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Local demand-pull policy and energy innovation: Evidence from the solar photovoltaic market in China

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ABSTRACT

Market demand is an important driver for inducing innovation, with many empirical studies supporting the demand-induced innovation hypothesis. Critiques of such studies, however, emphasize that new empirical evidence that can address existing empirical challenges is needed. Furthermore, existing literature disagrees about whether the locus of demand-pull policy matters. In this paper, we use empirical evidence from the distributed solar photovoltaic (PV) market in China to address the following questions: (1) Is there evidence of demand-induced innovation? (2) Does the effect of *local* demand-pull policy differ from the effect of *non-local* demand-pull policy on demand-induced innovation? To address these questions, we develop and analyze an original database of PV balance-of-system (BOS) patents in the distributed PV market filed between 2005 and 2014 in China. Our results support the demand-induced innovation hypothesis and suggest that only local demand significantly induces PV BOS innovations in the distributed PV market in China. The different effects of local demand and non-local demand emphasize the importance of local markets and local policies, lending some support to bottom-up approaches to clean energy governance.

1. Introduction

Technological innovation and competitiveness of regional economies are closely connected, driving governments to adopt various policy instruments to support innovation, hoping such support would translate into positive economic effects. A central challenge for governments, though, is to design innovation policies that can effectively influence the speed, direction, and scale of technological innovation. A commonly-used policy tool, especially by sub-national governments, is demand creation. Inspired by Griliches (1957) and Schmookler (1962), the literature started to emphasize that market demand is an important driver for inducing technological innovation. It is now recognized that going from innovation to market demand is not a sequential, linear process; rather it is an interactive, dynamic process whereby the influence (between innovation and demand) can flow both ways.

From a firm's perspective, the process of innovation involves interactions not only within a firm, but also with other elements outside the firm, such as other firms, consumers, and even the government (Rothwell, 1989; von Hippel, 1986). Thus, firms' innovative outcomes cannot be understood well if the environment in which they operate is not taken into account (Antonelli, 1996). This 'interactive' view of innovation further raises the question whether local market demand is essential to developing a competitive local industry. Existing literature offers different answers, often at odds with each other, to this question (Dechezleprêtre and Glachant, 2014; Lanjouw and Mody, 1996; Peters et al., 2012; Popp, 2006; Popp et al., 2011).

One area where a strong case for the positive, interactive feedback between geography, innovation, and localized economic effects may be expected involves technologies that have a significant knowledge dependence on local factors such as climate, regulations, building codes, and user preferences. Furthermore, to the extent innovation depends on local knowledge, it may be expected to advantage local firms more, since they presumably have better knowledge of the local context. This possibility should pique the interest of policymakers, who are often interested in seeing that public support for expanding local markets contributes to *local* technological innovation and economic competitiveness, rather than benefiting other jurisdictions more heavily (Lewis and Wiser, 2007; Maguire et al., 2012). However, empirical evidence in this area is relatively thin. Accordingly, we aim to inform this discussion through robust, empirically-driven analysis. Specifically, using patent data for the distributed solar photovoltaic (PV) market in China from 2005 to 2014, in this paper we address the following questions: (1) Is there evidence of demand-induced innovation? (2) Does the effect of *local* demand-pull policy differ from the effect of *non-local* demand-

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pull policy on demand-induced innovation? These questions are especially interesting since the essential role of local demand in inducing innovation has been challenged by the fact that China has taken the lead in the PV module manufacturing industry in the absence of a large domestic solar PV market demand when PV manufacturing in China flourished (Gallagher, 2014; Huenteler et al., 2016; Schmidt and Huenteler, 2016).

This paper considers solar PV balance-of-system (PV BOS) technologies as a case to address the above research questions. The choice to focus on PV BOS technologies is motivated by two factors: (1) large-scale deployment of distributed solar PV technologies is widely considered to be an important piece in addressing the environmental impacts of the electricity sector, making PV an important technology to study; furthermore, there is a general consensus that the biggest barrier for a wider deployment of PV is the high price of non-module components, including PV BOS (Barbose et al., 2015; Goodrich et al., 2012; Seel et al., 2013; Smith and Shiao, 2012; Yu et al., 2015), and (2) technological and operational aspects of non-module PV-system components make local conditions (climate, regulation, learning networks, etc.) salient, thus affording a rich empirical setting to explore the geography-innovation-economy interactions at the local level. Although innovations in PV BOS may be generally considered as incremental innovations, they are directly related to solar PV adopters' experience by making PV installations more user-friendly, safe, and reliable, while also reducing installation costs.

Using original and unique data on innovation in PV BOS technologies in the Chinese distributed solar PV market, this paper estimates the effect of local demand and non-local demand on technology innovations. This paper offers two main contributions to the existing literature. First, leveraging a clear demand-pull policy context and careful empirical design, we provide new empirical evidence to reinforce the explanatory ability of the demand-induced hypothesis. A big limitation in previous literature is that many empirical studies do not separate the shift in the demand curve from changes in other conditions (Chidamber and Kon, 1994; Mowery and Rosenberg, 1979; Nemet, 2009), thus confounding the impact of demand on innovation. In our empirical case, the market for distributed PV in China has largely been created by policies, meaning that *these market formation policies have led to a significant shift in the demand curve*. The clear existence of a policy-driven demand shift helps us effectively addresses a key limitation in prior literature. Moreover, strong policy signals, as in our empirical case, mean that installers and manufactures are more readily able to identify and respond to market demand, thus creating the basis for how demand is linked to innovation.

Second, we distinguish between the roles that local demand-pull policy and non-local demand-pull policy play in innovation, thereby highlighting the importance of local demand in driving locally-generated innovation. In particular, we exploit variation in province-level PV BOS patenting activities in China to address the influence of locational aspects of demand on innovation. Most empirical studies that have explored this locational aspect have focused at the national level (i.e., domestic vs. foreign), thus our use of subnational policy and demand variation adds a new perspective to the literature on this topic. We also exploit differences in technological characteristics within PV BOS to explore how the linkage between location of demand and innovation depends upon the characteristics of the involved technologies. Thus, our analysis also offers insights into the potential for tailoring market-creation policies based on technological characteristics.

2. Background and related literature

2.1. Related literature

Scholars from a range of disciplines have increasingly emphasized the role of technological innovation as an engine of economic growth (Schumpeter, 1934). Thus understanding the drivers of and barriers to technological innovation has excited much interest across a range of disciplines for several decades.

The induced innovation hypothesis, proposed by Schmookler and Griliches decades ago, emphasizes that the power of induced innovation lies in market demand (Griliches, 1957; Schmookler, 1962). Utterback further pointed out that market factors have a primary influence on innovation and that 60–80% of "important innovations" are demand-induced in a large number of fields (Utterback, 1974). Many recent empirical studies also provide strong evidence to support the demand-induced innovation hypothesis, namely that innovation can be induced by demand (Lanjouw and Mody, 1996; Lin, 2010; Nemet, 2009; Peters et al., 2012; Popp, 2006). It is noteworthy that demand-induced innovation is not a simple linear model. Feedback loops and interactions between different actors – between firms, between users and firms, and between governments and firms – are also important elements of technological innovation in the context of demand-induced innovation (Kline and Rosenberg, 1986; Rothwell, 1989; Taylor, 2008; von Hippel, 1986).

