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Do carbon offsets offset carbon?

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Abstract
We develop and implement a new method for identifying wasted subsidies, and use it to provide systematic evidence on the misallocation of carbon offsets in the Clean Development Mechanism - the world's largest carbon offset program. Using newly constructed data on the locations and characteristics of 1,350 wind farms in India - a context where it was believed, ex-ante, that the Clean Development Mechanism could significantly increase development above baseline projections - we estimate that at least 52% of approved carbon offsets were allocated to projects that would very likely have been built anyway. In addition to wasting scarce resources, we estimate that the sale of these offsets to regulated polluters has substantially increased global carbon dioxide emissions.

Key words: carbon offsets, infra-marginal support, misallocation, investment, subsidies, wind power.
JEL: H23, H43, L94, Q42, Q54.

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1 Introduction

Carbon offsets have become a popular tool in global efforts to mitigate climate change. These programs work by offering regulated polluters the opportunity to increase their own emissions if they subsidize equivalent emission reductions in unregulated markets. In theory, this allows the same total emissions abatement to be achieved at lower cost. The world's largest carbon offset program—the Clean Development Mechanism (CDM)—has supported more than $90 billion of renewable energy investments in developing countries, equivalent to 13% of their total renewable energy investments (Kossoy et al., 2015).

A key unanswered question is whether these carbon offsets resulted in additional emissions reductions in unregulated markets. If carbon offsets are awarded to projects that would have been developed without the subsidy, they do not represent emissions savings. This results in an inefficient allocation of scarce climate change mitigation resources and a net increase in global emissions. Researchers have struggled to quantify such misallocation due to the difficulty of identifying a credible counterfactual.

In this paper we propose a new approach to identifying projects that would have been built without a subsidy, and use it to provide systematic evidence on carbon offset misallocation in the CDM. Our approach identifies a subset of all infra-marginal projects, which we refer to as Blatantly Infra-marginal Projects (BLIMPs). BLIMPs are not just infra-marginal, but blatantly so, in the sense that there exist other projects that are strictly less profitable, yet were built without the same subsidies. The number of BLIMPs provides a lower bound on the degree of subsidy misallocation.

Our approach does not require us to estimate the net benefits of each project. This would require strong assumptions and be incredibly data intensive. Instead, we derive sufficient conditions for identifying project dominance based on observable characteristics. We determine that, conditional on being built in the same state and year, a subsidized wind farm strictly dominates an unsubsidized farm if it has a higher capacity, and is built in a windier location, and is built closer to a connection point. In this setting, these three conditions are sufficient to define a BLIMP.

As an illustration, consider the case of the 91.8 megawatt CDM-supported wind farm built in Jangi, Gujarat, in 2011. We observe that an unsubsidized wind farm was completed during the same year, just 10 miles away in Surajbari. The unsubsidized project had a capacity of only 7.5 megawatt, was estimated to deliver about 5% less power per installed megawatt because of less favorable wind resources, and was located 3 miles further away from the nearest electrical substation. These two wind farms were built in the same state and year, and were therefore subject to the same policies and market conditions, yet the CDM-supported project was both bigger and better located. We show that the existence of the less profitable unsubsidized project at Surajbari is a sufficient condition for identifying the larger CDM-supported wind project as a BLIMP.

To understand how prevalent this phenomenon is, we apply our framework to a new data set of 1,350 wind power projects in India—a context where it was believed, *ex ante*, that the CDM could significantly increase development above baseline projections (Purohit and Michaelowa, 2007). We independently geo-locate all of the Indian wind power projects identified by Bloomberg New

Energy Finance at the village-level (BNEF, 2013), and then cross-reference them with individual CDM applications from the UN Environment Program's CDM Pipeline database (UNEP DTU, 2021). For each project-site, we forecast power output using the hourly distribution of wind speeds and weather conditions from the European Centre for Medium-Range Weather Forecasts' global reanalysis data set (Muñoz Sabater, 2019). We also estimate the cost of connecting each wind farm to the electrical grid by using detailed grid-infrastructure data from Burlig et al. (2020). This provides a comprehensive database covering 1,350 Indian wind farms built between 1992 and 2013, of which 472 were registered to receive carbon offsets under the CDM.

Out of the 472 CDM-registered Indian wind farms in our data, we identify 265 BLIMPs. For each of these 265 projects, we can point to at least one unsubsidized wind farm built in the same state and year that is strictly less profitable. These projects account for 52% of carbon offsets approved for Indian wind projects. Under the assumption that these credits were later used by regulated entities to augment their emissions quotas, global emissions will have increased by 28 million tonnes of carbon dioxide emissions, equivalent to keeping a one-gigawatt coal plant running for nearly 5 years.[1] The misallocation is so severe that we find that the random assignment of subsidies through a lottery would have resulted in fewer offsets being allocated to BLIMPs.

Our findings are robust to a broad range of sensitivity tests. For instance, our results remain qualitatively similar even if we systematically deflate the power output and inflate the connection costs of CDM projects by as much as 20%. This addresses concerns that unobserved systematic differences between CDM and non-CDM projects could be driving our results. These differences could arise from measurement error in our data or from differential barriers to entry, such as credit or political economy constraints. We show that a confounding explanation would have to be almost perfectly correlated with a project being marginal and the CDM's observed decisions in order to undo our findings. Even if we assume that all BLIMPs are partially infra-marginal, i.e., that they would have been built in the absence of the subsidy, but to a smaller capacity, the CDM's allocation of carbon offsets still only performs on par with the lottery assignment mechanism.

Do carbon offsets offset carbon? Our analysis suggests that in many cases they don't. Carbon offsets are frequently given to BLIMPs, which means that they do not generate the emissions reductions needed to offset the emissions increases that they enable. It is still possible, however, that the remaining CDM-supported wind farms have offset more than their share of emissions. To counterbalance the increase in emissions from subsidizing BLIMPs, we would have to assume that the CDM-supported wind farms that are not BLIMPs reduced India's carbon emissions by 2.12 tonnes per offset. This is equivalent to assuming that all non-BLIMPs are marginal and collectively responsible for the realization of half of India's non-CDM wind power capacity.[2] This theoretical possibility doesn't undermine our finding that the CDM has subsidized a large number of infra-

[1] For scale, the average conventional coal plant in the US in 2019 had a capacity of 808 MW, according to figures reported by the US Energy Information Administration.

[2] Infra-marginal projects may also result in agglomeration effects, crowding in non-CDM capacity due to economies of scale. However, any crowding in that arises from infra-marginal CDM projects is also infra-marginal. These agglomeration effects would have arisen absent CDM support.

marginal projects. If our estimates are valid for the CDM as a whole, and we do not assume any indirect emissions reductions, the program will have approved enough offsets to increase global emissions by 6.1 billion tonnes of carbon dioxide, the equivalent of operating roughly 20 one-gigawatt coal plants for their entire 50-year lifespan.

These findings contribute most directly to our understanding of carbon offset programs. Carbon offsetting is an increasingly important policy tool. A growing number of countries and organizations are now committing themselves to achieving "net zero" carbon emissions (Black et al., 2021), and international negotiations are underway to develop and implement a successor to the CDM (Michaelowa et al., 2019). It is critical to carefully consider the design of these programs going forward to ensure that carbon offsets actually offset carbon. Previous work has already identified particular industrial processes that should not be subsidized with carbon offsets (Wara, 2007a,b; Schneider, 2011; Schneider and Kollmuss, 2015), but our results identify a significant misallocation of resources even for the type of projects that the CDM was made to support. Our study suggests that, despite good intentions, the CDM may actually have increased emissions. In this regard, our paper connects to a large literature documenting how well-intentioned policies can have unintended consequences (Davis, 2008; Oliva, 2015; Holland et al., 2016; Agan and Starr, 2017; Parker and Vadheim, 2017; Bharadwaj et al., 2019; Taylor, 2019; Doleac and Hansen, 2020; Filmer et al., 2021).

Our paper also contributes to the study of a broader class of policies that leverage the logic of offsetting. This includes everything from Corporate Average Fuel Economy standards (Kwoka, 1983; Anderson and Sallee, 2011; Ito and Sallee, 2018) to Renewable Portfolio Standards (Cullen, 2013; Gowrisankaran et al., 2016; Carley et al., 2018) to key provisions of the Clean Air Act (Shapiro and Walker, 2020). Compared with the traditional approach of using tax revenue to subsidize emissions-saving activities, these policies work by getting the private sector to cross-subsidize those activities directly without the funds passing through the public treasury. While this approach has some appeal, our findings highlight a very real downside. Unlike a traditional subsidy program, the consequence of misallocating offsets isn't just to create an inefficient transfer. It also generates external costs by underwriting an increase in global emissions. When choosing between offset-style regulation and the more traditional subsidy model, the potential external costs from misallocation should be an important consideration.

We also contribute to a broader literature that seeks to identify the existence and magnitude of infra-marginal support in subsidy programs. The empirical challenge in identifying infra-marginal carbon offsets is similar to the problem that researchers have faced when trying to determine whether new technologies would have been adopted without rebates (Chandra et al., 2010; Boomhower and Davis, 2014), whether firms would have invested in additional innovation without special tax credits or grants (Hall and Van Reenen, 2000; Bloom et al., 2002; Dechezlepretre et al., 2016; Howell, 2017; Azoulay et al., 2019; Pless, 2021), or whether firms or workers would have moved in the absence of discretionary incentives (Moretti and Wilson, 2014; Slattery, 2019; Mast, 2020; Slattery and Zidar, 2020). In certain cases, researchers have managed to find and exploit discontinuities in rules that have allowed for causal identification. However, this is not the norm. We have explored opportunities to apply these research designs in the context of carbon offsets and are not aware of any successful applications. Our framework offers a different approach to systematically evaluating grant-based subsidy programs.

To apply our framework three conditions must be met. First, one needs a context in which some activity is not subsidized (these activities are infra-marginal by definition). Second, one needs to establish which conditions are sufficient for project dominance. Third, one needs data to evaluate these conditions. We believe that our framework could be applied to grant-based agricultural subsidies, small-business grants, innovation grants, concessionary financing programs, and to other grant-based subsidy programs aimed at supporting renewable energy technologies, such as solar power and production of biofuels.

2 Institutional Background

In this section, we provide relevant institutional details about the CDM, discuss how marginal and infra-marginal projects are distinguished in practice through the registration process, and provide background information on the Indian wind power sector.

2.1 The Clean Development Mechanism

The Clean Development Mechanism (CDM) is the largest pollution offset program in the world. It was established as part of the Kyoto Protocol in 1997. Under this program, industrialised countries that had committed to reducing emissions domestically were permitted to meet some of their obligation by developing or financing equivalent emission reductions projects in developing countries. This additional flexibility ostensibly achieves the same global emissions reduction at a lower cost. In practice, the exchange of financing and emissions would be accomplished by the UN issuing Certified Emission Reduction (CER) credits to approved projects in developing countries, each CER signifying one avoided tonne of carbon dioxide. Those credits could then be sold to regulated firms in developed countries and counted towards their country's Kyoto target.

From a project developer's perspective, the CDM is much like any other subsidy program. Although developers don't receive money directly from the UN, they do receive valuable CERs that can be exchanged for money on the open market, including through the sale of carbon offset futures. It is the promise of this extra money that was intended to lure developers to build more renewable energy projects than they otherwise would have.

The CDM has been an extremely popular program. By 2030, it is expected that the CDM will have issued up to 11.8 billion credits, equivalent in magnitude to the total emissions of the United States and Europe in 2019. China (6.55 billion), India (1.32 billion), and Brazil (0.7 billion) account for over 70% of these credits. Over half of all CERs finance just two types of projects: hydro power (27%) and wind power (24%), the latter being the focus of our study. It has been estimated that the CDM has supported over $90 billion of renewable energy investment in developing countries, or roughly 13% of their total renewable energy investment (Kossoy et al., 2015). Although the CDM is now no longer accepting new applications, the Paris Agreement promises to expand the program under a new name: the Sustainable Development Mechanism.

To register under the CDM, a project had to go through two stages of evaluation. First, project developers would initiate the process by writing a Project Design Document (PDD) describing the project and proposing a demonstration of "additionality." In this context, "additionality" means that the project is expected to reduce emissions below the business-as-usual trajectory. A Designated National Authority (DNA)—in India, the Ministry of Environment and Forests—then evaluates whether the project, as described in the PDD, meets the CDM requirements, which include "additionality." Second, the CDM Executive Board, which supervises the CDM globally, decides whether or not to register valid projects submitted by the DNA. If a project is approved, the developer starts receiving CERs as soon as it starts delivering emissions reductions—a hydroelectric dam or a wind farm, for instance, would start receiving its approved allotment of CERs as soon as a third-party verifies that it has begun generating electricity.

It is critical that CDM projects are in fact marginal, since they receive CER credits that are used to relax someone else's emissions quota. If CDM projects are marginal, the CERs represent emissions reductions that offset emissions that are generated elsewhere, reducing abatement costs without compromising progress towards meeting global emissions reduction targets. However, if projects are infra-marginal, global emissions increase. The regulatory problem is the same as any subsidy program—the regulator's objective is to avoid supporting infra-marginal projects.

