896</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
</tr>
<tr>
<td>Prob. of Exit,</td>
<td>0.125</td>
<td>0.125</td>
<td>0.125</td>
<td>0.126</td>
<td>0.126</td>
<td>0.126</td>
</tr>
<tr>
<td>Difference</td>
<td>0.039</td>
<td>0.039</td>
<td>0.039</td>
<td>0.039</td>
<td>0.039</td>
<td>0.039</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Depreciation Rate</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year 2012</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prob. of Nonzero R&amp;D Investment, Difference</td>
<td>-0.499</td>
<td>-0.500</td>
<td>-0.501</td>
<td>-0.502</td>
<td>-0.502</td>
<td>-0.502</td>
</tr>
<tr>
<td>Probability of Nonzero R&amp;D</td>
<td>0.075</td>
<td>0.075</td>
<td>0.075</td>
<td>0.075</td>
<td>0.075</td>
<td>0.075</td>
</tr>
<tr>
<td>R&amp;D Investment (if &gt; 0),</td>
<td>0.182</td>
<td>0.181</td>
<td>0.181</td>
<td>0.181</td>
<td>0.181</td>
<td>0.181</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
</tr>
<tr>
<td>R&amp;D Employment,</td>
<td>0.379</td>
<td>0.376</td>
<td>0.373</td>
<td>0.371</td>
<td>0.370</td>
<td>0.369</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.081</td>
<td>0.079</td>
<td>0.078</td>
<td>0.077</td>
<td>0.077</td>
<td>0.077</td>
</tr>
<tr>
<td>Patent Applications,</td>
<td>0.282</td>
<td>0.279</td>
<td>0.276</td>
<td>0.274</td>
<td>0.272</td>
<td>0.270</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.052</td>
<td>0.051</td>
<td>0.051</td>
<td>0.050</td>
<td>0.050</td>
<td>0.050</td>
</tr>
<tr>
<td>Employment,</td>
<td>0.513</td>
<td>0.510</td>
<td>0.508</td>
<td>0.507</td>
<td>0.507</td>
<td>0.506</td>
</tr>
<tr>
<td>Ratio</td>
<td>0.083</td>
<td>0.083</td>
<td>0.082</td>
<td>0.082</td>
<td>0.082</td>
<td>0.082</td>
</tr>
<tr>
<td>Prob. of Exit,</td>
<td>0.137</td>
<td>0.137</td>
<td>0.137</td>
<td>0.138</td>
<td>0.138</td>
<td>0.138</td>
</tr>
<tr>
<td>Difference</td>
<td>0.041</td>
<td>0.041</td>
<td>0.041</td>
<td>0.042</td>
<td>0.042</td>
<td>0.042</td>
</tr>
</tbody>
</table>
### Depreciation Rate

<table>
<thead>
<tr>
<th>Year 2013</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prob. of Nonzero R&amp;D</td>
<td>-0.448</td>
<td>-0.450</td>
<td>-0.451</td>
<td>-0.452</td>
<td>-0.453</td>
<td>-0.454</td>
</tr>
<tr>
<td>Investment, Difference</td>
<td>(0.089)</td>
<td>(0.089)</td>
<td>(0.089)</td>
<td>(0.089)</td>
<td>(0.089)</td>
<td>(0.089)</td>
</tr>
<tr>
<td>R&amp;D Investment (if &gt; 0), Ratio</td>
<td>0.167</td>
<td>0.165</td>
<td>0.164</td>
<td>0.164</td>
<td>0.163</td>
<td>0.163</td>
</tr>
<tr>
<td>R&amp;D Employment, Ratio</td>
<td>0.426</td>
<td>0.420</td>
<td>0.414</td>
<td>0.410</td>
<td>0.408</td>
<td>0.406</td>
</tr>
<tr>
<td>Patent Applications, Ratio</td>
<td>0.200</td>
<td>0.196</td>
<td>0.193</td>
<td>0.190</td>
<td>0.188</td>
<td>0.186</td>
</tr>
<tr>
<td>Employment, Ratio</td>
<td>0.499</td>
<td>0.494</td>
<td>0.491</td>
<td>0.488</td>
<td>0.486</td>
<td>0.485</td>
</tr>
<tr>
<td>Prob. of Exit, Difference</td>
<td>0.084</td>
<td>0.084</td>
<td>0.085</td>
<td>0.085</td>
<td>0.085</td>
<td>0.085</td>
</tr>
<tr>
<td>Difference</td>
<td>(0.039)</td>
<td>(0.039)</td>
<td>(0.039)</td>
<td>(0.039)</td>
<td>(0.039)</td>
<td>(0.039)</td>
</tr>
</tbody>
</table>