A parallel stream of literature has explored the linkages between interactive learning and innovation (Christensen and Stoerring, 2012; Lundvall, 2012; Rothwell, 1989; von Hippel, 1986). Learning and innovation often result from an interactive process, which benefits from proximity, thus experience-based innovation is often characterized by localization and geographical agglomeration. The importance of local context factors (such as demand, interaction, culture, regulation, business environment, and supply chain) in the innovation process has been recognized (Asheim et al., 2007, 2011; Fabrizio and Thomas, 2012; Jaffe and Trajtenberg, 2002; Marshall, 1895; Nemet, 2012; Porter and Stern, 2001). Firms with more experience in a certain geographic area have comparative advantages because of their better understanding of the local context (Beise and Rammer, 2006; Fabrizio and Thomas, 2012; Kogut, 1995) and are stronger for business-to-consumer sectors, as they focus more on end-users and demand-induced innovation in those geographic areas (Brem and Voigt, 2009). Thus, it is plausible that demand-pull policy could expand local markets and help firms gain more localized experience, translating into (demand-induced) innovation. Furthermore, policymakers often prefer to see that public support for expanding local markets contributes to local technological innovation and economic competitiveness, rather than benefiting outside jurisdictions (Lewis and Wiser, 2007; OECD, 2011).

Recently some empirical work has begun to distinguish between the effects of local demand-pull policy and non-local demand-pull policy on technology innovation, suggesting substantial variation in these effects depending on the industry/sector of study (See Table 1). For example, Popp (2006) found that innovations for sulfur dioxide and nitrogen oxide control at coal-fired power plants primarily respond to domestic regulation instead of foreign regulation. Dechezleprêtre and Glachant (2014) found that technological improvements in wind power across OECD countries respond to both domestic and foreign demand-pull policies, although they also suggested that the marginal effect of domestic policies is twelve times greater than that of foreign policies. In contrast, Peters et al. (2012) found that both domestic demand-pull policies and foreign demand-pull policies could spur innovation in the solar PV (modules) sector, with similar magnitudes of effect for both foreign and domestic demand-pull policies. On the other hand, Lanjouw and Mody (1996) found that vehicle emissions regulation in the U.S. stimulated innovation in Japan and Germany. Popp et al. (2011) observed that technology innovation in the pulp and paper industry responded to both domestic and foreign regulations.

The variation in these results regarding the impact of policy locus on demand-induced innovation may depend on whether an industry faces a global market (Popp et al., 2011). For example, the U.S. is a major market for Japanese vehicle makers; thus Japanese technology development is appropriately responsive to emissions regulation in the U.S. The seemingly inconsistent results may also depend on whether local context is significantly important to technology innovations (Peters

Table 1
Summary of relevant empirical studies to test whether the location of demand matters for inducing innovation. A tick mark denotes if a study found domestic and/or foreign demand-pull policy to significantly induce (domestic) innovation. The text in the 'Domestic Policy' column denotes the relative impact on innovation of domestic vs. foreign demand pull.

Industry/Technology	Domestic policy	Foreign policy	Literature
Sulfur dioxide and nitrogen oxide control	√		Popp (2006)
Wind technological improvements	√ Twelve times greater	√	Dechezleprêtre and Glachant (2014)
Solar PV manufacturing	√ Similar magnitude	√	Peters et al. (2012)
Vehicle emissions		√	Lanjouw and Mody (1996)
Pulp and paper industry	√	√	Popp et al. (2011)

et al., 2012). If technology localization and producer-user interaction are important in an innovation process, such experience-based innovation might depend on a stable and sizable *local* market (Qiu and Anadon, 2012). This paper focuses on PV BOS technologies, for which local factors are known to be more significant than they are to PV modules. Innovations in PV BOS are a product of, among other things, local experience and local learning, as well as local climate, local rooftop characteristics, and local complementary industries (Neij et al., 2017; Venugopalan and Rai, 2015). Therefore, based on existing literature, we expect that PV BOS innovations should primarily respond to local demand-pull policies.

2.2. Background on distributed PV policies in China

Since 2005 China's solar PV manufacturing industry has developed rapidly. In 2007 Chinese solar PV manufacturing surpassed Japan, and China became the world's largest producer of PV modules. However, in 2011 the Chinese PV industry slowed down significantly due to shrinking foreign markets, Europe in particular. To help the Chinese PV industry digest overcapacity and get through the downturn, Chinese governments at various level expended much effort to expand the domestic market.

Since 2011 the Chinese national government has established several demand-pull policies to expand the distributed PV market, including a grid-connection policy, Feed-in-Tariff policy, generation subsidy policy, and financial services policy (National Development Reform Commission, 2013; National Grid Company, 2012; State Council, 2013; Zhang, 2016). The deployment of distributed PV in China is mainly through the following programs: the Golden Sun Demonstration Projects jointly led by China's Minister of Finance, China's Ministry of Science & Technology and National Energy Agent (Ministry of Finance, 2009); the Green Building Plan led by China's Ministry of Housing and Urban-Rural Construction (Ministry of Housing and Urban-Rural Construction, 2013; National Development Reform Commission, 2013); the distributed-generation PV application and demonstration projects led by National Energy Agent, and individual self-consumption distributed-generation PV.

Distributed PV systems[1] include projects with electricity generation located near users with total installed capacity no greater than 6 MW; the electricity is mainly consumed by end users, but excess electricity can be fed into the public grid (National Development Reform Commission, 2013; National Energy Agency, 2014; National Grid Company, 2012). Fig. 1 shows installed capacity of distributed PV in China since 2011.

Even though difficulties exist in finding proper rooftops, clarifying rooftop ownership, financing, and installing and interconnecting distributed PV systems, several provinces, especially the Eastern provinces, provide province-level subsidies, detailed grid-connection services, and financing services to local distributed-generation PV projects.

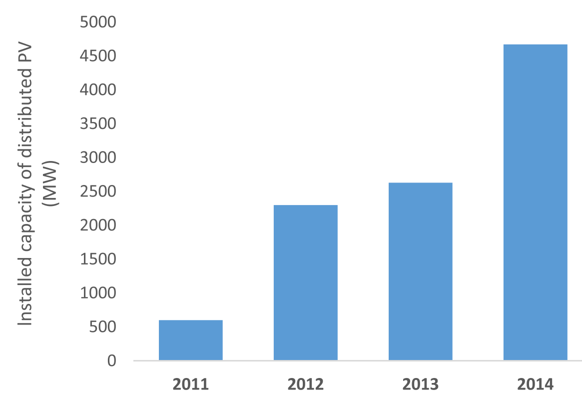

Fig. 1. Installed capacity (MW) of distributed PV in China, 2011–2014. Data source: NEA (2014, 2015) and Zhang (2016).

For example, the provincial government in Jiangsu assesses all available and suitable rooftop resources for distributed PV and helps address the problem of unclear rooftop ownership. The provincial government in Jiangsu also requests Grid Company to provide specific services to help costumers connect distributed PV electricity to the grid, so that consumers can sell their excess electricity back to Grid Company. Owing to such coordinated government support, distributed PV has developed rapidly in the Eastern provinces of China. Together, these developments yield helpful variation (for our analysis) in the level of demand-pull policies and distributed PV deployment across the Chinese provinces.

Increasing installation of distributed PV in China has significantly expanded the practical experience of PV installers with installing and maintaining distributed PV systems. As discussed above, incremental innovations, such as those in PV BOS, are expected to be closely related to local interactions, local customer preferences, local regulation, local business environment, and local supply chain (Bollinger and Gillingham, 2014; Fabrizio and Thomas, 2012; Maskell, 1999; Neij et al., 2017; Nemet, 2012; Porter and Stern, 2001). In turn, local firms have comparative advantages that result from a better understanding of the local context (Beise and Rammer, 2006). With expanding markets, installers have more opportunity to learn about the nature of local demand, local roof structures, and local codes and regulations. Such practical experiences provide increased opportunities for installers to improve and update their PV BOS related products and services.

3. Data and methodology

3.1. Data

To explore the effect of local demand on PV BOS innovation, we build an original database of PV BOS patents filed between 2005 and 2014 related to distributed PV based on patent information from the State Intellectual Property Office (SIPO) website. SIPO contains invention announcements, invention authorization, utility models, and

[1] The term "distributed PV system" is the official government term and it refers to roof-top mounted system.

Table 2
Search terms for PV BOS patents in Chinese and English.