The CDM Executive Board applies a set of standardized methodologies to determine whether or not a project is marginal. For renewable energy projects, the principle is straightforward. Calculate the project's internal rate of return with and without the extra revenue that would come from selling CER credits. If the internal rate of return with CER revenue exceeds a benchmark rate, but the rate without CER revenue does not, the project is judged to be marginal. The CER revenue is estimated by multiplying the electricity that would be generated by a "business as usual" emissions factor. Most projects use a factor equal to the generation-weighted average carbon dioxide emissions per unit of net electricity generation from all generating power plants serving the same regional grid (tCO_2/MWh). The assumption is that the new project would replace an equivalent amount of "business as usual" generation capacity, avoiding the associated emissions.

This approach to assessing the "additionality" of projects has a number of problems. First, it is difficult to objectively estimate or evaluate internal rates of return. In practice the PDDs frequently rely on subjective arguments or neglect to provide the underlying data used in their calculations (Schneider, 2009). Even when detailed information is available and analysis has been performed, the results are not verifiable by the authorities in charge of CDM registration (Michaelowa and Purohit, 2007). Second, even if all the information was correct and verifiable, the methodology itself builds in incredibly strong assumptions about the growth of renewable power (or more accurately, the lack of growth) in the absence of CER credits.

This raises clear issues of accountability and regulatory governance. However, the absence of evidence that projects are marginal that previous studies have pointed to is not the same as providing evidence that they are infra-marginal. The most notable direct evidence of infra-marginal projects concerns the potent greenhouse gas HFC-23, which is a by-product in the production of some refrigerants. Wara (2007b,a), Schneider (2011), and Schneider and Kollmuss (2015) persuasively show that Chinese and Russian refrigerant factories were running over-time just to produce more of this by-product, since the destruction of this highly potent greenhouse gas allowed them to claim CERs that were much more valuable than the refrigerant being manufactured. Once the problematic projects were identified, regulators could easily ban polluters from using these specific credits for compliance purposes.

2.2 Wind Power Generation in India

India accounts for nearly 15% of all CDM projects and 11% of CDM credits. It ranks second only to China.[3] The CDM is expected to generate 1.3 billion credits in India by 2030, which is equivalent to 50% of India's carbon dioxide emissions in 2019.

India is estimated to have a total wind power potential somewhere between 750 GW and 1,600 GW, with much of this potential concentrated in Southern and Western parts of the country (Phadke, 2012). At the turn of the century, however, India had almost no wind power, and neither was it building new wind farms. The main barrier to wind farm construction was believed to be the high up-front capital costs (Jagadeesh, 2000). Consequently, *ex ante* evaluations of the Indian wind power sector concluded that there was huge potential for the CDM to finance the construction of additional capacity and maximize the utilization of this untapped wind power potential (Purohit and Michaelowa, 2007).

Figure 1 plots the construction of new wind power capacity in India based on the Bloomberg's New Energy Finance database (see appendix A for details). Within a few years of the CDM coming online in 2000, wind farm construction accelerated and CDM-registered projects began to account for a substantial proportion of new capacity (Figure 1, top panel). The price of CERs had reached about $10 by this point, and it remained high until the final year of the Kyoto Protocol's commitment period. Over this whole period, India experienced more than a 20-fold expansion of its installed wind power capacity, and today India has the 4th largest installed wind power capacity in the world (Lee et al., 2021). Notably, nearly half of the capacity added between 2000 and 2013 belongs to projects that were registered to receive credits under the CDM (Figure 1, bottom panel). We calculate that these projects were expected to collectively generate roughly 50 million CERs over their lifetime. Our analysis will provide insight into the extent to which CDM subsidies actually contributed to the explosive growth of India's wind power capacity.

By studying the Indian wind power sector, we are consciously selecting a context where the CDM was expected to perform particularly well. This stacks the deck in favor of finding that the CDM Executive Board has been successful in supporting projects that would not have been built

[3] At the outset of this project we explored the possibility of working in China. However, it was not able to identify any non-CDM supported wind power projects.

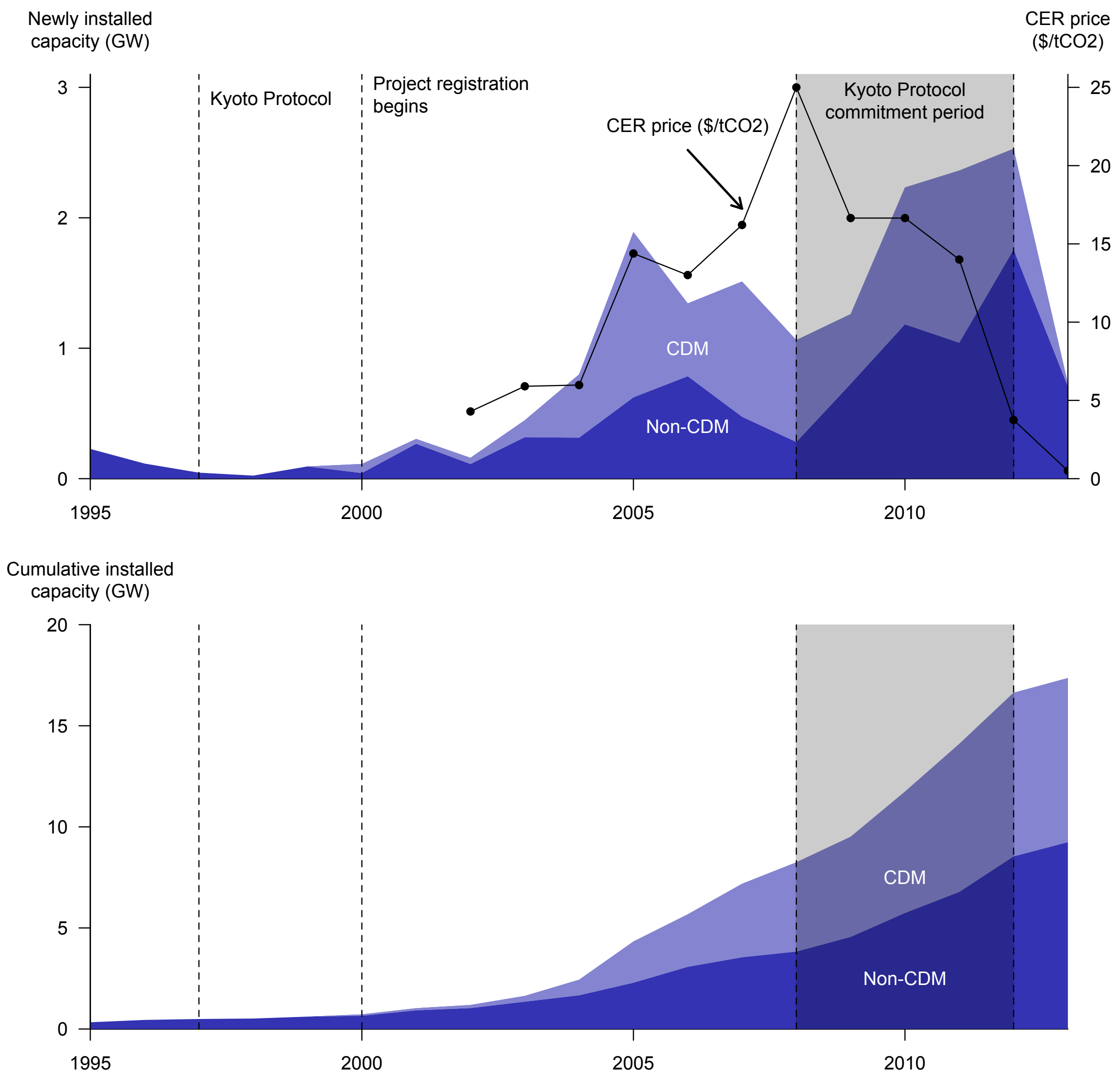


Figure 1: Installed wind power capacity in India. New capacity is calculated from Bloomberg New Energy Finance, and allocated to CDM and non-CDM by cross-referencing projects with the UNEP DTU CDM pipeline. The lower panel plots the cumulative sums of same data. Annual average CER prices are taken from reports by the World Bank and GIZ (World Bank Group, 2019; GIZ, 2014). Prices are estimated based on over-the-counter transactions prior to 2008, and then calculated from exchange-based transactions once CERs began to be traded on exchanges.

otherwise. This is an important difference from earlier studies, which have looked for examples of "non-additionality" mainly in places where they are most likely to be found, such as the case of HFC-23 (Wara, 2007b,a; Schneider, 2011; Schneider and Kollmuss, 2015). Finding that HFC-23 projects are infra-marginal is mainly helpful in highlighting a specific type of project that should not be subsidized. By searching for infra-marginal projects in a setting where we least expect to find them, we are providing something closer to an upper bound on the CDM's overall success in identifying and supporting marginal projects.

3 Conceptual Framework

3.1 Marginal and Infra-marginal Projects

Following Berry (1992), we consider a simple two-stage game for each market—entry followed by service provision. In the first stage, each potential entrant $n = 1, \ldots, N$ makes a choice whether or not to enter market k. In the second stage, entrants make investments that determine post-entry payoffs.

Solving backwards, we define a payoff function $V(s, x)$ for potential market entrants, where $s \geq 0$ is a subsidy and x is a vector of other payoff determinants. The essential features of $V(s, x)$ are that it is monotonically increasing in s, and that V depends monotonically on the entry decisions of other potential entrants.

Given the payoff function, potential entrants decide whether or not to enter the market. There is a reservation payoff, R, such that entry occurs if $V \geq R$.

Under these conditions, one can rank potential projects according to their payoffs in the absence of subsidies,

$$V(s=0, x_1) \geq \cdots \geq V(s=0, x_i) \geq R > V(s=0, x_{i+1}) \geq \cdots \geq V(s=0, x_N). \tag{1}$$

where the subscript indicates the rank order. We assume that V is such that this ranking is preserved for all values of s. Increasing s will only have the effect of shifting some projects from the right side to the left side of R without otherwise disturbing their ranking. Hence, for some subsidy $\bar{s} > 0$, it will be the case that

$$V(\bar{s}, x_1) \geq \cdots \geq V(\bar{s}, x_j) \geq R > V(\bar{s}, x_{j+1}) \geq \cdots \geq V(\bar{s}, x_N) \tag{2}$$

where $j \geq i$. Potential entrants with an index above j (to the right of R in equation 2) will not enter either with or without the subsidy, so we need not consider them any further. Potential entrants with an index between i and j will enter only with a subsidy, which means the subsidy is affecting their decision at the margin. We refer to these as "marginal projects" for convenience, which in this setting is equivalent to calling them "additional." Potential entrants with an index below i will enter with or without a subsidy, which means the subsidy is infra-marginal to their entry decision. We refer to them as infra-marginal projects, which in this setting is equivalent to calling them "non-additional."

3.2 Blatantly Infra-marginal Projects

The typical approach for determining whether or not a project n is infra-marginal is to attempt to estimate $V(0, x_n)$, $V(\bar{s}, x_n)$, and R, and then check whether $V(\bar{s}, x_n) \geq R > V(0, x_n)$. This approach faces several challenges, not least of which is the fundamentally unobservable nature of $V(0, x_n)$ once a subsidy has been awarded.

Fortunately, one does not need to estimate $V(0, x_n)$, $V(\bar{s}, x_n)$, and R to determine whether a project is infra-marginal (i.e. whether $n \leq i$). A sufficient condition for identifying a project as infra-marginal is that there exists some project $m > n$ that is not receiving a subsidy. Because no projects $m > i$ would enter the market without a subsidy, the existence of an unsubsidised project m is sufficient to infer that n must be less than i.

If one can identify and measure the variables in x (or proxies thereof), and can further identify some subset of these variables that produce monotonic changes in V, which we'll denote $\tilde{x} \in x$, then for each project n, one can determine whether or not there exists another project m such that:

1. m did not receive a subsidy ($s = 0$),

2. $\tilde{x}_m \leq \tilde{x}_n$ for each variable in $\tilde{x}$ (where, for convenience, the variables in $\tilde{x}$ are ordered so that higher values produce larger values of V), and

3. $x_m = x_n$ for each variable not in $\tilde{x}$.

If a project m exists that satisfies the first condition, it must be true that the value of V was large enough to justify entry even in the absence of the subsidy, which can be stated formally as $V(s = 0, x_m) \geq R$, or equivalently, $m < i$. If project m satisfies the second and third conditions as well, we know that $V(s = 0, x_n) \geq V(s = 0, x_m)$ (or $m < n$). Transitivity implies that $V(s = 0, x_n) \geq R$ (or $n < i$), which means that project n would have been built in the absence of a subsidy, too.

If project n is marginal, no other project satisfying all three conditions will exist. If project n is infra-marginal, then a project m satisfying all three conditions *may* exist. The existence of a project m is therefore a sufficient condition to infer that n is infra-marginal. To distinguish these infra-marginal projects from the rest, we refer to them as *blatantly* infra-marginal projects, or BLIMPs for short.

While infra-marginality is unobservable, being a BLIMP is fundamentally observable, defined by the relation between two observed projects. We note, however, that BLIMP-ness is an inherently conservative indicator of infra-marginality. An application of the definition of a BLIMP is likely to identify only a subset of infra-marginal projects, even when a researcher or regulator is in possession of a complete list of projects.

If our list of projects is incomplete, the measure only becomes more conservative. Consider starting with a complete list of projects and then dropping one. If this project is itself a BLIMP, we've reduced the number of BLIMPs by one. If this project is not a BLIMP, its presence could have served to identify other projects as BLIMPs. Any projects that we do not observe will tend to reduce the number of BLIMPs.

