CLIMATE POLICY INITIATIVE
NÚCLEO DE AVALIAÇÃO
DE POLÍTICAS CLIMÁTICAS
PUC-Rio

Misreporting in the Deployment of Wind Power: Evidence from Brazil

Climate Policy Initiative

Juliano Assunção
Joana Chiavari
Dimitri Szerman

May 2014

CPI Report

Descriptors

Sector	Renewable Energy, Wind
Region	Brazil
Keywords	wind, renewable energy, feed-in tariff, policy
Contact	Juliano Assunção juliano@cpirio.org

About CPI

Climate Policy Initiative is a team of analysts and advisors that works to improve the most important energy and land use policies around the world, with a particular focus on finance. An independent organization supported in part by a grant from the Open Society Foundations, CPI works in places that provide the most potential for policy impact including Brazil, China, Europe, India, Indonesia, and the United States.

Our work helps nations grow while addressing increasingly scarce resources and climate risk. This is a complex challenge in which policy plays a crucial role.

Misreporting in wind power contracts: Evidence from a Feed-in Tariff in Brazil

Juliano Assunção Joana Chiavari Dimitri Szerman

May 2014

Abstract

Feed-in tariff (FiT) schemes are the most commonly used policy mechanism to spur renewable energy, globally. We analyze FiT contracts between wind farms and a government-owned utility in Brazil. Under these contracts – offered through the Incentive Program to Alternative Sources (PROINFA) –, payments relied on capacity factors (CFs) reported by windfarms. We show that the distributions of reported and realized CFs have different shapes. We interpret this fact as systematic misreporting of CFs by windfarms, and argue that certain features of PROINFA contracts led to the observed behavior. Based on a model that incorporates the key aspects of PROINFA, we show that an interest rate penalty on overpayments can mitigate the incentives of misreporting capacity factors.

1 Introduction

Many nations around the world face an energy challenge. Meeting rising demand for electricity, enabling stable and secure supplies, and avoiding or offsetting greenhouse gas emissions are all factors in this challenge. Increasingly, renewable sources like wind and solar power are seen as important ways to reach these goals. Policymakers have used a wide variety of support schemes to drive market deployment of renewable energy, with varying degrees of success in terms of effectiveness and cost-efficiency (Butler and Neuhoff (2008), IEA (2011)).

Some of the most commonly used policies to spur renewable energy are feed-in tariffs (FiTs): By early 2012, FiTs were in place in at least 65 countries (REN21, 2012). Broadly, a FiT scheme is a long-term purchase agreement for the sale of electricity to the grid at prices typically set above market prices. Policy makers opting for a FiT are confronted with a myriad of alternative program designs and parameter choices, such as selection criteria of eligible technologies, capacity caps, and price schedules. Fine-tuning such policies through proper design is paramount for their success (Miguel Mendonça (2010), Ragwitz et al. (2012), Canton and Linden (2010)).

This paper analyzes long-term contracts between wind farms and a government-owned utility in Brazil. The contracts were offered through a FiT scheme used in Brazil, the Incentive Program for Alternative Sources of Energy (PROINFA), which drove most of the growth in wind capacity in Brazil between 2004 and 2012.[1]

PROINFA contracts relied on capacity factors (CFs) reported by windfarms for payment during the first two years of operation. The payment schedule was tiered, or as we refer to it throughout this paper, nonlinear: Windfarms reporting CFs below 32% were paid a high price per MWh produced; windfarms with CFs above 42% were paid a low price, but received larger contracts. In between these two cutoffs, windfarms were paid a price according to a downward sloping price schedule. After the first two years of operation, the regulator checked realized CFs and made payment adjustments.

[1] Other studies describe and analyze different features of PROINFA. See, for example, Dutra and Szklo (2008) and Kissel and Krauter (2006).

We show that this nonlinear payment scheme gave incentives for windfarms to misreport their CFs. In fact, the distributions of reported and realized CFs are different: whereas realized CFs follow a smooth distribution, reported CFs are clustered around the cutoffs that determined the prices payed to windfarms. We interpret this fact as indicating systematic misreporting of CFs, and argue that certain features of PROINFA contracts led to the observed behavior.