BOS category	Search terms	Translation in english
Inverter	“逆变器” and “光伏”or “太阳能”	"inverter" and "photovoltaic" or "solar"
Mounting	“支架” or “框架”or “齿条”or“屋顶”or “安装”or “围栏”or “轨道” and “光伏”or “太阳能”	"mounting" or "bracket" or "frame" or "roof" or "installation" or "rail" and "photovoltaic" or "solar"
Monitoring	“跟踪” or “评价” or “诊断” or “维持” or “保持” or “监视” or “监视器” or “维护” or “监控” and “光伏”or “太阳能”	"monitoring" or "evaluation" or "diagnosis" or "maintain" and "photovoltaic" or "solar"
Site Assessment	“卫星” or “地图” or “阴影” or “遮蔽” or “估计” or “预测” or “支持” or “安装”and “光伏”or “太阳能”	"satellite" or "map" or "shade" or "estimation" or "projection" or "support" or "installation" and "solar" or "photovoltaic"

design patents. After SIPO receives an application for an invention, it conducts a preliminary review. If the application passes the preliminary examination, the invention is typically announced 18 months after the filing date. After an invention application is announced, SIPO starts a substantive examination if requested by the applicant. If the application passes the substantive examination, it is authorized to be an invention. There is no substantive examination for utility models and design patents. A utility model is similar to an invention, but standards of novelty and inventiveness for utility models are not as high as those of inventions. A design model refers to new designs for a product's appearance, shape, and color.

China patent system was established in 1985, marked by the passage of the first patent law. Then Chinese patent law experienced four amendments in 1992, in 2000, in 2008, and in 2016, separately. The biggest change in the Chinese patent system happened in 2000. As China prepared to join the World Trade Organization (WTO), they were required to fulfill the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). While our descriptive analysis covers the Chinese PV BOS patents during 2005 and 2014, there are only few patents before 2008. Thus, the change of China patent system in 2008 should not have a significant impact on our descriptive analysis (reported in Section 4.1). Furthermore, our regression analysis covers the PV BOS patents from 2012 to 2014, during which there was no significant change in the Chinese patent system. Thus, patent data should be a stable indicator during our study period in regression analysis.

For identifying PV BOS patents for each province in China, we adapt the methodology developed by Venugopalan and Rai (2015), which focused on PV BOS patents in the U.S. The first step is to identify specific items and keywords for PV BOS. Following Venugopalan and Rai (2015), this paper classifies BOS into four categories: *inverter*, *mounting system*, *monitoring*, and *site assessment*. *Inverter* is used to convert power generated by solar PV cells/modules from direct current (DC) to alternating current (AC). *Mounting* structures are to physically support solar PV modules and/or arrays. *Monitoring* includes methods and devices that monitor health, connectivity and output of solar PV systems. *Site assessment* includes methods or mechanisms of appraising the photovoltaic output potential of a land parcel, determining the ideal placement of PV systems on potential sites, determining the extent to which obstructions or shade may impede the output potential of PV sites (Venugopalan and Rai, 2015). All these *non-module* components are used in the solar PV deployment process. In other words, solar panel/module is used to convert solar energy to DC; however, in order to complete a whole deployment process, non-module components (i.e., PV BOS) are needed for identifying the placement of PV modules, attaching PV modules to rooftops, converting DC to AC, and monitoring the operation and performance of PV modules.

Specific items we include for each category can be found in the Supplemental information (SI). We use the same search terms as Venugopalan and Rai (2015) in English and translate these English terms into Chinese. Note that one keyword in English could be translated into several relevant terms in Chinese. Table 2 lists keywords we used for searching relevant patents of PV BOS.

The second step is to use keywords for each category to search patents' full text on the SIPO website. This step gives us a large sample of *potentially* relevant patents, but not all patents we extract from keyword searching are *actually* relevant to PV BOS. After the second step, our search process yields a total of 7626 potentially relevant patents. The third step is the key step, wherein we review each patent's claims and identify whether the invention embodied in a patent is directly related to one of the four PV BOS categories.[2] Note that a patent may have been an application in earlier years, but went on to become a granted patent in the following years. We remove these overlapping patents. We also drop the patents that are related only to utility-scale PV, since the distributed and utility-scale markets are largely distinct and innovations in utility-scale PV are not expected to be induced by the demand for distributed PV. In any case, the “utility-scale only” patents that we remove account for a very small proportion of total potentially relevant patents.

After the review in the third step, we retain 2122 patents filed between 2005 and 2014 as being actually relevant to PV BOS innovation, and this set forms the basis of the analysis reported below. The fourth step is to extract the date and the location (province) of each patent. A patent has three important dates: filed date, application announcement date, and invention authorized date. Filing date is the better choice for measuring when an innovation actually took place (Griliches, 1990). We use location of the patentee to measure where an innovation took place. In this study, we include all 31 provinces, municipalities, and autonomous regions in China.

3.2. Measurement

We use the number of patents in PV BOS as the dependent variable to measure technology innovation in PV BOS. Though with limitations, patenting activity is frequently used as a meaningful proxy for measuring innovative activity. Numerous studies recognize that patent count is an appropriate and useful measure of innovative activity (Almeida et al., 2002; Choi et al., 2011; Griliches, 1990; Hausman et al., 1984; Jaffe and Trajtenberg, 2002; Lanjouw and Mody, 1996; Schmookler, 1962; Venugopalan and Rai, 2015). Patent data is also widely used in the literature as a measure of innovation in China (Choi et al., 2011; Choi and Williams, 2014; Dang and Motohashi, 2015; Sun

[2] For inverters, we review each claim to identify whether a patent has innovations in the following subcategories: power conditioning equipment and methods, power conversion equipment and methods, voltage detection, electrical safety, maximum power point tracking, electrical connection and management, and energy storage. For solar mounting/racking, we review each claim to identify whether a patent has innovations in the following subcategories: mounting hardware, structural equipment, connections and placement, solar tracking equipment, installation methods, and rails. For monitoring, we review each claim to identify whether a patent has innovations in the following subcategories: hardware maintenance/ repair, power generation continuity management, physical security and maintenance, remote diagnostics and alerts, system operation and control, and graphical interface. For site assessment, we review each claim to identify whether a patent has innovations in the following subcategories: remote geographic placement, shade detection/ estimation, estimation of PV output potential, and use of satellite imagery for placement.

and Du, 2010; Wang et al., 2015).

We acknowledge limitations of using patents as a measure of innovation. The number of patents does not map directly on to innovation (Botolfmaurseth and Verspagen, 2002). For example, implicit knowledge cannot be captured by patents. Likewise, not all firms are willing to protect their innovations by applying for patents, because they may not be willing to publicly disclose their ideas (Cohen et al., 2000). While there is no perfect measurement for innovation, given that patent data offer the most systematically compiled, spatially and temporally nuanced data about inventive activity in China (Choi et al., 2011) and the steps we take to check robustness of our results, we believe that patenting activity is an appropriate measure for the purposes of this study.

It is problematic to define the scope of demand-pull policy and categorize specific innovation-support policy as demand-pull policy or not (Kemp and Pontoglio, 2011; Taylor, 2008). A commonly-used measure of demand-pull policy in the PV industry is PV installed capacity (Dechezleprêtre and Glachant, 2014; Peters et al., 2012; Rai et al., 2013). In the case of distributed PV market in China, market demand is mainly created by government policies. Accordingly, we believe it is appropriate to use province-level distributed PV installed capacity as a proxy for demand-pull policy. The limitation of this measurement choice is that only three years of data are available in China, because the Chinese government began to promote the distributed PV industry and collect relevant data only since 2011. The limited availability of installed capacity data constrains our modeling choices. We discuss those limitations and how we address them in more detail below. Specific description of the measurement for each independent variable is provided in Section 3.3.