This conceptual approach imposes very mild conditions on the payoff function. It therefore lends itself to many different applications. For any given application, it is necessary to specify the payoff function with enough precision that the researcher can determine what variables are contained in x and in $\tilde{x}$. We now turn our attention to operationalizing the concept of a BLIMP in the context of wind power generation.

4 BLIMPs in India's Wind Power Sector

In this section we map the preceding framework onto India's wind power sector to develop an operational definition of a BLIMP in this context. We will discuss the functional form of the payoff function and how we measure the variables that enter into it.

4.1 An Operational Definition of a BLIMP

The following equation describes what we consider a reasonable description of the net present value from building a wind farm, i, in state ℓ, in year y.

$$V_{n\ell y} = \sum_{t=y}^{T} \frac{(p_{\ell yt} + s_{nt})(c_n \times f_n)(1 - l(d_n)) - v_{yt}(c_n) - \tau_{\ell yt}}{(1+r)^{(t-y)}} - F_y(c_n, d_n) \qquad (3)$$

The first term gives us the net present value of the stream of operating profits. Each kWh of electricity fetches a price of electricity, $p_{\ell yt}$, that may differ across states ℓ, across vintages, y, and across time t, as well as a per-kWh subsidy, s_{nt}, that varies across projects and time. Total annual revenue can then be calculated by multiplying the revenue per kWh by the annual power output, which can be written as the product of generation capacity, c_n, and the capacity factor, f_n (the power output per unit of capacity). Total output then needs to be multiplied by a factor that takes account of transmission losses, l. Transmission losses increase as a function of the distance to the where the wind farm connects to the grid, d_n. The operating profit in year t is what is left over after subtracting maintenance costs, v_{yt}, and taxes, $\tau_{\ell yt}$. Two projects built in the same year, y, with the same capacity, will have the same maintenance cost schedule. If they are built in the same state they will face the same tax schedule as well. Finally, the stream of profits is discounted at an annual rate of r, which is common to all projects.

The second term of equation 3 represents the up-front cost of construction, F_y, which depends on the generation capacity, c_n, and distance between the wind farm and its closest connection point to the grid, d_n.

As we indicate with our subscripts in equation 3, and will discuss in greater depth shortly, most of the variables vary across, but not within, states and vintages. Aside from the subsidy rate, only three variables vary across wind farms built in the same state and year, and we will argue that V is monotonic in all three: V is an increasing function of generation capacity (c_n) and the capacity factor (f_n), and a decreasing function of the connection distance (d_n). This gives rise to the following operational definition of a BLIMP in the context of India's wind power sector.

Definition 1 *For a CDM-registered wind farm n and an unregistered wind farm m that are built in the same state and year, n is a* BLIMP *if:*

1. *it is larger ($c_n \geq c_m$), and*

2. *it is built in a windier location ($f_n \geq f_m$), and*

3. it is built closer to a connection point ($d_n \leq d_m$).

Although equation 3 is helpful as motivation, our empirical analysis does not require us to estimate the value function. We only rely on the milder conditions stated in Definition 1, which are compatible with a larger set of alternative payoff functions. The remainder of this section is devoted to motivating the functional form assumptions contained in this definition and to describing how we measure each of the variables.

4.2 Payoffs Increase in Capacity

Generation capacity is easy to observe and measure, but its mapping to payoffs is more complicated. Each MW of capacity yields $c_n \times f_n$ kWh of power output in year t, which are then sold at a fixed price of $p_{\ell yt}$. In India, as in many other places, the price of wind power is agreed in advance through standardized power purchase agreements. Throughout the period of our study these prices were set by state-wide feed-in-tariffs. This means that all wind farms built in the same state and year will earn the same price per unit of electricity (Kathuria et al., 2015). These factors suggest constant marginal revenue from each additional MW of capacity.

Marginal revenue could be increasing or decreasing, however, depending on what subsidies are on offer, s_{nt}. The only relevant domestic program in this period is India's Generation-based incentive—a nation-wide program that supplements state-level feed-in-tariffs with an extra INR 0.5 per kWh of power. The only eligibility criteria is that the wind farm has at least 5 MW built capacity. The Generation-based incentive therefore results in increasing marginal revenue for projects exceeding 5 MW of capacity. Given that the GBI is available to all projects above 5MW, we have no reason to believe that it disproportionately serves non-CDM projects. We explore the the consequences of this assumption in sensitivity analyses.

The only other subsidy to consider is the CDM, which provides registered wind farms with carbon offsets in proportion to their power output. The price of offsets varies over time in response to global demand and supply, but since individual wind farms are price takers in the global offset market, two CDM-projects that are built in the same year will receive the same subsidy-per-kWh over the lifetime of the project. Non-CDM projects do not receive the subsidy. Unlike the Generation-based incentive, eligibility for the CDM is not determined by a capacity threshold. This is why Definition 1 starts by specifying that one wind farm is registered and the other one isn't. For such a pair, we can say that the larger CDM-project will have a higher subsidy rate than the smaller non-CDM project.

While the marginal revenue from an additional MW of wind farm is constant, or even increasing, the marginal cost of building and operating an additional MW of wind farm tends to decline as a function of capacity. The up-front capital cost of a wind power project, F_y, accounts for as much as 85% of the lifetime costs (Blanco, 2009). It can be broken down into four categories: turbine cost, construction cost, grid connection cost, and planning cost.

The bulk of the up-front investment is the cost of acquiring turbines (65-75%) and for construction (10-15%) (Blanco, 2009). Both of these costs scale more-or-less proportionately with wind farm capacity, which means we should expect a close positive linear association between project costs, F_y, and capacity, c_n. This prediction appears to be supported by our data. From the Bloomberg New Energy Finance project database, we observe both the built capacity and the total up-front cost for $\approx$ 30% of wind power projects. Figure 2 shows that, for this sample, these two variables display a strong positive linear association.

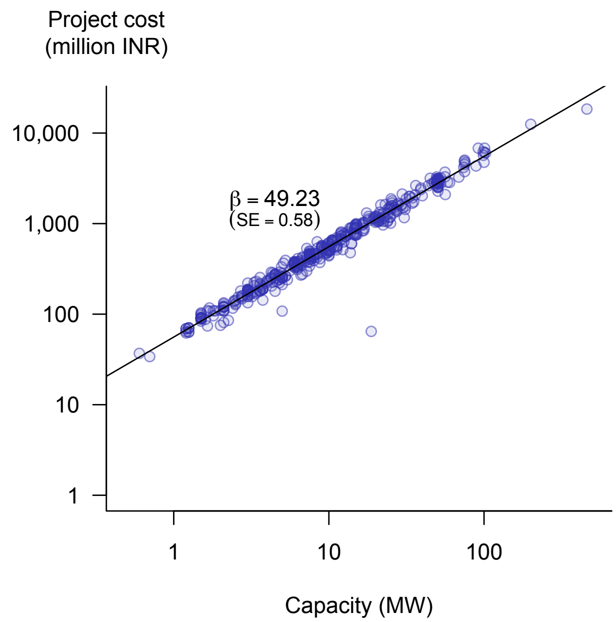


Figure 2: Capacity and project costs. Source: Bloomberg New Energy Finance

Planning costs are primarily made up of fixed fees that apply to projects of any size, which implies that the function F_y will have a positive intercept. Indeed, studies of European wind developments suggest that these costs make up about 8-10% of up-front investment (Blanco, 2009). If we regress project costs on capacity and distance for the subset where all three are observed, the intercept is $\approx$ INR 20 million, which corresponds to nearly 8% of project costs on average. The combination of a fixed up-front cost and a constant cost per MW means that the average cost per MW is declining in the scale of the project.

Maintenance costs, v_{yt}, and taxes, $\tau_{\ell yt}$, could in principle undo some of the benefits of scale, but in practice they do not. Similar to prices, maintenance costs are contracted at the time of construction, and they tend to follow an industry-standard schedule. A typical maintenance contract charges a flat fee per MW of built capacity, which subsequently increases by some fixed percentage with each passing year. Therefore, if we are comparing two wind farms of the same size, built in the same year, they will have the same maintenance cost over the lifetime of the project.

When it comes to taxes, wind farms pay the same state and national taxes in India as any other enterprise, with the exception of the Accelerated Depreciation Benefit. Starting in 1994, wind farm developers were permitted to apply a 100% rate of depreciation to their newly built projects. The rate was lowered to 80% in 2002, then to 0% in 2012, before returning to 80% in 2014. This means that wind farm developers in India would have paid almost no taxes on their developments during our period of study. To the extent that wind farm developments are subject to different tax regimes, these will differ primarily by vintage. We have found no evidence that there were any state tax policies that disproportionately increased the cost of building larger wind farms.

To summarize, power output is an increasing function of generation capacity, and to some extent, so is the revenue per kWh. Because of planning costs, larger wind farms will have a lower average up-front cost per MW. Maintenance and taxes do not increase fast enough, as a function of capacity, to undo the benefits of scale. Taken together, these facts support the presumption that, at least among wind farms built in a particular state and year, the payoffs to wind farm development are an increasing function of generation capacity. Developers are incentivized to build the largest projects that they are able to. In practice, the most important constraints on size appear to be the availability of land and capital.

4.3 Payoffs Increase in the Capacity Factor

For a wind farm of a given capacity, c_n, the amount of power that it generates depends on its capacity factor, f_n. The capacity factor is the ratio of actual-to-maximum output, and is sometimes also referred to as the plant load factor. If a 1 MW wind turbine produced at maximum capacity it would generate 1 MWh of power in one hour, or 8,766 MWh in a year (1 MW $\times$ 8,766 hours). Since the wind doesn't blow constantly, however, turbines will generate much less power in practice, typically between 10% to 20% of maximal output. For all intents and purposes, the capacity factor measures the windiness of the site on which you put your turbine, but it does so in relation to the optimal wind profile of the turbine.

There is no real cost to building in a windier location, so it is straightforward to see that the payoff is an increasing function of the capacity factor. The challenge, in this case, is that neither we nor the developers know in advance how much the wind will blow at a particular site. To assess the value of a potential wind farm we both have to estimate the capacity factor.

We have already calculated the denominator for a 1 MW capacity factor—simply multiplying the maximal power output by the number of hours in a year—and the same can be done for turbines of any rated capacity, c. To estimate the numerator, the actual power output, we need to know the turbine's power curve:

$$P(\rho, w) = \begin{cases} 0 & \text{if } w < \underline{w} \text{ or } w \geq \overline{w} \\ \min\left(\frac{1}{2}\rho A w^3 C(w), c\right) & \text{if } \underline{w} \leq w < \overline{w} \end{cases} \tag{4}$$

where the power output P is given as a function of the wind speed, w, and air density, ρ. The swept area, A, the cut-in speed, $\underline{w}$, cut-out speed, $\overline{w}$, power coefficient, C, and rated capacity, c, are all features of the turbine itself.[4]

[4]See appendix B for a lengthier description of power curves.

Like many economists working in countries where the quality and quantity of historical weather data is limited, we have opted to use reanalysis data to estimate wind resources at each project-site (Auffhammer et al., 2013). We use the ERA5-Land database produced by the European Centre for Medium-Range Weather Forecasts (Muñoz Sabater, 2019). It uses a global circulation model to interpolate meteorological variables in observationally sparse regions, yielding data that are more uniform in quality and realism than observations alone, and that is closer to reality than any model could provide on its own. ERA5-Land includes a complete set of hourly observations going back to 1981, at a spatial resolution of roughly 9 km over land.[5]

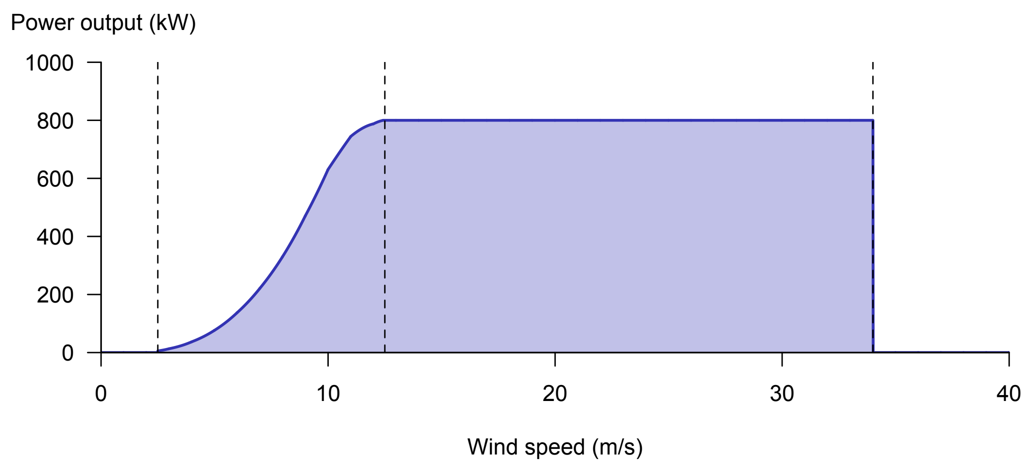


Figure 3: Power curve for the Enercon E-53 800 kW turbine. The power curve is drawn here for a standard air density of 1.225 kg/m^3. Going from left to right, the dashed vertical lines indicate the cut-in wind speed, the rated wind speed, and the cut-out wind speed, respectively.