The consequences of the discrepancies between reported and realized CFs in PROINFA are twofold. First, they introduced imbalances between expected and actual production. Wind farms contracted by PROINFA were supposed to produce 14% more MWh's than what was actually delivered. Second, they created a financial burden on PROINFA. Of the total payments to wind farms in their first year of operation, 12% were over-payments, i.e., payments for energy that was not delivered. Although these payments were eventually returned to the government-owned utility company, no interest was paid on these amounts. More generally, discrepancies between predicted and realized CFs undermined both the ability of regulators to plan grid expansion as well as the effectiveness of policies aimed at deploying wind capacity.

Our analysis is based on a simple model in which the government hires an entrepreneur to develop a wind project. The entrepreneur receives a perfectly informative signal about his project's true CF, and this signal is private information; the government only knows the distribution of CFs in the economy. We restrict the analysis to the class of contracts that mimics those offered by PROINFA. Based on that, entrepreneurs must report their CF, and face a trade-off between the perceived cost of misreporting and the benefits of exploring the gains provided by the payment system.

We use a unique dataset of wind projects to fit our model. We collect detailed data from the regulator's records on all 92 wind projects that applied to PROINFA, including a complete follow-up on the 41 projects that were awarded a contract and were in operation as of December 2012.[2] We have data on each project's reported CF as well as the realized CF after the project started operating. The fitted model captures the most striking pattern of the data,

[2]There are 13 projects that were awarded contracts but were not operating as of May 2013. We do not consider non-operative projects in this paper. In a related paper, we analyze PRONIFA's project selection mechanism, and address the issue of such delays in deployment.

which is a gap of reported values in the downward sloping portion of the price schedule.

Next, we perform two counter-factual simulations. In the first simulation exercise, we predict wind farms' CF announcements under a constant unit price set at the mid-point of the original price range. We find that the distribution of reported CFs becomes smooth, although misreporting actually increases: the gap between expected and actual energy output increases to 90 %. This is due to the fact that the nonlinear price schedule partially offsets incentives to over-report CFs by offering a higher unit price to low-CF farms. In the second simulation exercise, we add an interest rate penalty on overpayments, while keeping the original nonlinear price schedule. We find that an interest rate of 1 % would cause misreporting to vanish altogether. This result suggests that a simple change in the PROINFA contracts would solve the problem stemming from costly monitoring of wind data gathered in prospective sites.

This paper contributes to multiple strands of the literature. Boccard (2009) documents systematic discrepancies between estimated and realized capacity factors at the country level, a phenomenon he called the "capacity factor puzzle". The author identifies potential explanations for the observed underperformance, which includes long-term variations in wind speed, political interference, and mode of finance. We show that such discrepancies can also arise at the plant level, and offer an alternative explanation – that of poorly designed contracts which give entrepreneurs an incentive to misstate the capacity factor of their wind farms.

Several authors perform case studies of renewable energy policies to assess key determinants of success (Becker and Fischer, 2012), (Kitzing et al., 2012). Works using quantitative methods are less common, and typically perform cross-country or cross-state comparisons to assess the advantages of one policy over another (Carley (2009), Dong (2012), Jenner (2012), del Rio and Tarancon (2012)). Our work bridges these two strands by providing micro-evidence on the importance of policy design.

Finally, much of the debate around renewable energy policies has focused on the issue of feed-in tariffs versus renewable portfolio standards (Schmalensee, 2012) or the use of auctions (Butler and Neuhoff, 2008). Our analysis underlines the more general point that the details of policy design and implementation, rather than the choice of actual policy type, are of first-order importance to renewable energy policy. Although the general policy framework is undoubtedly important, our conclusions are in line with recent trends in policy making arenas (see, for instance, IEA (2011) and IRENA, 2012).

The remainder of this paper is organized as follows. Section 2 discusses the background and specific features of PROINFA. Section 3 describes the data we use in the analysis. In section 5 we develop a simple model that captures the misreporting of capacity factors. Section 6 discusses the identification and estimation procedure of the model. In section 7 we present our empirical results and perform counterfactual exercises. Section 8 concludes with a brief discussion of the implications of our work.

2 Background

Capacity factors and the wind industry The capacity factor of a power plant is defined as the ratio of the actual electricity generated over a period of time and the hypothetical maximum possible. For wind farms, wind availability is the single most important determinant of a farm's CF, although technology, placement of wind turbines, and other atmospheric and geographic conditions also play a role (Blanco, 2009).