Since innovative activity is influenced by provincial-level innovation capacity and innovation environment (Cohen and Levinthal, 1990; Cooke et al., 1997; Lundvall, 2012; OECD, 2011; Porter and Stern, 2001; Prajogo and Ahmed, 2006), these factors need to be accounted for in our analysis. Provincial-level innovation capacity in China varies a lot (Sun and Liu, 2010; Yang and Lin, 2012). Innovative provinces might be more likely to engage in PV BOS innovation activities; thus, we use total number of patents in each province as a control for overall innovative capacity. The incentives for patenting likely vary across provinces, as provinces may implement various pro-patent policies and/or have variations in accessing the patenting system (Li, 2011). A province with more favorable patent promotion policies is likely to have more patenting activity. Thus the general propensity to patent may also be controlled by the total number of *all* patents in a province. In addition, the development of complementary sectors could also influence PV BOS innovation activities (Choi and Anadón, 2014; Pisano and Teece, 2007). We use earnings of four sectors including manufacturing, utility, wholesale & retail, and scientific & technical services as controls for development of complementary sectors. Table B1 in Supplemental information summarizes descriptive statistics of key variables and Table B2 shows the correlation table between the independent variables.

3.3. Empirical models

Since the number of patents is a type of count data, two appropriate count models are Poisson regression and negative binominal regression. Additionally, the number of patents for each province in this paper has over-dispersion. Since the mean and variance of a Poisson regression are the same, Poisson regression cannot be used for data with over-dispersion. However, a negative binominal distribution has two parameters, one of which is an over-dispersion parameter, thus negative binominal regression is a better choice for count data with over-dispersion.

In our database, variation of provincial level installed distributed PV within province over time only accounts for about 9% of the total variation[3] in provincial level demand, and variation of provincial level installed distributed PV between provinces accounts for 91% of the total variation. Variation of annual added installed capacity within province over three years (2012–2014) may not be enough for an efficient two-way fixed effect model. When variation across provinces is great but variation within each province over time is little, fixed effect estimates would be imprecise and standard errors are likely to be too large to tolerate (Allison, 2009). In this case, a random effect model that takes advantage of both within-province variation and between-province variation may be a better choice. Therefore, we use the Hausman Test to compare a random effect model and a fixed effect model. We estimated the following model by using both fixed effect estimation and random effect estimation[4]:

$$patent_{it} = (\mathrm{u}_t + \alpha_i) + \beta_1 \ln local_{it} + \beta_2 \ln nonlocal_{it} + \beta_3 \ln x_{it} + \epsilon_{it}, \tag{1}$$

$$patent_{it} = \mathrm{u}_t + \beta_1 \ln local_{it} + \beta_2 \ln nonlocal_{it} + \beta_3 \ln x_{it} + (\alpha_i + \epsilon_{it}), \tag{2}$$

$$patent_{it} = (\mathrm{u}_t + \alpha_g) + \beta_1 \ln local_{it} + \beta_2 \ln nonlocal_{it} + \beta_3 \ln x_{it} + \epsilon_{it}, \tag{3}$$

where the dependent variable $patent_{it}$ is the number of PV BOS patents[5] for province i in year t; $\ln local_{it}$ is logged local installed capacity (i.e., for a given province) of distributed PV for province i in year t; $\ln nonlocal_{it}$ is logged non-local installed capacity (i.e., all of China minus a given province) of distributed PV for province i in year t, and $\ln x_{it}$ is a vector of log of time variant control variables (fully listed in Table B1 of Supplementary information) for province i in year t. u_t is time fixed effects, which could be different for each year. α_i is the unobserved time-invariant individual effect, which only varies among provinces. ϵ_{it} is an error term. This error term is different for each province in each year. For the first fixed effect model (Eq. (1)), α_i and u_t are considered as a part of the intercept, so it allows correlation between α_i and the predictors. In a random effect model (Eq. (2)), α_i is considered part of the error term, so it does not allow any correlation between α_i and the predictors.

We expect that differences in learning processes exist between subcategories of PV BOS technologies (inverter, monitoring, mounting, and site assessment). Inverter technologies are expected to have the least local nature, compared to the other three subcategories, because inverters are closer to globally-traded products that are relatively easily adaptable to the local context. Therefore, we split the PV BOS patents into inverter and non-inverter (to include monitoring, mounting, and site assessment) patents, meaning that we use the total number of inverter and non-inverter patents as two separate dependent variables to run the regression models. The differentiation between inverter and non-inverter patents allows us to explore the technological dependence of whether or not local demand is a prerequisite for inducing localized innovation. Huenteler et al. (2016), Schmidt and Huenteler (2016), and

[3] Total variation includes both within-province variation and between-province variation.

[4] Two appropriate ways to model panel data are fixed effect models and random effect models. Fixed effect models can control for all time-invariant differences between individual units (provinces in this case). But if some unobservable variables vary over time but are fixed between individuals, random effect model might be a better choice. Random effect models have a strong assumption that unobservable variables are not correlated with observable variables in the empirical model. The *Hausman test* checks the validity of this assumption and enables to choose the more efficient model between the random effect model and the fixed effect model. If the result of the Hausman test is not statistically significant, it means the assumption that unobservable variables are not correlated with observable variables in the empirical model is not violated, thus coefficients of a random effect model and a fixed effect model are consistent, but the random effect model would be more efficient due to smaller standard errors.

[5] As explained later, what gets included in the 'number of PV BOS patents' depends on the model we build. For example, some models include all types of patents, while others include only inventions.

Quitzow et al. (2017) found that whether or not firms in developing countries without a large home market are able to catch up with developed economies in certain sectors depends on the nature of associated learning processes, suggesting the criticality of the location of demand in the development of comparative advantage. This provides the basis for our inverter/non-inverter split models. We expect that the effect of non-local demand on inverter patents will be much larger than the effect on non-inverter patents.

The inverter/non-inverter splitting serves another important purpose. While we use the total number of patents in a province to control for potential differences in propensity to patent *across provinces*, the potential differences in propensity to patent *across BOS categories* should also be taken into account. In principle, there are two reasons (Basberg, 1987; Fontana et al., 2009) that potentially cause differences in patenting propensity across BOS categories. First, it may be hard to codify an innovation as a patent. In the case of PV BOS, inverter technologies are most likely to be codified. But non-inverter technologies, such as installation methods, mounting skills, and personalized design, contain more tacit knowledge. As such they are relatively harder, and thus also less likely, to be codified. As a result, an inverter-related innovation is more likely to be filed for a patent. Second, inventors may believe that their innovations are not innovative enough to be granted patent, leading them to forgo attempting to patent, given the non-trivial effort and costs associated with the patenting process. In the case of PV BOS, non-inverter technologies are more likely to be incremental innovations, compared to inverter technologies, and thus are less likely to be filed as patents. Considering these two reasons, in order to account for the potential differences in propensity to patent across BOS categories, it is appropriate to split patents into inverter and non-inverter patents.

To check whether our regression results are sensitive to the quality of patent data, we conduct robustness checks by including only 'inventions', which are known to be of the highest quality among different types of patents in China. In other words, we redefine the dependent variable as the annual number of PV BOS *inventions* for each province from 2012 to 2014, thus excluding utility models and design patents when constructing the dependent variable. Another purpose of this robustness check is to compare the strength of the effects of local and non-local demand on all patents vs. only inventions (high-quality patents).