To complete our calculations, we use the technical specifications of the Enercon E-53 800 kW turbine, the power curve of which is plotted in Figure 3. In our setting, using the same "benchmark" turbine for all sites has crucial advantages over trying to match the particular turbines at each location. In particular, when trying to judge which projects are and aren't deserving of a subsidy, this approach avoids penalizing developers for choosing superior turbines, and avoids rewarding them for selecting inferior turbines. Using the same turbine to evaluate wind resources of all sites avoids these perverse incentives, and instead provides a common standard for evaluation. While there are many different turbines to choose from, the E-53 is the most common in our data set by far, accounting for about 15% of all turbines we have been able to identify. It seems reasonable to expect this turbine to be widely available during this period, and that it would have been a suitable choice across a range of locations. This makes it a suitable benchmark.[6]

[5] Appendix B includes a detailed description of the data, and a comparison with historical weather data for India.

[6] Appendix B contains a fuller discuss of the choice of benchmark turbine. As a sensitivity analysis, we will later replicate our analysis using an alternative benchmark turbine.

4.4 Payoffs Decrease in Connection Distance

Another important consideration for a wind farm developer is the cost of connecting the turbines to the electrical grid. The cost of doing so accounts for 10-15% of the up-front investment on average (Blanco, 2009), and since most of this cost is the laying of cables, these costs increase roughly in proportion to the distance between the turbines and the connection point, d_n. Longer connection distances also imply greater transmission losses, once the wind farm is built. Since greater remoteness, in and of itself, provides no particular benefit, it is easy to see that the payoff is a decreasing function of connection distance.

We do not observe the connection distance directly and so need to estimate it. To do this, we need the geographical coordinates of the electrical substations as well as of turbines themselves. The coordinates of electrical substations were collected by Burlig et al. (2020), while the coordinates of the turbines were found using a combination of information found in the Bloomberg New Energy Finance database, the UNFCCC's CDM project database, and extensive online research, including press releases, news reports, and documents published by the Indian government. Rather than pinpointing turbines individually, we record the coordinates of the village in which the turbines are located. This was partly out of practical necessity, but also means that our findings cannot be driven by arbitrarily small differences in location. Any variation in location that we might have been able to generate at the sub-village level would likely have contained more noise than signal.[7]

Under the assumption that wind farm developers will do their best to minimize connection costs, we calculate the minimum distance to connect each project to the electrical grid, using a modified minimum spanning tree algorithm.[8] Figure 4 illustrates the results for one multi-site wind power project that is spread across ten villages.

This approach may underestimate connection distances, since it does not take into account topographical obstacles. The magnitude of any bias will tend to scale with the connection distance. As a result, this type of measurement error will not distort the *ordering* of connection distances, and therefore does not affect our empirical analysis.

Classical measurement error is not expected to affect our analysis. This is because it would be just as likely to lead to an erroneous BLIMP inference as an erroneous non-BLIMP inference. In our setting, a problem would arise only if our estimation method systematically underestimated the distance for CDM projects relative to non-CDM projects, or vice versa. This might occur, for example, if CDM projects are disproportionately built in places where topographical features increase the the real connection distance relative to the distance measured as the crow flies. In sensitivity analysis, we how sensitive our findings are to this possibility by deliberately inflating the distances for CDM projects relative to non-CDM projects.

[7] Appendix A provides additional details about how the raw data was processed.

[8] To avoid inflating the distances for wind farms spread across widely dispersed sites, we modified the standard algorithm. Instead of trying to connect all points in one step, we first connect the electrical substations to each other. Only then do we extend the graph to include the wind farm sites. This means that the total connection distance will include the edges that connect each cluster of turbines to its nearest substation, but avoids any edges that would be necessary to connect distant clusters. See appendix C for a more detailed description of the algorithm.

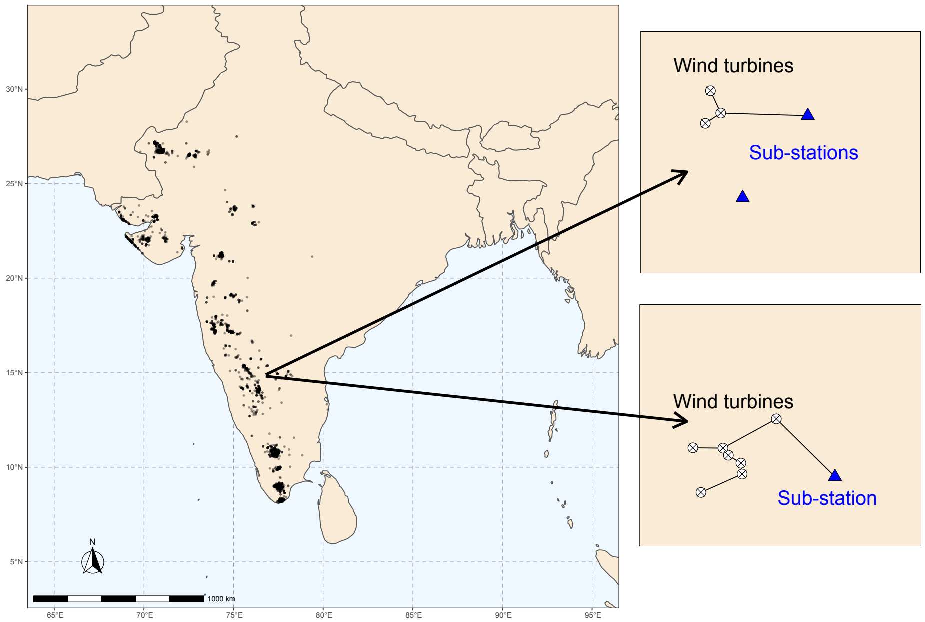


Figure 4: Estimating connection distances. The left plot shows the geographical distribution of wind project-sites across India. The two panels on the right zoom in on a single wind project spread across 10 sites, and illustrates the shortest distance of cable needed to connect all 10 sites to an electrical substation.

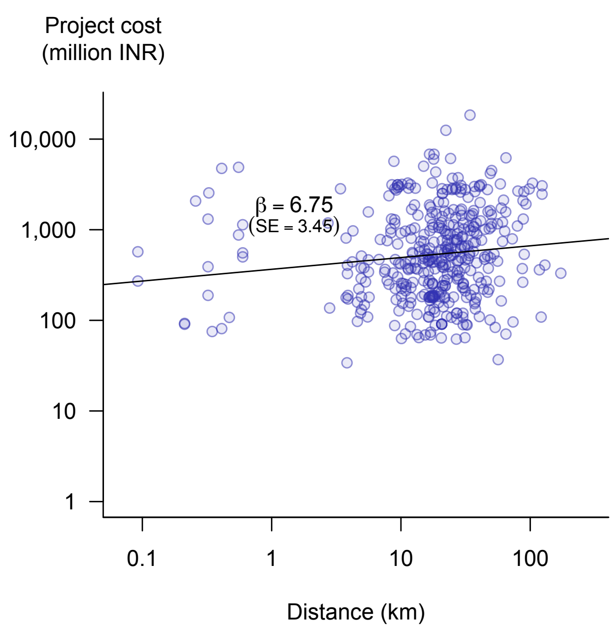


Figure 5: Connection distances and project costs

Figure 5 shows that the estimated connection distance is positively associated with project costs for the sub-sample where both are observed. The association is comparatively weak, consistent with the premise that distance to the grid affects only a small portion of overall project costs.

4.5 All Else Equal

We have argued that, *all else equal*, the developer's payoff is increasing in generation capacity and capacity factor, and decreasing in connection distance. But what things need to be held constant?

The most important factor is the electricity price, $p_{\ell yt}$. Electricity prices do vary across states and time, but they do not vary across wind farms built in the same state and year. The same goes for maintenance and tax schedules, $\tau_{\ell yt}$ and v_{yt}.

The final piece of equation 3 is the discount rate r. If we wanted to determine the real payoff to any particular wind farm developer, we would need to know the rate of interest at which they are able to access capital. However, our objective is somewhat different, in that we are trying to determine whether the a project is worth subsidizing or not. Obviously, we do not want to subsidize wind farms simply because their developers are risky borrowers. The relevant quantity is not the market rate of interest, but the social discount rate.

The way that the UN Executive Board evaluates applications is by setting V equal to zero and then working out whether the implied internal rate of return $\tilde{r}$ exceeds some common threshold value or not. This is equivalent to letting r equal the social discount rate and working out whether V exceeds some common reservation payoff. For the purpose of evaluating projects for carbon offsets we should apply a common discount rate to all projects. Since electricity prices and taxes only vary across states and years, and there is no additional variation coming from the discount rate, the "other things equal"-condition will be met so long as we are comparing wind farms built in the same state and year. In sensitivity analysis we impose more restrictive comparison groups.

5 How Many BLIMPs is Too Many?

The ideal number of BLIMPs receiving subsidies is clearly zero. BLIMPs are only a subset of infra-marginal projects, and they are a conservative indicator of infra-marginality. A program could in principle subsidize many infra-marginal projects without subsidizing any BLIMPs. The number of BLIMPs therefore provides a conservative lower bound on the total number of infra-marginal projects. On some level the existence of any BLIMPs is a sign of something having gone wrong in the CDM's decision making process.

The total number of BLIMPs, however, can provide a useful indication of the degree of mis-allocation. To give this number a meaningful interpretation we require an alternative allocation mechanism of known quality that can serve as a benchmark. We can then compare the realized number of BLIMPs in the CDM's allocation to the number of BLIMPs that would have received support in counterfactual allocation scenarios.

We argue that a lottery is a useful benchmark mechanism. A lottery provides a floor for performance. In expectation, a lottery would allocate subsidies in a way that is uncorrelated with whether a project is marginal or infra-marginal.

By repeating the lottery many times, we can obtain a distribution of the number of BLIMPs that a lottery would subsidize. Each time the lottery is repeated, we let the CDM Executive Board randomly select a fixed number of wind farms for registration in each year, equal to the number they actually registered. Some iterations will, by chance, register a lot of small wind farms in remote and windless locations (i.e. few BLIMPs). Other times chance alone will result in a large number of BLIMPs. This distribution gives us a scale. The quality of the realized CDM allocation can be measured by the probability that the lottery results in fewer subsidised BLIMPs. A small probability means the real program has performed much better than a lottery, while a large enough probability implies that the real program is indistinguishable from a lottery. One would hope that no real-world program would produce more subsidised BLIMPs than a lottery.

Unlike the real CDM, however, the lottery can only select project from among those that were actually built, since those are the only projects in our database. This gives the CDM a built-in advantage. If there are any potential projects that weren't built on account of lacking support from the CDM, they would be invisible to us and to the lottery. The larger we imagine this set of potential projects to be, the more we will tend to over-represent the performance of the CDM.

6 Results

6.1 Main Results

Out of the 1350 Indian wind farms in our database, 472 are registered under the CDM. Of those, we identify 56% as BLIMPs (figure 6). For each of these 265 projects we can point to another unsubsidized wind farm built in the same state and year that is smaller, has a lower capacity factor, and is more remote.

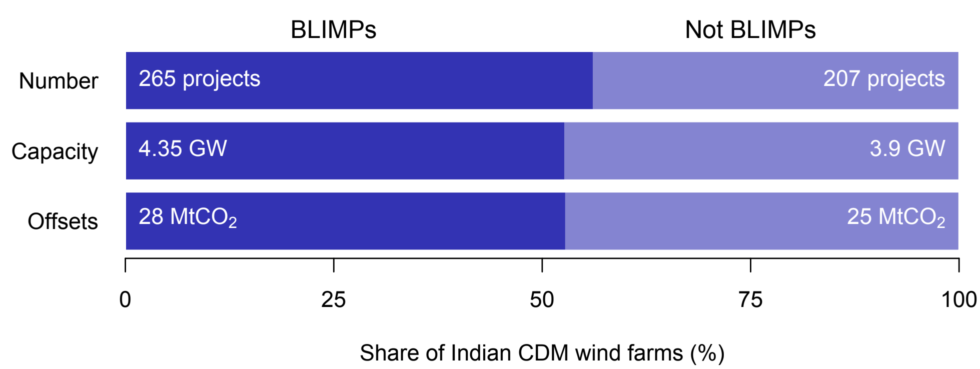
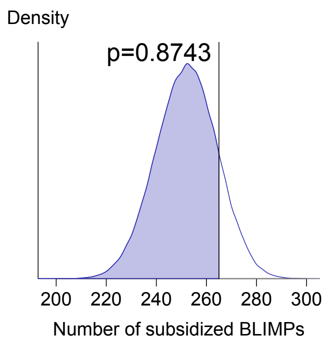


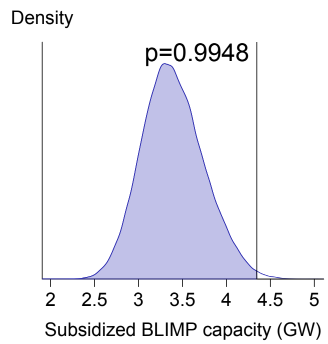
Figure 6: Number, Capacity, and Quantity of CERs approved for BLIMPs

Relative to the allocations that a lottery mechanism might have produced, the CDM appears to have performed poorly. Figure 7a plots the observed number of BLIMPs against the distribution of 100,000 hypothetical lottery realizations. The p-value tells us that, 870 times out of 1,000, the lottery would give rise to fewer BLIMPs than the CDM. Had the CDM chosen projects at random from the whole population of wind farms, then, it would likely have registered fewer blatantly infra-marginal projects than it did.