The economic viability of a wind farm is primarily driven by CFs. It is therefore crucial that entrepreneurs have a good grasp of the wind conditions of prospective sites. In fact, prior to installing turbines developers forecast their CFs by gathering wind data on site and then feed these data into forecasting models. Holding equipment efficiency constant, the higher the CF, the more energy a wind farm will be able to produce.

There is scope for manipulation in both the forecast and realized CF of a wind farm. Forecasts rely on both measured and simulated wind data, both of which can be selectively picked besides being sensitive to methods, assumptions, and instruments used in data collection. Realized CFs are harder to manipulate, since energy production is directly measured by a third party – typically an operator or regulator. To manipulate realized capacity factors, power plants must manipulate production – e.g., switching off turbines.

PROINFA PROINFA represents the first major attempt to deploy electricity generation from renewable sources other than hydro in Brazil. It was enacted in 2002, one year after major power outages resulting from a combination of low rainfall and over-reliance on hydro sources. PROINFA was initially designed to be implemented in two successive phases.[3] For the first phase, the goal was to deploy 3.3 GW of installed capacity evenly split between wind, small hydro, and biomass. That represented an 19.8% increment on installed capacity in 2002 from sources other than large hydro.[4] Low take up from biomass developers led the government to contract extra capacity from wind to meet the overall 3.3 GW target. PROINFA's second phase was never implemented, and several factors account for the program's disruption.[5] The program's performance in terms of deployability was poor: While projects were scheduled to start operating by December 2006, only six projects were operational before 2009. In addition, a major reform in the power sector came into force in 2004, making auctions the contracting mechanism for electricity in Brazil.

We focus our analysis on wind projects for two reasons. First, as mentioned above, wind was the single most important source within PROINFA in terms of capacity. Second, there are specific features to contracts for wind projects which make the analysis interesting.

Application and Selection Interested project developers had two years to gather wind data from prospective sites before applying to participate in 2004. Project developers had to submit their forecast CFs along with wind speed readings and the methodology used in the forecasting process, each step of which must be certified by a third party. The regulator had no involvement in the forecasting process. We checked the submitted forecasts as well as the accepted CFs for all applicants to PROINFA. In all cases, applicants were granted the estimated capacity factors that they submitted. It is worth noting that in other contexts regulators perform more thorough checks on generators' bids. For example, in the UK's Non-Fossil Fuel Obligation "will-secure" tests are performed on generators' forecasts (see

[3]Law 10,438 (26 April 2002) sets out the targets and timescales for PROINFA, as well as the mechanisms for selecting projects and determining the prices at which electricity would be sold. This Law was later revised and adjusted by Law 10,762 (November 2003) and Decree 5,025 (March 2004).

[4]In 2002, total installed capacity in the country was 80.1 GW, of which 63.5 GW consisted of large hydro power plants (greater than 30 MW). Capacity in wind power plants totaled 22 MW, and small hydro accounted for 972 MW.

[5]The target of this second phase was to supply 10% of Brazil's annual electricity consumption from renewable sources within 20 years.

Agnolucci (2007)).

Selection followed state-specific queues, organized on a "first come, first served" basis.[6] Queues were then formed within each of the 27 Brazilian states, and no state could end up with more than 220 MW of installed capacity, unless the overall 1,100MW target was not met. As this was indeed the case, three states ended up with more capacity than the initial 220 MW quota, and together they accounted for 70% of the contracted capacity in PROINFA.[7] The idea was to incentivize development of wind farms in non-prime locations, which can be desirable to reduce risks in energy generation.

Contracts Selected projects were awarded 20-year contracts for generation of electricity. During their first year of operation, plants were paid according to their forecast CFs rather than their actual energy production. Payments depended on the forecast CFs through both quantities and nonlinear prices. The amount of MWh contracted in the first year was simply the product of the plant's installed capacity and its forecast CF, multiplied by the number of hours in a year.

The price per MWh explicitly depended on the CF through a (weakly) decreasing price schedule. Figure 1 depicts the price schedule. Plants with forecast CF lower than 32.4% were paid a price of R$204.3 per MWh, while plants with a forecast CF larger than 41.9% were paid a price of R$180.2. Plants with CFs between these two points faced a downward sloping price curve connecting the two points.[8]

After the first year of operation, any discrepancies between estimated and realized capacity factors were compensated for in the subsequent year, and contracts were revised every two years. Such compensation however did not take into account interest rates, only inflation adjustments.