Finally, in order to further address the limitation posed by our relatively small sample size ($n = 90$) and the small variation in annual added installed capacity within the provinces over three years (2012–2014), we also develop an alternative model. Since the two-way fixed effect model including province fixed effect and year fixed effect will discard information (variation) across provinces and thus lead to large standard errors, in the alternative model we group provinces and estimate a two-way fixed effect model including year fixed effect and *group* fixed effect (Eq. (3)). In Eq. (3), α_g is the unobserved time-invariant *group* effect. We use three ways to group provinces. The first approach is based on geography, where we group provinces into seven groups: Eastern provinces, Northern provinces, Western provinces, Southern provinces, Central provinces, Northeastern provinces, and Southwestern provinces. The provinces in the same geographic areas share similar climate, culture, business environment, and economic growth conditions. The second approach is based on Gross Domestic Product (GDP). We rank the provinces according to provincial GDP in 2014 and group provinces into six groups according to the ranking: top 5 richest provinces, top 6–10 provinces, top 11–15 provinces, top 16–20 provinces, top 21–25 provinces, and top 26–31 provinces. The third approach is based on a comprehensive competitiveness index according to the province ranking in the "Blue book of China's provincial competitiveness" (Li et al., 2015). We also group provinces into six groups according to the ranking. Figs. C1–C3 in Supplementary information illustrate the three ways to group 31 provinces in China.

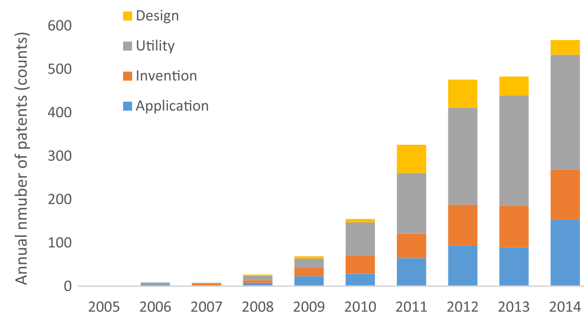

Fig. 2. Annual distribution of PV BOS applications, inventions, utility and design (counts).

3.4. Omitted variables and potential endogeneity

Omitted variable bias potentially exists, because location-specific variables and institution-relevant variables, such as social value, culture, norms, customs, and institutional structures, are potential confounding variables. However, these confounding variables typically change rather slowly, so we do not expect omitting them to impact the results from our models, which focus only on a three-year period. As such, since these confounding variables may be treated as time-invariant during our study period, they would be adequately controlled for through the province-level fixed-effects in our models.

Reverse causality – PV BOS innovations driving demand over the three-year study period – is not a major concern in this study, because the Chinese government's support for expanding the domestic PV market since 2011 is driven by a shrinking foreign market, Europe in particular. The effort in creating domestic market demand is to help the Chinese PV industry digest overcapacity and get through the downturn. Put differently, market demand (the independent variable) in this case is genuinely exogenous variation, which is not a result of the development of innovations in the field of PV BOS (the dependent variable) in China.

4. Results

4.1. Descriptive analysis of PV BOS patents in China

Our Chinese PV BOS patent dataset illustrates trends for PV BOS innovation activities in China from 2005 to 2014. Fig. 2 shows the number of PV BOS patents in China over time. The number of PV BOS patents increased from 2 in 2005 to 567 in 2014. A big jump in the number of PV BOS patents occurred in 2011, increasing by over 100% from 155 in 2010 to 326 in 2011, which is the year the Chinese government began to change policy direction from large-scale PV to distributed PV deployment. Under the Chinese government's strong support, installations of distributed PV in China increased from 0.6 GW in

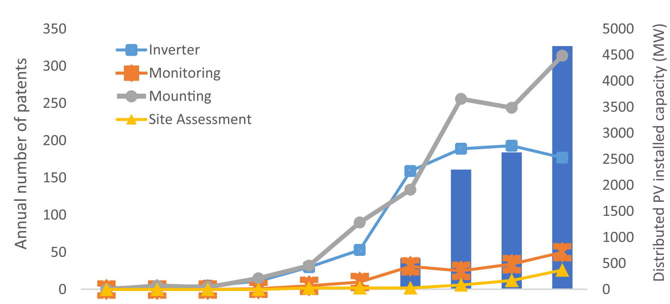

Fig. 3. Annual number of PV BOS patents including invention application, invention, utility and design (count), by category and installed capacity of installed distributed PV (MW). The left axis is the number of PV BOS patents (count) and the right axis is installed capacity of installed distributed PV (MW).

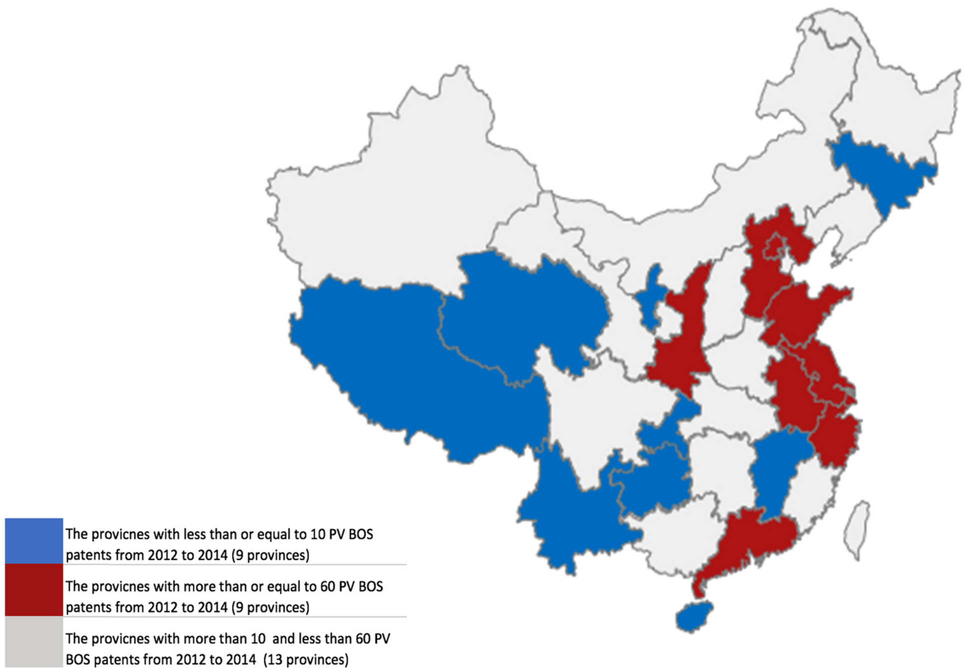

Fig. 4. Geographic distribution of the provinces with less than or equal to 10 PV BOS patents from 2012 to 2014 (blue) and the provinces with more than or equal to 60 PV BOS patents from 2012 to 2014 (red).

2011 to 2.3 GW in 2012. Utility patents account for a higher proportion of the total number of patents than inventions, which indicates that PV BOS patenting activity in China has tilted more toward incremental improvements rather than disruptive innovation.

Fig. 3 shows distribution of annual number of patents by category. The overall trend for all four categories is increasing from 2005 to 2014. The relatively flat number of inverter patents since 2012 mainly results from the decreasing number of design patents filed (which refer to new designs for a product's appearance, shape, and color). The number of monitoring patents and site assessment patents have increased slowly but steadily since 2011. Patenting activity related to mounting is more relevant to the expansion of local markets, since better understanding of local context, such as buildings and rooftops, provides comparative advantage for local firms.

The geographic distribution of PV BOS patenting activity correlates with the geographic distribution of distributed PV installations in China. Figs. 4 and 5 show the geographic distribution of both distributed PV installations and number of PV BOS patents. Nine provinces in China[6] have few PV BOS patents during 2012–2014, which coincides with almost zero distributed PV installation in these provinces; these provinces mainly focus on utility-scale PV systems. Five provinces[7] have more than 100 PV BOS patents in China during 2012–2014, three of which (Jiangsu, Guangdong, and Zhejiang) are the top three provinces with highest cumulative distributed PV installations. These richer provinces suffer from frequent electricity shortages, but land-intensive utility-scale PV conflicts with their scarce and expensive land. As a result, distributed PV is a reasonable and necessary choice for these rich Eastern provinces.