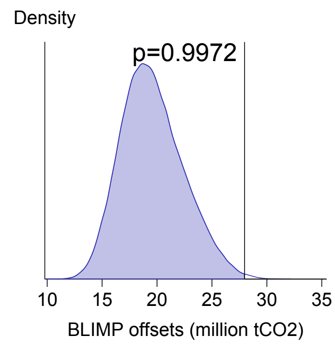
Figure 7: Comparing the Number, Capacity, and Quantity of CERs to a Lottery



(a) Number



(b) Capacity



(c) CERs

Not all BLIMPs represent mistakes of equal magnitude. It is possible that the CDM's registration process gives rise to a relatively large number of smaller BLIMPs, whereas the imagined lottery might be consistently distributing carbon credits to a smaller number of much larger wind farms. We explore the severity of misallocation by looking at the total capacity of BLIMP projects, rather than their number.

Figure 6 shows that the BLIMPs registered under the CDM have a collective capacity of 4.35GW, accounting for about a quarter of India's total installed wind capacity in 2013. Meanwhile, Figure 7b shows that 995 times out of a 1,000, a lottery would have subsidized less total BLIMP-capacity than the CDM.

Ultimately, we care about the number of BLIMP carbon offsets, not the number or capacity of the BLIMPs themselves. This requires an extra step. Unlike the number or capacity of projects, we do not observe the number of CERs that would have been given to non-CDM wind farms. We need this number to determine how many CERs the lottery would have awarded under counterfactual scenarios. Fortunately, the quantity of CERs received by CDM projects is strongly predicted by capacity (Figure 8). We use this relationship to impute the quantity of CERs that we imagine a non-CDM project would be awarded under alternative allocation scenarios.

Figure 6 shows that out of the 53 million CERs estimated to have been approved for Indian wind farms, just over half, almost 28 million, went to BLIMPs.[9] When sold as carbon offsets, these carbon credits have allowed regulated polluters around the world to emit an additional 28 million tonnes of carbon dioxide. Since a tonne of coal produces about 2.25 tonnes of carbon dioxide when

[9]We are referring here to the expected number of CERs at registration. This number provides us with a measure of the quality of the CDM's allocation process itself, even if there are sometimes problems later, in the completion or operation stages, that prevents all of these offsets from being issued.

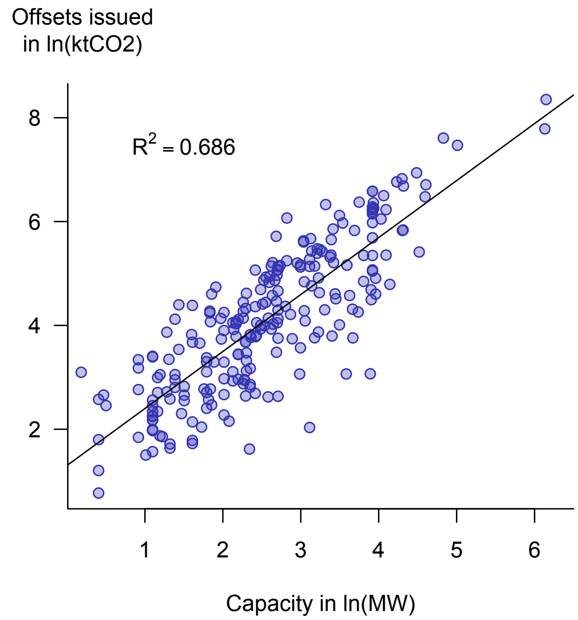


Figure 8: Relationship between capacity and approved carbon credits

burned, these carbon credits have given license to burn an additional 12 million tonnes of coal, equivalent to running a typical one-gigawatt coal power plant for nearly 5 years.[10] Figure 7c shows that a lottery would have awarded fewer carbon credits to BLIMPs 997 times out of 1,000.

In summary, despite the Indian wind power sector having been identified *ex ante* as offering significant opportunities to support marginal projects, we find evidence of meaningful support for infra-marginal projects. Our analysis reveals that the program registered a high number of BLIMPs, even when compared to a lottery. Moreover, we find that wind farms supported by the CDM tend to be larger and to have received more carbon credits, on average, than the BLIMPs that would have been subsidized under a lottery. These results pose a serious challenge to claims that the CDM is successfully offsetting emissions. The BLIMPs themselves were approved to receive 28 million CERs, despite being very unlikely to have reduced emissions.

6.2 Sensitivity Analysis

Measurement Error: Our analysis relies on two inputs that have been estimated—the cost of connecting wind farms and their capacity factors. These may have been measured with error. As mentioned earlier, our results are not biased by classical measurement error in either or both variables, since symmetrically distributed errors would turn as many BLIMPs into non-BLIMPs as vice versa. In expectation, the result would be the same.

[10] If we extrapolate this rate of infra-marginal support to the CDM as a whole, the program would have increased global emissions by 6.1 billion tonnes of carbon dioxide. This is roughly equivalent of operating roughly 20 one-gigawatt coal plants for their entire 50-year lifespan.

To investigate whether we have introduced bias through non-classical measurement error, we start by re-computing our results using alternative estimates of connection costs and capacity factors. Since each method of estimation is likely to produce different errors, it would be revealing if this exercise yielded substantially different results.

One possible source of asymmetric error in our estimates of connection costs is our assumption that wind farms are always connected to the nearest substation. It might be that CDM projects need extra support because they face greater obstacles to connect to nearby substations and instead can only connect to more distant substations. In this case, we will have systematically underestimated the connection costs of CDM projects relative to non-CDM projects.

To address this concern, we re-estimate connection distances while imposing the constraint that wind farms may only be connected to substations in the same state. State boundaries are the most important obstacles preventing wind farms from connecting to the nearest substation, so this should redress any systematic imbalance between CDM and non-CDM projects with respect to the administrative obstacles associated with transecting state boundaries. The results, reported in row (1) of Table 1, are almost identical to the original estimates. If anything, the CDM's performance slightly deteriorates both in absolute terms and relative to a lottery.

Another possible source of error in our estimates of connection costs comes from the comparative difficulty in obtaining high-quality data on the locations of electrical substations. Our main analysis uses a data set compiled by Burlig et al. (2020). If this list happens to disproportionately miss substations with no CDM project nearby then we would artificially increase connection distances for non-CDM projects.

We can examine this hypothesis indirectly by substituting a range of alternative lists of plausible grid connection points. In row (2) of Table 1 we report the results using the locations of conventional power plants. In row (3) we use the location of cities that, according to the 2001 Indian census, had a population of at least 100,000. In row (4) we use the location of cities listed in the 2001 Indian census as having electrical power. The results barely change, indicating either that all four lists suffer from the same exact bias, or that the list compiled by Burlig et al. (2020) does not suffer from systematic omissions.

Turning now to our estimates of capacity factors, we consider two possible sources of measurement error—the benchmark turbine and the air density estimation. In our main analysis we use the technical specifications of Enercon's E-53 turbine to estimate capacity factors. This is the most common turbine in our database. The power curve of any particular turbine, however, will undoubtedly favor some wind profiles, i.e. locations, over others. If these locations happen to be correlated with CDM registration, this would bias our results. We address this concern by swapping out Enercon's E-53 turbine for Suzlon's S82 turbine—another very common turbine in our data set that has a different power curve. In row (5) of Table 1 we see that this substitution makes very little difference to the results.

The air density estimates could contribute measurement errors through the same mechanism. Capacity factors are often estimated using data on wind speeds alone, while assuming a standard

Table 1: Summary of sensitivity analyses (p-values in parentheses)

	BLIMP fraction (in percent)	BLIMP capacity (in GW)	BLIMP offsets (in million tCO_2)
Main result	56	4.349	27.984
	(0.8743)	(0.9948)	(0.9972)
Measurement errors			
(1) Connect within States	57	4.443	28.298
	(0.9056)	(0.9968)	(0.9973)
(2) Connect to Power stations	52	4.845	31.075
	(0.7647)	(0.9999)	(0.9999)
(3) Connect to Cities of >100,000	56	4.283	26.366
	(0.9653)	(0.9999)	(0.9999)
(4) Connect to Cities with power	52	4.181	25.954
	(0.8804)	(0.9990)	(0.9988)
(5) Suzlon benchmark turbine	56	4.322	27.791
	(0.8193)	(0.9936)	(0.9965)
(6) Standard air density	56	4.346	27.975
	(0.8603)	(0.9941)	(0.9964)
(7) Adjustment factor $\beta = 1.2$	36	2.779	17.350
	(0.0001)	(0.1038)	(0.4856)
Omitted variables			
(8) Match manufacturer	30	1.981	10.329
	(0.0651)	(0.7094)	(0.6709)
(9) Match number of sites	39	2.844	15.741
	(0.1012)	(0.8981)	(0.8457)
(10) With 5MW threshold	45	3.358	19.670
	(0.5587)	(0.9190)	(0.8863)
(11) Within District-year	33	2.598	14.056
	(0.2070)	(0.9388)	(0.8675)
(12) Within Village-year	14	0.966	5.149
	(0.0023)	(0.8898)	(0.8510)
(13) CDM developers only	32	2.761	16.719
	(0.6956)	(0.6750)	(0.6894)
Mis-specification tests			
(14) Match connection distance	24	1.769	10.477
	(0.0445)	(0.9797)	(0.9659)
(15) Match capacity factor	21	1.605	9.203
	(0.1011)	(0.9915)	(0.9938)
(16) Match capacity	10	0.411	2.240
	(0.0004)	(0.7244)	(0.8337)
Incomplete data			
(17) With unconfirmed projects	43	4.734	29.182
	(0.3469)	(0.7526)	(0.9578)
Allowing for mistakes			
(18) Margin of error $\alpha = 1.2$	32	2.599	16.577
	(0.90560)	(0.9846)	(0.9994)
(19) Two inferior projects	34	2.756	16.027
	(0.3371)	(0.8907)	(0.8704)
Partial infra-marginality			
(20) Next biggest project bound	56	1.957	9.095
	(0.8743)	(0.6879)	(0.3850)

air density. If our estimates of air density are noisier for some locations than others, and this pattern correlates with CDM registration, it could affect our results. However, row (6) of Table 1 shows that using a common air density measure has no meaningful effect on our findings.

It is possible that there are other sources of systematic measurement error that we haven't thought about. How much measurement error would be necessary to qualitatively alter our findings? If connection costs are systematically underestimated, or capacity factors systematically overestimated, for non-CDM projects compared to CDM projects, we would need to correct for this adjustment factor before concluding that a CDM project is a *BLIMP*. To explore this we impose the assumption that CDM projects are actually $\beta \geq 1$ times more remote, and only $1/\beta$ times as windy as our estimates indicate. As we increase β, CDM projects look less and less desirable as investment opportunities, compared to non-CDM projects.

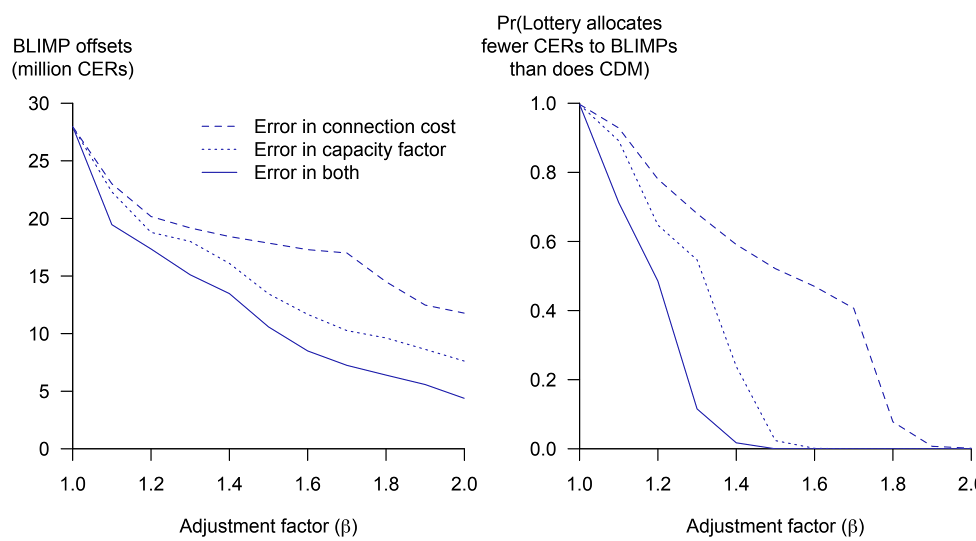


Figure 9: Sensitivity to asymmetric measurement error in connection costs and capacity factors

Row (7) of Table 1 shows the results for $\beta = 1.2$.[11] At this value, the number of BLIMPs drops sharply, however, the BLIMPs that remain still account for a large number of carbon offsets. Figure 9 (left panel) provides a graphical representation of all β values between 1 and 2. The right panel of 9 shows, that the CDM only performs on par with lottery assignment when CDM projects are handicapped by a 20% penalty in both connection costs and capacity factors.

Omitted Variables: Factors other than capacity, capacity factors, and connection costs could, conceivably, produce systematic differences in profitability even among wind farms built in the same state and year. If any of those factors are correlated with capacity, capacity factors, or connection costs, our results would be biased.