The aim of this nonlinear price schedule was to ensure the economic viability of wind farms in non-prime locations. In this sense, it complemented the state-wise quotas, whose goal

[6] "First come, first served" selection criteria are common for feed-in tariff schemes. In the case of PROINFA, the issuance date of projects' environmental licenses was used to manage the queue of projects, with older licenses having priority. Ties are solved at random.

[7] These are Ceará, Rio Grande do Sul and Santa Catarina.

[8] Note that the unit price applies to all units sold, not only the marginal unit.

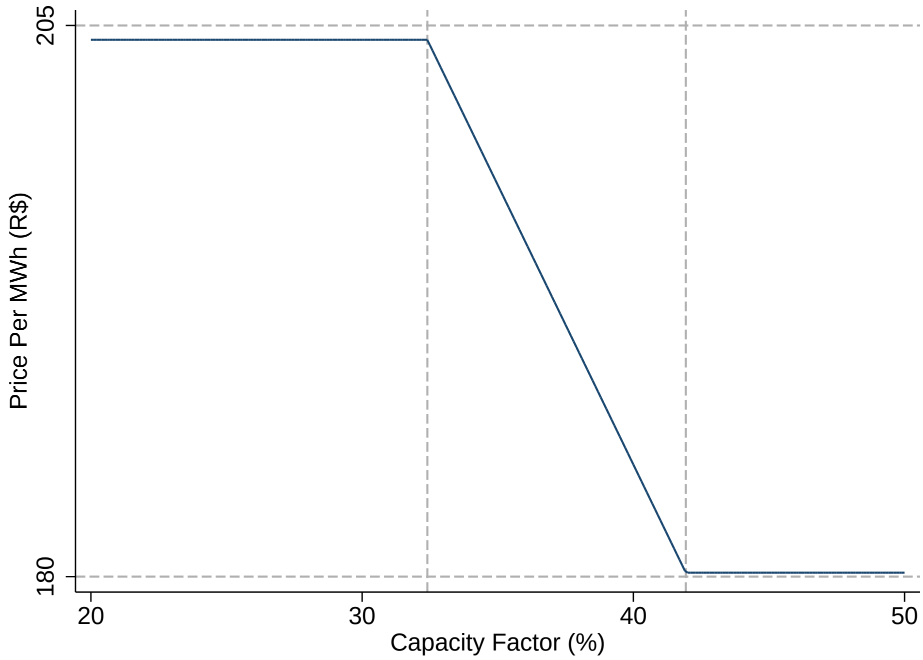

Figure 1: PROINFA's Price Schedule

Notes: The figure shows PROINFA's price schedule in March 2004 Brazilian Reais (R$).

was the geographical dispersion of wind farms.

3 Data

We use publicly available data at the project level obtained from the regulator (Agência Nacional de Energia Elétrica, ANEEL). The main source is the set of records on wind projects that applied to participate in PROINFA. These records contain detailed information on technical specifications of each project. For the purposes of this paper, we use each project's estimated CF and installed capacity.[9] We followed up on the projects that were awarded contracts, and collected data on each project's operation starting date as well as its monthly electricity output. Of the 54 projects that were awarded contracts, only 41 were in operation as of December 2012. We are thus able to construct each project's realized CF using the

[9]Application to PROINFA took place in 2004; between application and their start date, projects changed their estimated capacity factors. Such changes might reflect changes in equipment choice, better wind readings, or may be purely strategic. We are agnostic in this regard, and use the latest estimated CF before the project starts to operate, because this is the estimated CF which matters for contract and payment purposes. There are few exceptions in which the estimated CF changes, but the regulator does not take those changes into the contract. In those cases, we still use the latest estimated CF submitted by the windfarm.

following formula:

$$\text{Realized CF}_i = \frac{\sum_{n=1}^{N_i} E_{in}}{K_i \times N_i \times 730} \qquad ,$$

where N_i is the number of months since plant i started operating up to December 2012, E_{in} is electricity generated in month n (measured in MWh), K_i is the plant's capacity, and 730 is the average number of hours in a month.