4.2. Regression model results

Regression results for Eqs. (1) and (2) are presented in Table 3. Column 1 shows the regression results of the two-way fixed effect model. We are interested in the effect of local demand and non-local demand on PV BOS innovative activity. The results show that local demand has a positive relationship with local PV BOS patenting activity, but that non-local demand has a negative relationship with local PV BOS innovation. Neither of these two coefficients is statistically significant, which is consistent with our previous expectation that only 9% of variation within provinces over three years in our database could lead to large standard errors. Column 2 shows the regression results of the random effect model. The random effect model takes advantage of variation between provinces and within provinces over time. The result of the Hausman test shows that the coefficients of the two-way fixed effect model (model 1) and the random effect model (model 2) are consistent, but estimates of the random effect model (model 2) are more efficient, which means the random effect model is a more appropriate model. The results of the random effect model show that the effect of local demand for distributed PV in stimulating local PV BOS innovation is positive and statistically significant.

The regression results shown in column 3 of Table 3 try to follow the approach used in Peters et al. (2012). The methodology used in Peters et al. (2012) includes an aggregated time trend variable to reflect three development phases of PV in Europe. For Europe, Peters et al. (2012) defines 1974–1985 as the first time-trend, 1986–1994 as the second time-trend, and 1995–2009 as the third time-trend, and thus use time-trend fixed effect instead of year fixed effect, which would be much more granular (as is the case with model 1 and model 2 in Table 3). In our case, since (for modeling purposes) we have data for only three years (2012–2014) and all these three years may be taken to be part of the first boom of distributed PV development in China, we take this to mean that we have only one time-trend. Thus, in effect, this means that we do not need a dummy variable for this time trend. Therefore, model 3 includes only the province fixed effect. The results of model 3 are similar to those of model 2. Both models show that local demand (i.e., within a province) can positively stimulate local PV BOS innovations. As expected, the total number of patents in each province is also statistically significant. The total number of patents reflects the overall innovative capacity of each province, which is positively related to the number of PV BOS patents.

Table 4 shows the regression results of our province grouping

[6] These nine provinces include: Xizang, Guizhou, Jilin, Ningxia, Shanxi, Chongqing, Jiangxi, Hainan and Qinghai.

[7] These five provinces include: Jiangsu, Guangdong, Zhejiang, Shanghai and Beijing.

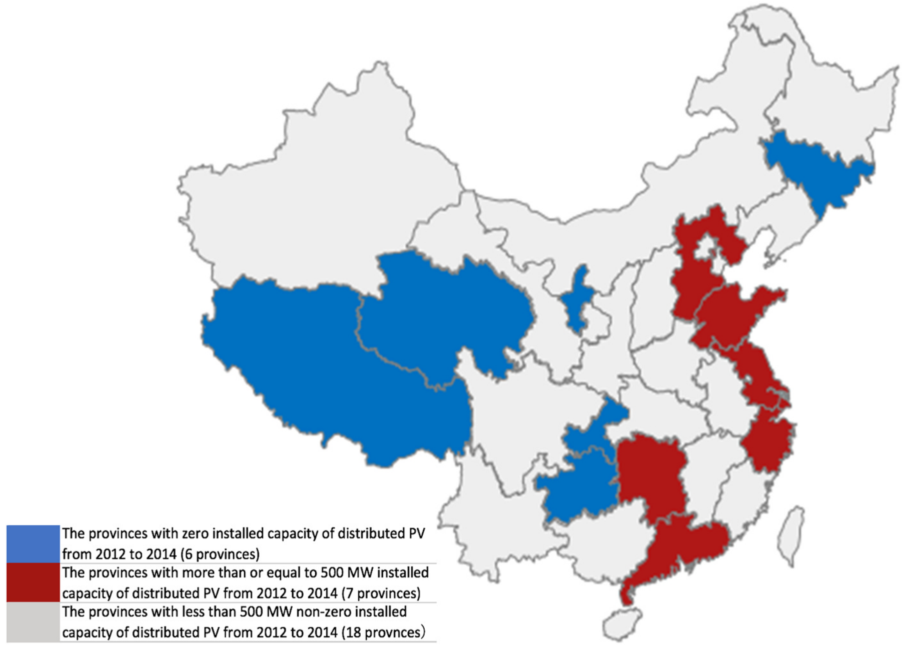

Fig. 5. Geographic distribution of the provinces with nearly zero MW installed capacity of distributed PV from 2012 to 2014 (blue) and the provinces with more than or equal to 500 MW installed capacity of distributed PV (red).

Table 3
Regression results for Eqs. (1) and (2) using different estimation methods.

	Model 1 Fixed effect	Model 2 Random effect	Model 3 Fixed effect
Log local demand (MW)	0.121 (0.127)	0.208*** (0.0770)	0.244** (0.0987)
Log non-local demand (MW)	− 3.096 (2.069)	− 2.426 (1.879)	− 0.893 (0.578)
Log total patent (counts)	0.536* (0.275)	0.505*** (0.113)	0.453* (0.257)
Log manufacture salary (¥)	0.868 (2.223)	− 0.420 (1.420)	0.466 (2.107)
Log utility salary (¥)	0.770 (0.785)	− 0.116 (0.568)	0.748 (0.800)
Log wholesale & Retail salary (¥)	2.435* (1.336)	1.615 (1.077)	2.041 (1.344)
Log scientific & technical services salary (¥)	− 0.657 (0.933)	0.332 (0.630)	− 0.957 (0.944)
Constant	− 14.33 (23.54)	0.454 (15.64)	− 19.67* (11.95)
Year fixed effect	Yes	Yes	No
Province Fixed effect	Yes	No	Yes
Observations	90	90	90

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

approach to address the problem that variation within province over time only accounts for 9% of total variation in province-level annual installed capacity (see Section 3.3). As discussed in Section 3.3., we apply three ways to group provinces and include both year fixed effect and group fixed effect in these three models (Eq. (3)). Models 4, 5, and 6 (Table 4) show regression results for the model grouping provinces based on province ranking in the "Blue Book of China's Provincial Competitiveness (2015)," geography, and GDP, respectively. The coefficients of local demand in all three models are positive and statistically

Table 4
Regression results for different grouping methods (Eq. (3)), based on competitiveness index according to the city ranking in the "Blue book of China's provincial competitiveness," geography, and GDP.

	Model 4 Fixed Effects Group by index	Model 5 Fixed Effects Group by geography	Model 6 Fixed Effects Group by GDP
Log local demand (MW)	0.257** (0.107)	0.165** (0.0757)	0.241** (0.0952)
Log non-local demand (MW)	1.010 (3.189)	− 2.703 (2.379)	− 2.847 (3.367)
Log total patent (Counts)	0.626*** (0.156)	0.748*** (0.0963)	0.666*** (0.164)
Log manufacture salary (¥)	0.271 (1.400)	− 1.829* (1.028)	− 0.432 (1.515)
Log utility salary (¥)	− 0.161 (0.634)	− 0.103 (0.610)	0.00903 (0.732)
Log wholesale & Retail salary (¥)	0.224 (1.309)	0.391 (0.976)	0.00388 (1.511)
Log scientific, & technical services salary (¥)	0.784 (1.007)	1.039* (0.553)	1.207 (0.766)
Constant	− 24.47 (24.07)	18.87 (20.20)	7.743 (29.10)
Year fixed effect	Yes	Yes	Yes
Group Fixed effect	Yes	Yes	Yes
Observations	90	90	90

Robust province cluster standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

significant, ranging from 0.17 to 0.26. The magnitude and standard error of the coefficients of local demand in model 4 and model 6 are consistent with our results in model 2 and model 3. All these models show that *only* the local demand for distributed PV significantly promotes local PV BOS innovation, and that non-local demand for distributed PV does not affect local PV BOS innovation.

Table 5
Regression results for differentiation between inverter and non-inverter patents. Note that Model 7 is the same as Model 2.