[11] This value, applied only to CDM projects, inflates connection distances by 20% and reduces capacity factors by 20%.

One possible omitted variable is the turbine manufacturer. To the extent that turbine manufacturers differ in their pricing, quality, technical specifications, ability to supply large developments, maintenance costs, etc., we could imagine that the choice of manufacturer affects both the profitability of a wind farm and features like its capacity or capacity factor. In row (8) of Table 1, we therefore require projects to use turbines from the same manufacturer in order to allow one of them to be classified as a BLIMP. Unsurprisingly, BLIMPs are much rarer occurrences if we require that wind farms are built in the same year, in the same state, and use turbines from the same manufacturer. However, taking into account that the same difficulty extends to counterfactual CDM assignments, we see that the CDM still performs quite poorly compared to a lottery (except for the number of BLIMPs).

Another potential omitted variable is the number of sites a project is spread across. The number of sites could affect the cost to build and to connect a wind farm. Row (9) matches projects on state, vintage, and number of sites. As before, this makes it harder to identify BLIMPs, but in relative terms, the CDM still performs poorly when compared to a lottery.

Another possibility is that projects above 5MW are somehow different than projects below 5MW. As discussed, the Generation-Based Incentive specifically supports wind farm developments that exceed 5MW in capacity. If the policy is in place to compensate for some unobserved cost of scale, such as the loss of support from local governments then our results may be biased. In row (10) we match wind farms on the year of construction, the state, and on whether it exceeded the 5MW capacity threshold. This improves outcomes for the CDM, but a lottery would still outperform the CDM most of the time.

Arguments about omitted policy variables can be extended down to the district-level, and in the limit, down to the village-level. Perhaps there is systematic variation in policies (or factor prices) between districts or villages within the same state, which affect costs. In rows (11) and (12) we match wind farms built in the same districts and the same villages. It now becomes much more difficult to find comparable wind farms and to spot BLIMPs. Matching at the village-year level has the side-effect of also eliminating variation in connection distances and capacity factors, so BLIMPs are only identified based on size differences. Even so, measured either in BLIMP capacity or offsets, the CDM still performs poorly relative to a lottery.

It is also possible that differences in project developer are more important than a feature of the wind farm, or a function of its location. Project developers may differ systematically in their engagement with local stakeholders, in their adherence to local regulations, and in their ability to develop wind projects more broadly. The CDM may quite reasonably support only projects put forward by reputable developers. If smaller, more remote wind farms are all built by less reputable developers. If so, our results may be driven by the fact reputation is only observed by the CDM. Row (13) shows that the CDM's performance relative to a lottery improves when we limit our sample to projects built by developers with at least one CDM-registered wind farm. However, even within this restricted sample, the lottery outperforms the CDM ≈ 700 times out of 1,000. While there might be some merit in the "developer quality"-hypothesis, it explains at best a small part of the CDM's apparently poor performance.

To address omitted variable concerns more generally, we investigate how much omissions is required to alter our conclusions. If the CDM observes some factors, hidden from us, that support the project's claim of being marginal, then their approval should provide a signal to us that the project is more likely to be marginal. Introducing an omitted variable is therefore equivalent to putting more faith in the CDM's decisions. Rather that determining counterfactual CDM assignments through a lottery where every project has an equal probability of being selected, we should perhaps give the real CDM projects a $\Gamma > 1$ times greater chance of being selected. As Γ rises, the lottery assignments will conform more and more closely to the actual CDM assignment. This makes the CDM look better and better.[12] How much faith, short of deferring to the CDM unquestioningly, is required to materially alter our conclusion?

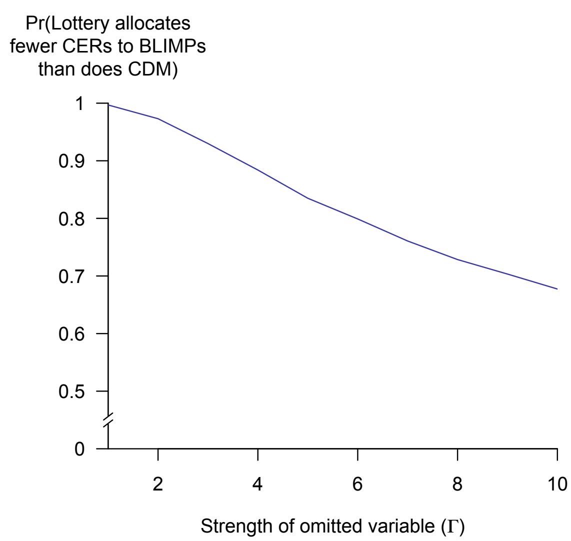


Figure 10: Sensitivity to generic omitted variable

Figure 10 shows what happens to the p-value as we increase Γ from 1, the value implicit in our main results, all the way up to 10, at which point CDM projects have a ten-fold higher probability of being selected.[13] Increasing Γ in this way does reduce the p-value, but even when we put more faith in the CDM's decisions, a lottery still assigns fewer CERs to BLIMPs 70% of the time. For an omitted variable to explain the CDM's assignment, it would have to be almost perfectly correlated with a project being marginal and the CDM's observed decisions.

Mis-specification Tests: While the general framework we introduce in this paper is flexible enough to accommodate a wide range of payoff functions, our empirical application relies on having

[12] Although our interpretation of Γ differs somewhat from Rosenbaum (1987), our sensitivity analysis with respect to a generic omitted variable here is formally equivalent to his.

[13] Note that Γ has no effect our ability to spot BLIMPs, so the number of BLIMPs, the BLIMP capacity, and the quantity of BLIMP offsets all remain constant as we increase Γ.

a detailed understanding of the factors that determine the profitability of wind farms in India. Though we have ample reason to think that larger wind farms, with higher capacity factors, located closer to electrical substations, will be more profitable developments, it is still worth investigating which of these monotonicity conditions are most important for determining the result.

In rows (14), (15), and (16) of Table 1, we relax each monotonicity condition in turn. We accomplish this by making sure that CDM wind farms are matched to non-CDM wind farms for each monotonicity condition and then use the remaining two conditions to determine whether the project is a BLIMP. In row (14) we match CDM wind farms to non-CDM wind farms within $\pm 5\%$ of their connection distance, d_n, and then use their relative capacities and capacity factors to determine whether each project is a BLIMP or not. For rows (15) and (16), we match on capacity factor or capacity and rank-order projects based on the remaining two monotonicity conditions.[14]

As we relax each monotonicity condition, we instead require projects to be matched in more dimensions, which naturally results in a drop in the size of the test statistics. Still, the CDM is more likely to produce greater BLIMP capacity and a greater quantity of BLIMP offsets than a lottery. We also see that most of the identification of BLIMPs in our original analysis comes from relative capacity. This is reassuring for two reasons. First, of the three variables that enter monotonically into the value function, capacity is the only one we have direct measurements of and do not estimate. Capacities are easily observed and therefore are at least risk of measurement error. The second reason is the strong empirical association between capacity and project costs. The strength of relationship provides an additional reason for confidence in the monotonicity condition on capacity.

Incomplete Data: If our database is missing any wind farms, we will tend to under-count the number of BLIMPs. If a lot of these missing projects are smaller CDM projects, in more remote locations, and with lower capacity factors, then their inclusion might improve the CDM's observed pattern of decision-making compared to a lottery.

The CDM pipeline includes nearly 200 Indian wind farms that were scheduled to start delivering electricity by 2013, but which we were unable to match to anything in our database. It is likely that these unconfirmed projects were never completed, in which case our earlier analysis stands without modification.[15] We explore the consequence of including them, however, just in case they were built and we were unable to independently confirm their existence.

Row (17) of Table 1 shows the results under the assumption that all 200 of the unconfirmed wind farms were actually built. The total quantity of CERs allocated to BLIMPs would increase, but increases slightly more under a lottery, which makes the CDM look better by comparison. This arises because the 200 unconfirmed projects are, on average, smaller, more remote, and have

[14] For capacity factor and capacity, we were able to match projects within $\pm 1\%$ without totally negating our ability to identify any BLIMPs.

[15] In a traditional subsidy program, supporting 200 projects that are never built would be a big waste of resources. However, since the CDM offers a conditional subsidy—CERs are only distributed once a project starts delivering electricity—there is no cost to registering proposed projects that fail to materialize. These are the projects with an index number greater than j in equation 2. Our suspicion that these projects were not completed is also supported by the fact that adding these projects to our database results in more built capacity than nation-wide figures indicate. See appendix A for more.

lower capacity factors, which makes them better candidates for support. It is unfortunate, then, that these wind farms seem not to have been completed despite being registered under the CDM. This suggests that the CDM not only registered too many blatantly infra-marginal projects, but also failed to provide adequate support to potentially marginal projects that did manage to get registered. Still, this is clearly the lesser problem. Even if the CDM had shepherded all 200 of these unconfirmed projects to completion, a lottery would still have allocated fewer CERs to BLIMPs 950 times out of 1,000. This is likely an overestimate of the CDM's performance, since we are only including uncompleted projects that registered under the CDM. If we were able to include uncompleted projects that did not apply, but would have been completed with the CDM's support, this would further improve the performance of the lottery.

Allowing for mistakes: One challenge to our findings is that, perhaps, we are applying our criteria too unsparingly. Maybe developers sometimes mistakenly invest in projects that are unlikely to be profitable, or the CDM mistakenly approves an application that they shouldn't have. When the mistakes are small, perhaps it is reasonable to make allowances.

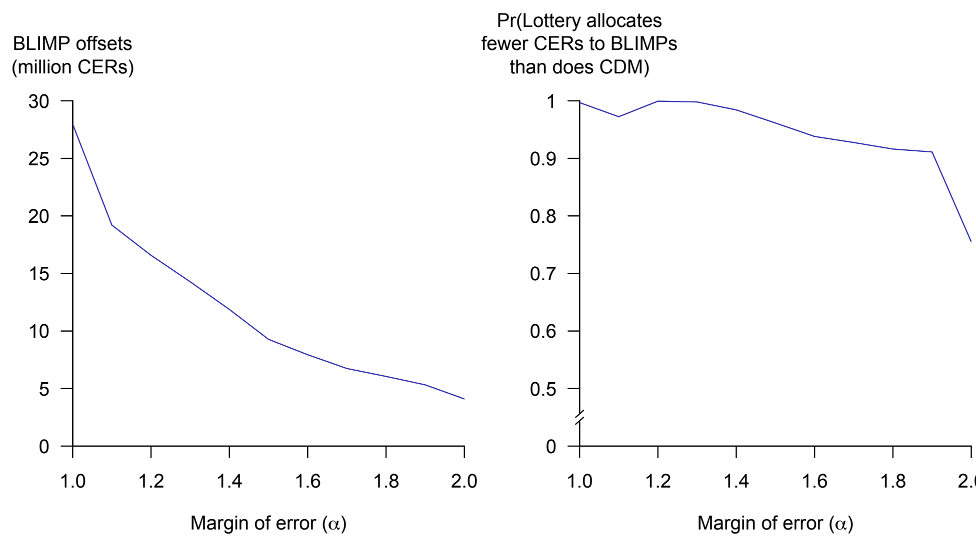


Figure 11: Sensitivity to small differences in capacity, capacity factor, and connection distance

One way to address this concern is to generalize the definition of a BLIMP so that only subsidized project that are *much* bigger and better located than the comparison projects qualify. More precisely, let's say that a subsidized project is a BLIMP only if another project, built in the same state and year, has $\alpha \geq 1$ times the connection distance, $1/\alpha$ times the capacity, and $1/\alpha$ times the capacity factor. In the main analysis $\alpha = 1$, but Figure 11 shows what happens when we gradually increase the margin of error to $\alpha = 2$. At this point we are demanding to see projects that are twice as remote, with half the capacity, and with half the wind, before calling something a BLIMP. The full results for $\alpha = 1.2$ are also reported in row (18) of Table 1. The number of BLIMP offsets declines, however, it remains above 5 million CERs even for very high values of α. The CDM's performance does not improve much compared to the lottery assignment. This is because a more forgiving definition reduces the number of BLIMPs under alternative subsidy assignments as well.

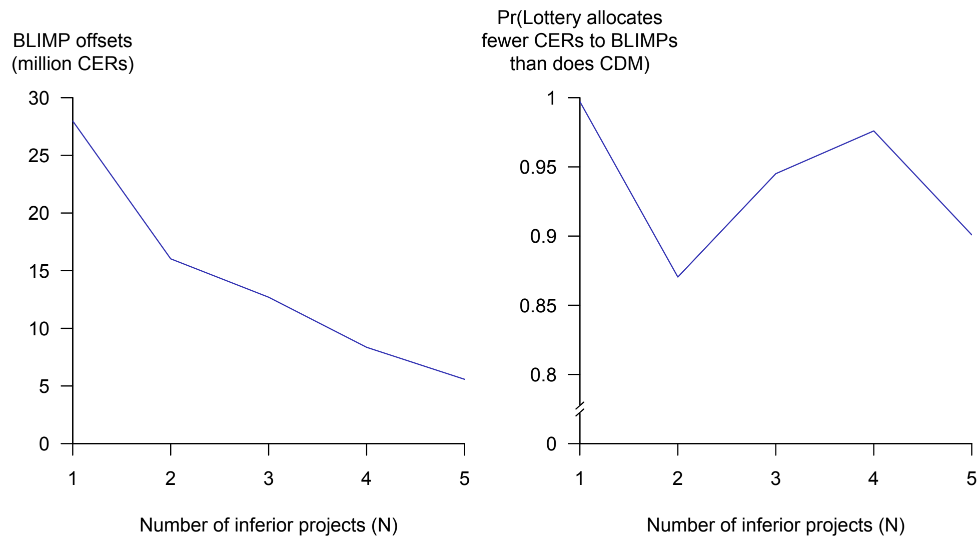


Figure 12: Sensitivity to the number of unsubsidized inferior wind farms

Another way to generalize the definition of a BLIMP would be to demand to see not just one, but $N \geq 1$ inferior projects. Row (19) of Table 1 shows the results for $N = 2$, and Figure 12 increases the number of inferior wind farms we demand to see up to 5, within a given state and year. The number of CDM projects that qualify as BLIMPs naturally falls when we demand to see two, three, four, or even five inferior wind farms for each one. Even when setting a very high threshold, however, the BLIMPs that remain were approved to receive well over 5 million CERs. A lottery assignment would still have a high probability of awarding fewer offsets to BLIMPs than the CDM.