Table 1 shows descriptive statistics for our data. The first two rows show that estimated CFs are systematically larger than realized ones: the average estimated CF is 35.4%, while the average realized CF is 31.1% (two-sided p-value less than 0.001). This pattern is also true for the median, minimum and maximum and the distributions. The third row of Table 1 shows that the typical plant in our sample was in operation for 42 months (only one plant was in operation for less than 24 months). Having generation data for more than three years on most projects gives us confidence that realized CFs are close to true CFs. Finally, the fourth row shows that there is considerable variation in plants' sizes: the range goes from 4.25 MW to 104.4 MW.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Median	Min	Max
Contracted Cap. Factor (%)	35.41	7.97	32.19	25.13	53.97
Realized Cap. Factor (%)[a]	31.10	6.90	29.81	19.76	50.39
Months in Operation	42.41	14.96	42.00	18.00	77.00
Installed Capacity (MW)	29.31	28.42	23.40	4.25	104.40
# of Plants	41				

Notes: Table shows summary statistics for 41 wind farms that were awarded PROINFA contracts and were in operation as of December 2012. (a) Realized CFs were calculated with all available data for each wind farm.

4 Misreporting capacity factors: Evidence

The discussion so far can be summarized as follows. Entrepreneurs have room to misreport their forecast CFs because the regulator takes their announcements at face value. In addition to reputation issues, the fact that forecasts must be certified by a third party presumably introduces costs to misreporting. Finally, misreporting may be advantageous: entrepreneurs can bring forward some cash flow by appropriately misreporting their forecast CFs.

To illustrate how misreporting capacity factors may be advantageous, we simulate revenue streams for hypothetical wind projects as a function of their actual and estimated capacity factors. We then compute the present discounted value of the first three years of operation. Figure 2 depicts the results. Three patterns emerge. First, within feasible levels of CFs, entrepreneurs maximize their revenues by announcing a CF at the price schedule's first kink point. Second, the incentives to report at this point are higher for projects at the two ends of the CF distribution. For example, a project with a true CF of 20 percent will see its discounted revenues rise by 4 percent in the first two years of operation. For a project with a CF of 46 percent, this figure is 2.5 percent. Projects with CFs closer to the price schedule's kink point at 32 percent gain less for misreporting – around 1.5 percent in revenues. Finally, entrepreneurs minimize their revenues by reporting a CF at the price schedule's second kink point.

Figure 3 gives more direct evidence on misreporting of capacity. The left graph shows the distribution of reported CFs, while the right graph shows the distribution of realized CFs. A comparison between the two distributions reveals three patterns. First, there is more mass to the right of the 42% threshold in the distribution of reported CFs. Second, there is less mass of projects in the range between the two thresholds. Finally, there is considerable bunching to the left of the 32.4% threshold in Figure 3a. In principle, such concentration could result from a combination of geographic concentration of plants and time-specific wind trends, or even be a statistical fluke. However, Figure 3b suggests that this is unlikely. It shows the realized capacity factors, which display no bunching around the price schedule's kink points. Furthermore, although there is some concentration around other values, which is probably due to geographic concentration of plants, such concentration is much less pronounced than that of the left graph.