Dependent variable	Model 7 All BOS patents	Model 8 Inverter patents	Model 9 Non-inverter patents
Log local demand (MW)	0.208*** (0.0770)	0.267** (0.105)	0.217** (0.0910)
Log non-local demand (MW)	− 2.426 (1.879)	0.998 (2.826)	− 3.091 (2.104)
Log total patent (counts)	0.505*** (0.113)	0.727*** (0.147)	0.445*** (0.127)
Log manufacture salary (¥)	− 0.420 (1.420)	1.854 (1.904)	− 2.724 (1.684)
Log utility salary (¥)	− 0.116 (0.568)	− 1.444** (0.732)	0.945 (0.672)
Log wholesale & Retail salary (¥)	1.615 (1.077)	− 0.755 (1.414)	2.904** (1.360)
Log scientific, & technical services salary (¥)	0.332 (0.630)	0.260 (0.875)	0.871 (0.739)
Constant	0.452 (15.64)	− 14.21 (22.61)	− 0.0751 (17.61)
Year fixed effect	yes	yes	yes
Observations	90	90	90

Standard errors in parentheses. *$p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 6
Regression results for including only inventions in the dependent variable.

Dependent variable	Model 10 All BOS inventions	Model 11 Inverter inventions	Model 12 Non-inverter inventions
Log local demand (MW)	0.249** (0.120)	0.274** (0.136)	0.391* (0.221)
Log non-local demand (MW)	1.183 (3.289)	5.704 (3.906)	− 3.591 (4.253)
Log total patent (counts)	0.700*** (0.162)	0.907*** (0.191)	0.564** (0.236)
Log manufacture salary (¥)	− 0.0484 (2.114)	2.729 (2.173)	− 2.804 (3.556)
Log utility salary (¥)	− 0.607 (0.835)	− 2.161*** (0.749)	1.157 (1.360)
Log wholesale & Retail salary (¥)	0.812 (1.729)	− 0.657 (1.728)	2.229 (2.604)
Log scientific, & technical services salary (¥)	0.131 (1.002)	− 0.518 (0.863)	1.053 (1.299)
Constant	− 19.41 (26.28)	− 48.18 (30.52)	18.78 (1012.7)
Year fixed effect	yes	yes	yes
Observations	90	90	90

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5 shows the regression results for models where we split the patents into inverter and non-inverter patents. The dependent variables in models 7, 8, and 9 are, respectively, the annual number of all BOS patents[8] at the province level, the annual number of inverter patents at the province level, and the annual number of non-inverter patents at the province level. The coefficients of local demand are consistent with the results of model 1–model 6 (Tables 3, 4), further confirming that local demand has an essential role in spurring local innovative activity in PV BOS. While the coefficients of non-local demand are not significant, likely due to limited variation in the non-local demand variable, the opposite signs of the coefficient estimates on inverter and non-inverter patents offer interesting insights. The coefficient for non-local demand on inverter patents is positive, while it is negative on non-inverter patents. This indicates, as expected, that innovations in inverters – a technology that is more globally traded than any of the other BOS categories considered here – could potentially learn from non-local markets. This also helps explain why non-local demand seems to have little or no impact on BOS innovations but positively impact innovations in PV modules. Essentially, previous literature suggests that innovation in PV modules is a phenomenon of global learning, but innovation in PV BOS, on the other hand, is strongly driven by local learning (Neij et al., 2017; Shum and Watanabe, 2008; Wene, 2000; Wiser et al., 2007). Since local learning is predominantly driven by local demand, local learning appears to be the linkage between the positive impact of local demand on PV BOS technologies. In other words, these results suggest that whether or not a local market is a precondition for inducing local innovative activity depends on technology characteristics: local market has an essential role for technologies that have a significant local nature and, thus, depend on local learning for innovations in them.

Table 6 shows the regression results for models where the dependent variable includes only patent inventions, which are known to be of the highest quality among different types of patents in China. To be specific, the dependent variable in models 10, 11, and 12 are the annual number of all inventions[9] at the province-level, the annual number of inverter inventions at the province-level, and the annual number of non-inverter inventions at the province-level, respectively. These regression results are consistent with previous models (Tables 4, 5). As before, only local demand has a significant and positive effect on local innovations. Results from these models also indicate that the strength of the effect of local demand on BOS inventions (high-quality patents) (model 10) is somewhat larger than the effect on all BOS patents (model 7). Most interestingly, as expected, the coefficient of local demand on non-inverter inventions (model 12) is much larger compared to inverter inventions (model 11), which may indicate that local demand has a stronger positive effect on non-inverter inventions compared to inverter inventions. This finding needs to be tempered, though, since the coefficient of local demand on non-inverter inventions (model 12) is significant only at the 10% level. Overall, these results suggest that local demand might play a critical role in inducing high-quality local patents in PV BOS. This intuitively makes sense, since larger demand offers greater opportunity to benefit from innovations – and the magnitude of those benefits, in turn, will be larger for higher-quality patents, thus providing a multiplicative incentive.

5. Discussion and limitations

Our results show that for PV BOS in China only local demand significantly induces *local* PV BOS innovation, while non-local demand has no effect. This emphasizes that local demand could translate into local innovative activity. But why should local PV BOS innovation be spurred only by local market experience (i.e., demand)? We suggest that learning by doing and learning from geographical agglomeration are the two main mechanisms through which such a translation might happen.

On one hand, with expanding local markets, installers have more

[8] 'All BOS patents' include invention announcements, invention authorization, utility models, and design patents.

[9] Inventions in China are *granted patents* that typically have the highest quality among different types of patents in China.

opportunity to learn about local factors relevant to the design and installation of a PV system, such as local roof structures, codes and standards, supply-chain, and the nature of consumer demand – which, for novel technologies such as PV is expected to have market-specific heterogeneity, especially in early phases of the market. Such local installation experiences provide increased opportunities for installers to improve and update their PV BOS related products and services. On the other hand, with increasing local demand, knowledge gained by each firm operating in the local market contributes to the overall local pool of knowledge. A stronger local knowledge base, in turn, also improves local firms' innovative potential. Such knowledge is often described as if *it were in the air*, and local firms benefit from local knowledge just because of "being there" (i.e., without having to expend much effort). Moreover, from the view of competition, in order to compete better in the local market, local competition pushes firms in the local cluster to improve their practices and innovations (Bathelt et al., 2004).

However, the perspective of geographic agglomeration also highlights an inherent limitation of this paper: our analysis does not fully capture the benefits associated with tacit knowledge that are gained from local clusters, because inventive activities that are captured by patent data mainly embody codified knowledge. Geographic agglomeration is expected to be more important for tacit knowledge, as the spillover of tacit knowledge significantly benefits from face-to-face communication, deep interaction, and even local gossip, and the difficulty in codifying tacit knowledge prevents its diffusion to other locations (Gertler, 2003; Haldin-Herrgard, 2000; Venkitachalam and Busch, 2012). Thus, using only patenting activity as a measure of innovative outcome in this paper means that we likely *underestimate* the effect of local demand on local innovations in PV BOS.

It is worth noting three other limitations of our analysis and how we have tried to address them. First, as noted before, patenting activity is not necessarily a good measure of technological innovation. Previous literature particularly points to concerns about the quality of Chinese patents compared to that of U.S. or European patents. In this paper, because the timeframe of our analysis is very recent (2012–2014) to effectively detect forward citations, we are unable to weight patent count by using forward citations as a way of addressing the quality of patents. Instead, we conduct a robustness check by excluding utility models and design patents – known to be lower quality patents in China – from our models in order to check whether our regression results are sensitive to the quality of patent data. Dropping lower quality patents does not change our main findings. A second noteworthy limitation of our analysis is that fixed-effects models have limited ability to infer causal relationships, compared to conducting random experiments. Previous literature shows that confounding variables, especially institutional factors and various patenting incentives across provinces, should be carefully controlled for in studies using China patent data. In this paper, we do not include data on provincial-level institutional factors. However, we believe that these institutional factors, such as social value, culture, norms, customs, and institutional structures, are slow-changing variables. As such, these factors may be expected to not change significantly within three years (2012–2014, the focus of our analysis). Thus, we include province fixed-effects in our models to control for these (time invariant) variables. Thirdly, PV installed capacity is a commonly-used proxy measure for demand-pull policy in the PV industry (Dechezleprêtre and Glachant, 2014; Peters et al., 2012; Rai et al., 2013). This is partly because it is problematic to define the scope of demand-pull policy and categorize specific innovation-support policies as demand-pull policy or not (Kemp and Pontoglio, 2011; Taylor, 2008). Yet, we acknowledge that using distributed PV installed capacity at the province level as a proxy for local demand pull is not the most direct way to measure demand-pull policies. Future work could try to address this limitation by leveraging the variation of specific demand-pull policies province-by-province to improve measurement of the local demand-pull variable.