Partial Infra-marginality: The definition of a BLIMP already gives a great deal of deference to the CDM's assessment of which projects are marginal—we only question their assessment in cases where we can point to another wind farm, built in the same state and year, with less generation capacity *and* lower capacity factor *and* greater connection distance. To give the CDM the greatest possible benefit of the doubt, we explore how our results are affected if we assume that every BLIMP is only partly infra-marginal.

While we argue that *BLIMP*s would have been built regardless, they might not have been built to the same capacity. Had the CDM not promised an additional revenue stream, perhaps the developer would have ultimately failed to build the proposed 10MW wind farm and instead would have been constrained to build only an 8MW project. Our main analysis would count all 10MW as infra-marginal, but in this hypothetical, only 8MW of the project should be considered infra-marginal.

To operationalize this idea, we use the next biggest inferior non-CDM project to bound from below the counterfactual capacity of *BLIMP*s. The next biggest non-CDM project shows what capacity each *BLIMP* could have been built to, at least, without CDM support. This approach yields a lower bound on infra-marginal capacity, by imposing the assumption that every BLIMP is only partly infra-marginal.

Row (20) of Table 1 shows the results of this exercise. Since we have built in the assumption that every BLIMP is partly infra-marginal, the blatantly infra-marginal capacity is much lower—about half of the number in our main results. The number of carbon credits allocated to support this infra-marginal wind capacity is also lower, about a third of our main finding. This should be thought of as a conservative lower bound on infra-marginality. At this lower bound the CDM performs on par with the lottery allocation mechanism.

7 Conclusion

The last decade has seen billions of carbon offsets issued to project developers around the world, providing opportunities for regulatory compliance at lower cost. However, when offset programs support projects that would have been developed anyway, they not only waste the limited resources available to mitigate climate change, but also contribute to climate change by increasing global emissions. In the context of the CDM—the world's largest carbon offset program—we estimate that at least 52% of approved carbon offsets were allocated to projects that would very likely have been built anyway. This is a substantial misallocation of resources.

When the CDM was created, India's wind power sector was identified as a context where there was huge potential for supporting marginal projects and increasing development beyond baseline projections. Yet, we estimate that the CDM has approved at least 28 million tonnes-worth of carbon offsets to infra-marginal projects. If we extrapolate this rate of infra-marginal support to the CDM as a whole, we calculate that the program may have increased global carbon dioxide emissions by 6.1 billion tonnes, equivalent to running 20 one-gigawatt coal power plants for their entire 50-year lifespan.

We also find that the allocation of offsets to Indian wind power projects compares unfavorably with a lottery, indicating that there is substantial room for improvement in the design and implementation of the project selection mechanism. Having a process that accurately screens out projects that do not require subsidies is essential to safeguarding the integrity of offset programs.

Why is the CDM failing to screen out these projects? We cannot answer this question definitively, though we observe that the vast majority of Indian wind power projects whose applications made it to the UN Executive Board were approved. Of the 666 CDM applications submitted for Indian wind farms, including the nearly 200 that we could not link to any real projects, 98% were approved. Even though we have identified hundreds of CDM applications that perhaps should have been denied, final approval appears to be almost automatic.

In practice, most of the screening is accomplished earlier in the process through some combination of India's Ministry of Environment and Forests, which decides which applications to forward to the UN for final approval, and through self-selection on the part of the developers themselves. We do not have data on submissions to the Ministry, but two observations suggest that self-selection might be an important factor. First, our sensitivity analysis revealed that the CDM favors the larger and better located wind farms even among the subset of projects belonging to developers with at least one CDM-project. Second, for developers that submit applications for multiple projects, direct inspection reveals that the application documents are often nearly identical. Both of these facts are consistent with there being substantial costs of applying, and developers choosing not to submit applications for smaller projects that would be less likely to generate enough carbon offsets to recoup the cost.

We acknowledge that our analysis only explores the direct effect of the CDM. It is possible that, despite increasing emissions, the transfer of wealth from developed to developing countries increased welfare. It is also possible that any marginal support provided by the CDM may have had an indirect effect on establishing the wind power sector in India. Non-BLIMPs may have offset more than one tonne of carbon dioxide per credit if their existence resulted in the entry of non-CDM projects. To compensate for the emissions increases due to BLIMPs, we calculate that each offset awarded to a non-BLIMP would, on average, have to generate an emissions reduction of 2.12 tonnes. This is equivalent to assuming that all non-BLIMPs are marginal and collectively responsible for the realization of half of India's non-CDM wind power capacity. This theoretical possibility does not undermine our finding that the CDM appears to have substantially misallocated resources. If anything, the possibility that marginal support could deliver indirect emissions reductions implies an even greater opportunity cost to subsidizing infra-marginal projects.

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Online Appendices – Not for Publication

Contents

A Data overview

This section provides a brief description of the main data sets used in this paper. Some of the data are described in greater detail in other appendices.

A.1 Bloomberg New Energy Finance

Bloomberg New Energy Finance (BNEF) database collects information on renewable energy projects all over the world (BNEF, 2013), though for this project, we have used only the list of wind power projects built in India up through 2013. BNEF provides information about when and where these projects were built, about the developer, capacity, equipment, cost, and more. A lot of this information is recorded within the context of long-form project descriptions, so we have processed and extracted only the variables we need for out analysis.

Since the coordinates of wind power projects are not available, we had to extract the names of states, districts, tehsils, and villages where the projects are located. These data were used as the basis for collecting specific coordinates using Google Maps. In cases where the data from BNEF was incomplete or imprecise, we conducted supplementary searches of the UNFCCC's CDM project database (UNEP DTU, 2021), as well as extensive online research, including press releases, news reports, and documents published by the Indian government.

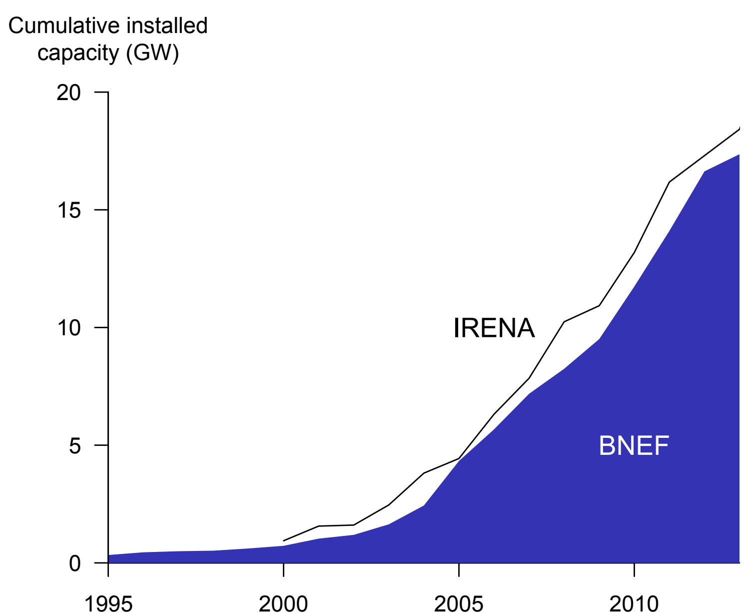

Figure A1: Comparison of BNEF and IRENA.

The BNEF database appears to provide a reasonably comprehensive picture of India's wind power sector during the period covered by our study. Figure A1 plots the total installed wind power capacity calculated from BNEF against national aggregates compiled by the International Renewable Energy Agency (IRENA). The figures calculated from BNEF trail closely behind the IRENA figures. Since 2005, BNEF makes up about 90-95% of the national aggregates in any given year.

A.2 UNFCCC CDM database and UNEP DTU CDM Pipeline

The UN Framework Convention on Climate Change (UNFCCC) provides an online database of all CDM project applications. The United Nations Environment Program (UNEP), in partnership with the Technical University of Denmark (DTU), provides a processed version of this database, called the CDM pipeline (UNEP DTU, 2021), which includes many key details of the proposed projects, as well as the status of the applications.

We have relied primarily on the UNEP DTU CDM pipeline for this project. To link these data to the BNEF database, we cross-referenced details about the location, timing, and characteristics of projects. In cases where matches were difficult to identify, we took the extra step of reading the Project Design Documents in the UNFCCC CDM database to see if we could find any additional details that could be cross-referenced. Even after this secondary search, however, we were unable to match up almost 200 Indian's wind farms in the CDM pipeline. The most likely explanation for this failure is that the projects were registered under the CDM but never completed. In fact, were we to assume that all of these projects were completed and add them to the BNEF data (as we do as part of a robustness check), the total installed capacity in some years exceeds the nation-wide figures collected by IRENA.

A.3 2001 Indian Village Census

The 2001 Indian Village Census (Meiyappan et al., 2018) provides a map that divides the country into states, districts, tehsils, and villages, and in addition, provides basic information about each geographical unit and sub-unit, including population and access to electricity.

We use these data for two purposes. The first is to harmonize administrative units—we use the census map to assign coordinates to specific villages, districts, and states. This resolves some inconsistencies in the BNEF database (e.g. villages close to borders are sometimes assigned to one state when mentioned in the context of one project, and then to another state when mentioned again for another project). This also allows us to be consistent in how we assign electrical substations to states, for the purposes of calculating connection distances using only in-state substations.

The second way we use the census data is to extract lists of cities with a population in excess of 100,000, and a list of cities with access to power. The coordinates of these cities are used as substitutes for electrical substations, as part of our sensitivity analyses.

A.4 ERA5-Land

The European Centre for Medium-Range Weather Forecasts provides a range of gridded data products, including ERA5-Land (Muñoz Sabater, 2019). It uses the global circulation model H-TESSEL to interpolate meteorological data to provide greater coverage of observationally sparse regions, yielding data that are more uniform in quality and realism than observations alone, and that is closer to reality than any model could provide on its own. ERA5-Land is discussed in greater detail in appendix B, where we describe how we use these data to estimate capacity factors.

B Estimating capacity factors

The kinetic power of the wind, P, that passes through a hoop with an area of A square meters is given by the following equation.

$$P = \frac{1}{2}\rho A w^3 \tag{5}$$

where ρ is the air density (kg/m^3), and w is the wind speed (m/s). What matters is how much air is being pushed through the hoop at a given point in time.

There are three physical constraints that prevent turbines from extracting all of this power. First, you need a minimum amount of force to get the blades moving in the first place, which means that wind turbines do not produce any electricity below its cut-in wind speed, $\underline{w}$. Second, the air slows down as it pushes the blades of the turbine. This means that the air following behind it must use some of its energy to push the stagnating air out of the way rather than to push the blades. As a result, the turbine can only convert some fraction C of this energy into electricity. This fraction is known as the "power coefficient", and it generally varies with the wind speed. Third, due to the limitations of the materials, turbines cannot safely and reliably rotate at any speed. Once the wind reaches the turbine's rated speed, $\tilde{v}$, the turbine operates at maximum capacity, even if the wind speed increases further. If the wind exceeds the cut-out speed, $\overline{w}$, the turbine needs to be shut down altogether. A turbine's power curve incorporates these three constraints, telling us how much power a turbine will produce as a function of weather conditions.

$$P(\rho, w) = \begin{cases} 0 & \text{if } w < \underline{w} \text{ or } w \geq \overline{w} \\ \min\left(\frac{1}{2}\rho A w^3 C(w), c\right) & \text{if } \underline{w} \leq w < \overline{w} \end{cases} \tag{6}$$

where c is the turbine's maximal power output, also called the "rated capacity." When we call something a 1 MW wind turbine, we are referring to this rating. This equation simply states that the turbine does not produce any power at all below its cut-in wind speed or above its cut-out wind speed. Between these two values, the power output is governed by the kinetic energy of the wind, subject to constraints imposed by engineering, which are reflected in C and c.

To estimate the maximum output of a turbine (the denominator of the capacity factor), it is sufficient to know the rated power of the turbine, c. Simply multiply c by the number of hours in the year. To estimate actual output (the numerator), we also need to know some of the turbine's other technical specifications (the cut-in and cut-out wind speeds, the swept area, and the power coefficient). Since these details vary across turbine models, we would need to know the turbine model used for a given project.

Although developers will know this information, this level of detail is often difficult to obtain for outside observers. We have only been able to confirm all of these details for 55% of the projects in our database. However, even when we do have this information, it isn't clear that this information-intensive approach is desirable in the context of trying to assess infra-marginal support.