**Notes:** Difference is outcome with subsidy shock minus outcome without shock. Ratio is outcome with subsidy shock over outcome without subsidy shock. In each case, the mean across firms of the estimate difference or ratio is reported. Delta method standard errors in parentheses.

linear probability rather than probit formulations for the probabilities of nonzero R&D investment and exit, and use delta-method rather than bootstrap standard errors. Three successive panels of estimates pertain to the years 2011, 2012, and 2013. Only estimated differences, not ratios, are reported for the probabilities of nonzero R&D investment and exit, because linear probability models often yield negative estimates making mean ratios across firms effectively meaningless. The estimates reveal very little sensitivity to alternative depreciation rates.

#### D.9 R&D Elasticities with Respect to Firm Size

Approximate elasticities of R&D inputs and output with respect to firm size (employment) were estimated in models using the logarithms of one plus employment, one plus R&D employment, and one plus patent applications. Exact elasticities, among observations with nonzero values of R&D employment or patent applications, can be obtained in two ways. First, in a model \( \log(1 + y_u) = \lambda \log(1 + x_u) + \ldots \), the exact partial elasticity implied by the model is
Table A12. Alternative Estimates of Elasticity of R&D Measures with Respect to Employment

<table>
<thead>
<tr>
<th>R&amp;D Measure</th>
<th>Approximate Elasticity</th>
<th>Average Exact Elasticity</th>
<th>Exact Elasticity from Models without “1+” Offsets</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D Investment (if &gt; 0)</td>
<td>0.82</td>
<td>0.79</td>
<td>0.83</td>
</tr>
<tr>
<td>R&amp;D Employment</td>
<td>0.64</td>
<td>0.73</td>
<td>0.71</td>
</tr>
<tr>
<td>Patent Applications</td>
<td>0.34</td>
<td>0.47</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Notes: Approximate elasticity is the estimated coefficient of \( \log(\text{Employment}_{i+1}) \) in Table 3A. Average exact elasticity is among observations in which the R&D measure is nonzero. Exact elasticity estimate from models without “1+” offsets is estimated using observations in which the R&D measure, employment, and (for R&D investment and R&D employment) lagged employment are nonzero.

\[
\frac{\partial y_i}{\partial x_i} \left( \frac{y_i}{x_i} \right) = \frac{1}{y_i} \cdot \frac{x_i}{1 + x_i} \cdot \hat{\lambda},
\]

or in a model \( \log y_i = \lambda \log(1 + x_i) + \ldots \), the exact partial elasticity implied by the model is

\[
\frac{\partial y_i}{\partial x_i} \left( \frac{y_i}{x_i} \right) = \frac{x_i}{1 + x_i} \cdot \hat{\lambda}.
\]

Thus for the R&D investment, R&D employment, and patent applications estimation equations, exact elasticity estimates can be computed for each firm-year observation (using the estimated approximate elasticity \( \hat{\lambda} \) in place of \( \lambda \)) and the average estimated exact elasticity can be determined.\(^{37}\) Second, single-equation models can be estimated without the “one plus” offsets, among observations with nonzero values of \( y_i, x_i \), and (for instrumental variables models) \( x_{i-1} \), to estimate exact elasticities directly. The resulting estimated elasticities appear in Table A12.

\(^{37}\) For the R&D investment probability, the change with respect to employment is identical to the change with respect to one plus employment.
References for Online Appendix


Online Appendix


Online Appendix


Online Appendix


Online Appendix


Online Appendix


https://web.archive.org/web/20190729162226/https://www.netztransparenz.de/portals/1/Content/Erneuerbare-Energien-Gesetz/EEG-Anlagenstammdaten/Netztransparenz%20Anlagenstammdaten%202017%20Amprion%20GmbH_V03.zip


Online Appendix


Archival link to Excel file at the Internet Archive:


Online Appendix