6. Conclusion and policy implications

In this paper we have addressed the following question: is local demand essential in inducing local innovation? Our empirical design exploits the subnational variation in (policy-created) demand to study the impact of geographically-differential (local vs. non-local) demand on local innovation. Specifically, we use a new patent dataset for photovoltaic balance-of-system technologies at the province level in China to study the effect of local demand and non-local demand on province-level PV BOS innovation.

Geographic distribution of distributed PV installations is unequal across the 31 provinces in China, but it is strongly correlated with geographic distribution of PV BOS patents. The consistency between the explosion of PV BOS patents and local demand is especially telling in the case of mounting technologies: to enable adequate physical support over the life of the PV system (20–30 years), mounting equipment need to be designed for *local* climatic conditions and variations therein, rooftop structures, and framing and roofing materials. Thus, greater local demand is expected to strongly drive innovations in mounting technologies to cater to that local demand, as we indeed find to be the case.

We find that only local demand for distributed PV significantly contributes to local PV BOS innovation in China. This suggests that local distributed PV markets created by demand-pull policies (of both provincial and local governments) significantly promotes (only) local innovative activity in PV BOS. The effect of non-local demand on patenting activity in inverters, while insignificant, is large and positive, but is negative on patenting activity in non-inverter BOS technologies. This suggests, consistent with expectations, that innovations in inverters may benefit from non-local markets, given the more fungible nature of inverter technologies. As expected, overall innovative capacity at the provincial level – as measured by all (i.e., not just PV BOS) patenting activity within each province – significantly and positively affects PV BOS innovation. The significantly different effects of local demand and non-local demand indicate that local context (including local knowledge and local experience) is a key element in the learning and innovation process for PV BOS. The importance of local knowledge and local context in demand-induced hypothesis has a valuable market implication: to the extent innovation depends on local knowledge, it advantages local firms more, since they presumably have better knowledge of the local context. In such cases local demand-pull policies may be more politically feasible, since policymakers would view the potential economic benefits from market creation to be more appropriable by local actors.

Furthermore, our findings serve to inform that drivers of innovation depend on market *and* technology characteristics. PV BOS helps emphasize that within the same technology (an integrated PV system, here) the technological trajectories of different subcomponents (modules, inverters, etc.) potentially interact differently with local market conditions. Previous studies have suggested that different learning processes are likely at play for PV cell/module vs. PV BOS (Neij et al., 2017; Shum and Watanabe, 2008; Wene, 2000; Wiser et al., 2007). PV module innovation is a phenomenon of global learning, and there is no clear boundary between local PV module learning and global PV module learning. However, PV BOS innovation is strongly driven by local learning, which comes from accumulated learning of installations in specific, local markets (Neij et al., 2017). The differences in technology characteristics and the associated learning processes help explain the apparent inconsistencies of our findings with the results of Peters et al. (2012). Peters et al. (2012) analyzed innovation that is directly related to PV cells and modules. They noted that user feedback and producer-user interaction are weak for PV cells and modules[10] – a

[10] But even for PV cell and modules, a technology that faces a global market, Peters et al. (2012) found that local (national) demand-pull policy can promote

situation that does not hold for PV BOS technologies, the focus of our study.

Moreover, differences in learning processes are not limited to just between PV cell/module and PV BOS technologies; rather, those differences exist even between *subcategories* of PV BOS technologies (inverter, monitoring, mounting, and site assessment). Indeed, we find that for the highest-quality patents (i.e., *inventions* in the Chinese patent system) local demand has a *stronger* positive effect in inducing innovation in non-inverter BOS technologies compared to inverters. This is consistent with the fact that mounting structures and site assessment technologies have the most prominent local nature. In the case of inverters, on the other hand, although local demand is still a significant factor in spurring innovation, we also find weak support that inverter innovations in China may have been driven by non-local markets. Overall, these findings suggest that whether local demand is an essential precondition to local industry development (i.e., innovations) depends on technological characteristics and the nature of associated learning processes, highlighting the need to open the “technology black box”. In other words, a better understanding of the impact of market-creation policies on the geography of innovation necessitates accounting for technology characteristics and, in particular, how those characteristics accentuate certain learning processes over others.

Our findings also inform the discussion on ‘green industry development’. The ultimate goal of green industrial policies is to integrate multiple policy goals including, but not limited to, environmental protection, energy security, technological innovation, and economic competitiveness (Rodrik, 2014; Schmidt and Huenteler, 2016). Our results suggest that demand-pull policies for the distributed PV market in China have significantly shaped local innovative activities. However, the important role of local demand-pull policy in inducing innovation has been challenged by the fact that China has taken the lead in the PV module manufacturing industry even in the absence of a large domestic solar PV market demand when PV manufacturing in China flourished (Gallagher, 2014; Huenteler et al., 2016; Schmidt and Huenteler, 2016). These arguments have raised a critical question to the literature on green industrial policy: is local demand essential in the development of green industry? Our study suggests that the answer to this question depends, at least in part, on technology-specific factors. Specifically, by comparing technology subcategories within PV BOS as well as comparing PV BOS technologies with PV module, we find that technology characteristics are critical factors in explaining the role of local demand in green industry development. If learning and innovation processes depend on local context, then local demand is a prerequisite for developing a local competitive industry. Moreover, most empirical studies that have explored this locational aspect have focused at the national level (i.e., domestic vs. foreign). Thus our use of sub-national policy and demand variation adds a new perspective to the literature on this topic. Importantly, our study hints that the arguments typically made in the discussion regarding green industry development may also be applicable to sub-national levels of policy-making. Demand-pull policy could be an important strategic element in the local policy mix of developing green industry, particularly, for technologies that have a significant local nature. By the same token, it also might be difficult for lagging provinces/states to close the technology innovation gap without developing a stable local market demand. This perspective of looking at the sub-national level is especially important for large countries, such as China, but it may be less relevant to small countries.

The success of subnational governments’ efforts in expanding market demand and translating it into local innovative activities underscores the potential viability of a bottom-up approach to renewable energy governance, at least for some technologies. The localized economic gains from expanding local market demand could mobilize a large number of subnational actors in support of advancing certain renewable energy technologies locally. Thus, if the central/federal government is slow to move on environmental policies, or only focuses on supporting export-led growth, subnational policymakers could still take voluntary, interest-driven actions to expand the market demand for renewable energy, because they would view the potential economic benefits from market creation as more appropriable by local actors. These subnational actions could be voluntary and interest-driven, thus potentially underlying a viable mechanism for the bottom-up approach, even if not coordinated.

Finally, one fruitful direction for further work could be development of a *framework* to explain the conditions under which local demand is a prerequisite for developing a competitive local industry. These conditions include, but are not limited to, technology characteristics, the degree of market maturity, the development stage of technology, local policies, and local institutional ecosystem. This broader framework can help generalize the results of solar PV BOS to other technologies. A broader framework that *situates* the role of local demand in inducing local innovation could further help explain relevant mechanisms of localized learning.

(*footnote continued*)
PV cell and module innovation, although the inducement effect on innovation is roughly equal for local and foreign demand.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2018.12.056.

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