We have opted to use a "benchmark" turbine to calculate capacity factors for all sites, regardless of the specific turbines chosen by each wind farm developer. If the benchmark turbine matches the actual turbine for a particular site, our calculation will match the developer's, of course. If a developer has chosen an inferior turbine for a particular site, we will overestimate the capacity factor. This is desirable in the context of trying to identify infra-marginal projects. The alternative would create a perverse incentive to choose inferior turbines to increase the chances of being judged deserving of a lucrative subsidy. If a developer has chosen a superior turbine for a particular site, using a benchmark turbine will lead us to underestimate the capacity factor. Again, this error is desirable in the context of trying to detect infra-marginal projects, since underestimating the capacity factor in this case means that we are choosing to not penalize developers for investing in better turbines. From the regulator's perspective, it is preferable to use a single, widely available turbine to uniformly evaluate the relative windiness of different sites. While a regulator might get more accurate capacity factor estimates by using information about the specific turbines for each project, this would also create perverse incentives for turbine choice, and is likely to degrade their ability to identify infra-marginal projects rather than enhance it.

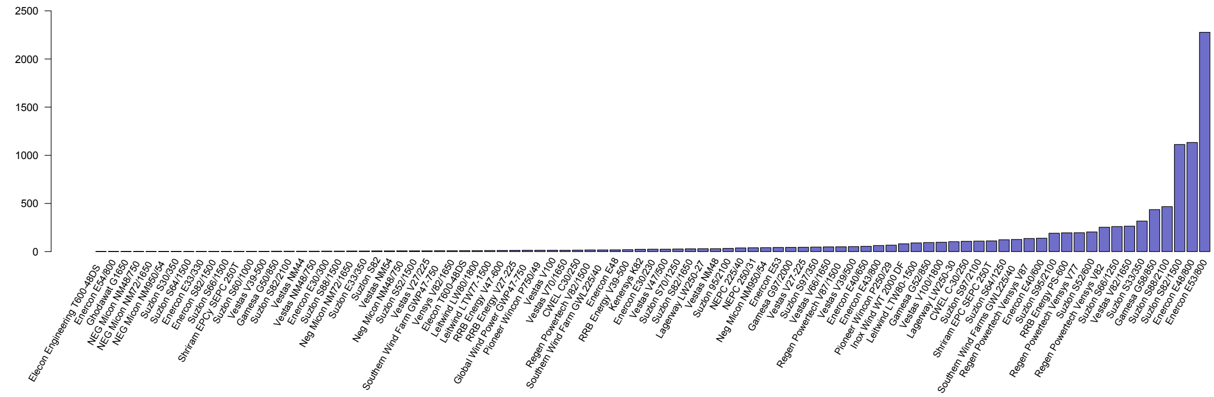

Figure A2: Frequency distribution of turbines. Excludes 611 wind farms for which information about the turbine make, model, or frequency are missing.

For our calculations, we use the technical specifications of the Enercon E-53 800 kW turbine. While there are many different turbines to choose from, the E-53 is the most common in our data set by far. It accounts for ≈15% of all the turbines we have been able to identify (Figure A2). It seems reasonable to expect this turbine to be widely available during our study period. It is also suitable across a broad range of locations and wind profiles. This makes it a reasonable choice as a benchmark. Using the technical specifications provided by the manufacturer, we can use equation 6 to calculate how much electricity the E-53 will produce at a given wind speed and air density.

As a sensitivity analysis, we replicate our analysis using Suzlon's S82 1.5MW turbine. As Figure A2 shows, the Suzlon S82 is another heavily used turbine, and it has the distinction of being the turbine used in most projects—it is used in 25% of all wind farms for which we can identify the make and model[16] The technical specifications of this turbine are quite different from the Enercon E-53. This means that the alternative turbine choice introduces meaningful variation into our capacity factor estimates.

Having chosen a benchmark turbine, we are now in similar position to a wind farm developer. We now know the technical characteristics of the turbines we wish to evaluate and we know the site at which they are being erected, but neither of us knows what the weather will be over the life of the turbine. Just like the developer, we have to estimate the site-specific joint distribution of wind speed and air density.

Developers will typically install anemometers at a selected site at least 12 months in advance to collect on-site data, which is then correlated with measurements from adjacent locations to construct a more accurate representation of long-term weather conditions (Carta et al., 2013). Unfortunately, the data to replicate these calculations are not available to us. Neither has it been economically feasible to replicate their primary data collection at thousands of wind farms across India. Instead, we estimate weather conditions using alternative data.

One possibility is to use readings from nearby weather stations, without local anemometer readings. Measurements from Indian weather stations are available through the Integrated Surface Database (Smith et al., 2011), but these data leave much to be desired. First, the network of stations is quite sparse, which means you often have to travel very far from a given wind farm to

[16]Projects often use multiple turbine types.

reach a weather station (Figure A3, left panel). Only 5% of wind farms are located within 10 km of a weather station. In some instances you'd have to travel over 100 km. The average distance is 34 km. Although weather conditions are correlated across space, there's likely to be significant measurement error in a contemporaneous wind speed measurement taken so far away from the turbine.

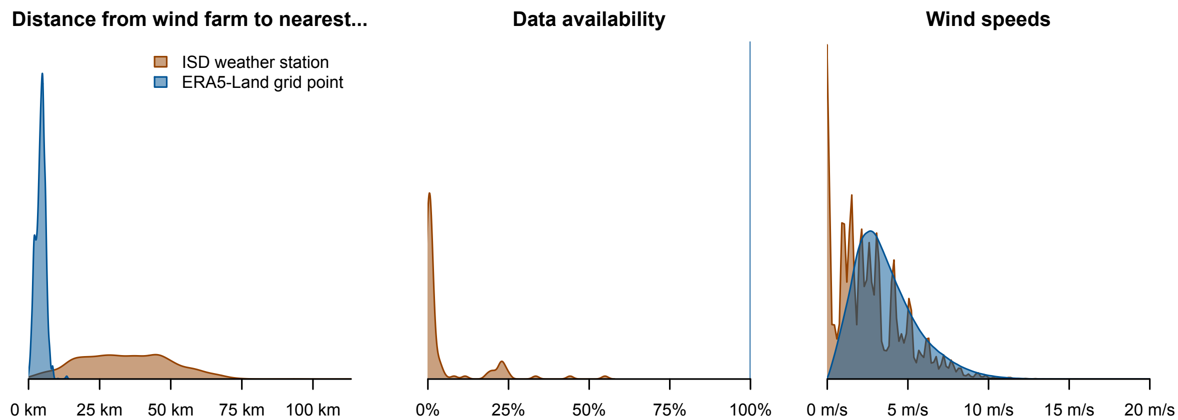

Figure A3: Comparison of data for weather stations and gridded data. The *left panel* compares the distances from each wind farm site to the nearest weather station in the Integrated Surface Database and to the nearest grid point in the ERA5-Land database. The *middle panel* compares the availability of hourly readings at weather stations and ERA5-Land grid points that are nearest to at least one wind farm site. The vertical line for the ERA5-Land data represents the point mass of 1 on 100%. The *right panel* compares the hourly readings for wind speed at weather stations and ERA5-Land grid points that are nearest to at least one wind farm site.

A second problem with the weather station data is how frequently readings are missing. For the subset of weather stations that are nearest to at least one of the wind farm sites, there is only enough information to determine the wind speed and air density for 5.1% of hourly readings between 1990 and 2019 (Figure A3, middle panel). Half of all weather stations report fewer than 0.7% of hourly readings, and not a single station reports more than 55% of readings.[17] A small part of this can be explained by weather stations that operated for only part of this period.

A third problem is that, even when readings are available, they give reason for pause. Perhaps most conspicuously, there is a large excess probability of very low wind speeds, and nearly 20% of readings are exactly zero (Figure A3, right panel). This is in conflict with the properties of wind speed distributions (Monahan et al., 2011; Lakshmanan et al., 2009). The atmosphere is constantly moving relative to the Earth's surface and it is extremely rare to actually record wind speeds within a rounding-distance of zero.

Like many economists working in countries where the quality and quantity of historical weather data is limited, we have opted to use reanalysis data (Auffhammer et al., 2013). We use the ERA5-Land database produced by the European Centre for Medium-Range Weather Forecasts (Muñoz Sabater, 2019). It uses the global circulation model H-TESSEL to interpolate observationally sparse

[17] These figures are only slightly better for the network of Indian weather stations as a whole. Only 8.4% of hourly readings between 1990 and 2019 contain adequate information to determine both wind speed and air density. Half of all weather stations report fewer than 1.8% of hourly readings, and not a single station reports more than 90% of readings.

regions, yielding data that are more uniform in quality and realism than observations alone, and that is closer to reality than any model could provide on its own.

ERA5-Land includes a complete set of hourly observations going back to 1981, at a spatial resolution of roughly 9 km over land. At this spatial resolution, the average distance from one of the wind farm sites in our data set to the nearest ERA5-Land grid point is 4.3 km (Figure A3, left panel). A small fraction of wind farms are sited along irregular coastlines, which limits the number of available grid points over land. Although we would generally expect a grid point no farther than roughly 6 km from any wind farm site, a few cases do exceed the Pythagorean limit. The farthest one is 13.4 km away from a wind farm site.

Reassuringly, weather conditions are so highly correlated at this spatial scale that it would make little difference whether we calculated capacity factors using the time-series from the nearest grid point or from the next nearest grid point in ERA5-Land (Spearman correlation = 0.996). This reanalysis data set appears to provide the best available estimates of weather conditions in the vicinity of the Indian wind farms we are studying.

From the ERA5-Land database we use the u and v components of wind to calculate wind speeds, and the mean temperature, dew point temperature, and surface pressure to calculate air densities (following Picard et al., 2008). Using our chosen turbine specification, we then obtain the power output from equation 6 and compare the cumulative output at each site to the maximal output.

Auffhammer et al. (2013) warn that the precise timing of deviations of weather variables from their means is somewhat idiosyncratic across alternative gridded data products. We do not rely on timing to calculate capacity factors. We use the full-time series at each location to estimate a location-specific distribution of wind speed and air density. That distribution is our best guess for what a wind farm developer would have estimated at any point during this period.

Finally,while turbines like the E-53 have a hub height of at least 50 meters, ERA5-Land interpolates wind at a height of 10 meters and the other variables at 2 meters, the heights at which most measurement instruments are placed. Since wind speeds increase monotonically with height, capacity factors also increase with height, which means that we will slightly underestimate the true capacity factors. In particular, the so-called "wind profile power law" states that, under neutral stability conditions, the ratio of wind speeds at heights k and l is related to the ratio of k and l by the following equation, $\frac{v_k}{v_l} = \left(\frac{k}{l}\right)^{\frac{1}{7}}$. From this relationship we can deduce that the wind speed at 50 meters height is roughly 1.26 times faster than at 10 meters. Air density, by contrast, falls monotonically as you ascend, though the change is very small when close to the surface. Since air density enters linearly rather than cubically in the power function, the rising wind speed dominates.

This means that, were a wind farm developer to use the same data and methods as we have to forecast capacity factors, they would have to multiply the estimate by some height-adjustment factor to get a more accurate forecast. Our analysis relies only on the *ordering* of capacity factors across sites, which would not be affected by a monotonic transformation. As such, this extra adjustment provides no additional value.

C Estimating connection distances

Connection distances are estimated by computing the smallest length of cable that would be needed to connect wind farm sites to electrical substations. The geographical coordinates of electrical substations were collected, and generously provided, by Fiona Burlig. The coordinates of the turbines were found using a combination of information found in the Bloomberg's New Energy Finance database, the UNFCCC's CDM project database, as well as extensive online research, including press releases, news reports, and documents published by the Indian government. We recorded the coordinates of the village in which the turbines are located, rather than pinpointing individual turbines. This was partly out of practical necessity, but also means that our findings cannot be driven by arbitrarily small differences in location. Any variation in location that we might have been able to generate at the sub-village level would likely have contained more noise than signal.

We calculate the connection distance using a modified minimum spanning tree (MST) algorithm. A standard MST algorithm considers only one type of node, and will search for a set of edges that connects all of the nodes together, yet whose combined length is as small as possible. This approach would yield strange results, however, for multi-site wind farms, sometimes with sites spread across large distances. In these situations, developers may not wish to connect all sites to each other, but instead exercise the option of connecting different clusters of sites to different electrical substations. To avoid inflating the connection distances for wind farms spread across multiple sites, we needed to modify the standard algorithm.

The modified MST algorithm has three steps.

1. Connect the entire network of electrical substations to each other (by any method) and record the total edge length.

2. Append the wind farm sites for each project as unconnected nodes in the network, and then use a standard MST algorithm to add the set of edges of shortest length that creates a graph without any unconnected nodes. Record the total edge length of the augmented graph.

3. Subtract the total edge length in step 1 from the total edge length in step 2 to retrieve the minimum length of cable needed for every wind farm site to be connected, either directly or indirectly, to at least one electrical substation.

As part of our robustness checks, we further modify this algorithm to permit only connections to electrical substations located in the same state as the wind farm site. This is accomplished by running the above algorithm separately for the electrical substations and wind farm sites located in each state, and then summing the results across states. In other robustness checks, we use the above algorithm as stated, with the only difference that we swap out the electrical substations for power stations or cities.

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