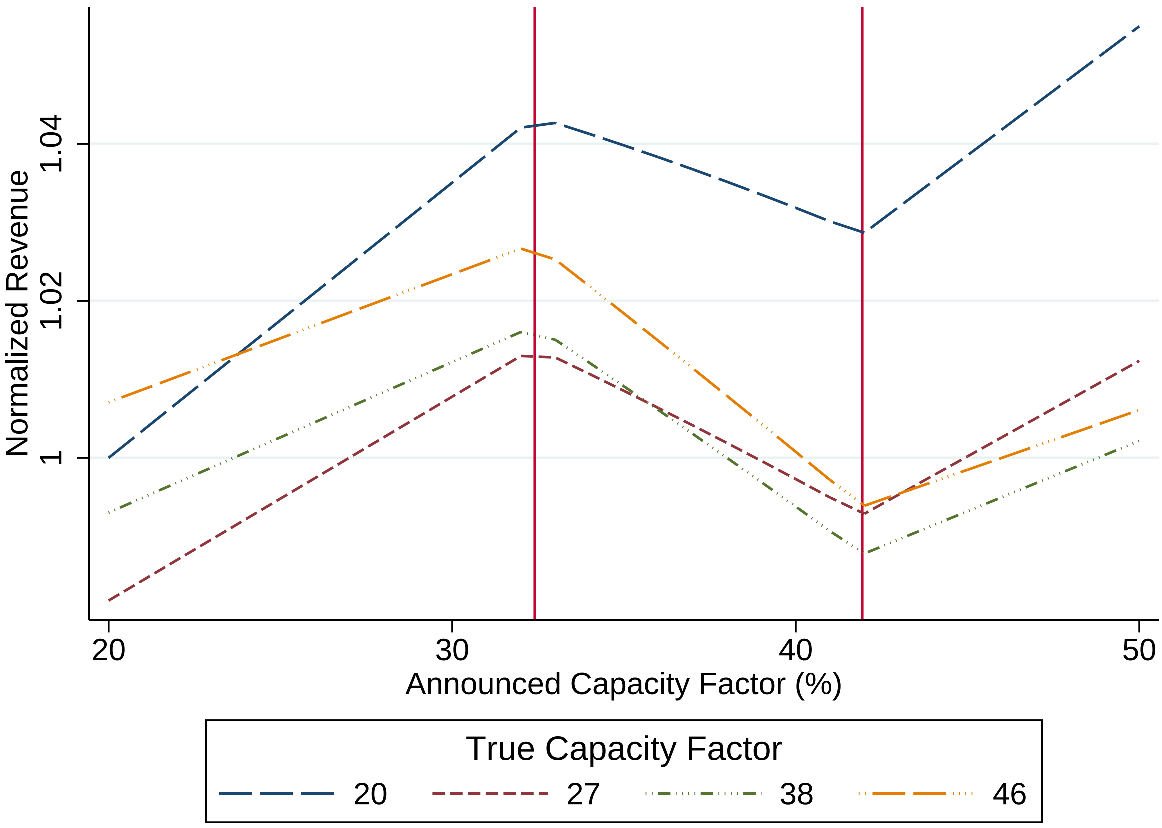

Figure 2: The effects of misreporting CF on revenues

Notes: The vertical axis measures the normalized distance from a project's revenues when the reported CF is the true CF. Revenues are measured in the first three years of operation, under the following assumptions: (i) installed capacity is 30 MW; (ii) the discount rate is 0.9; (iii) generation is deterministic, and constant on a year basis.

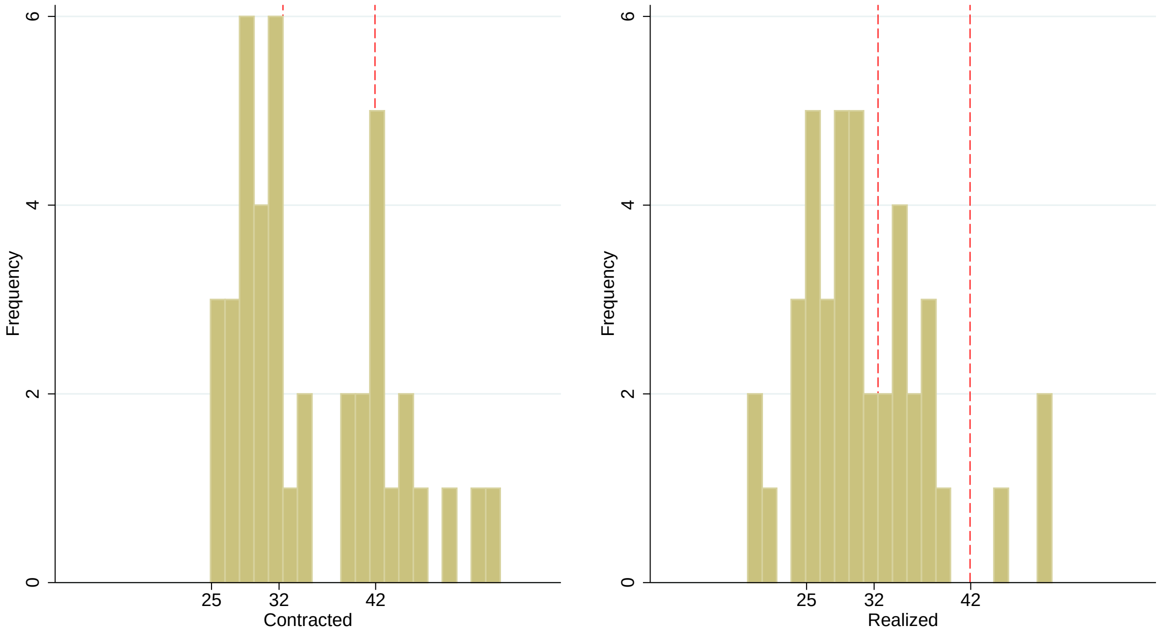

Figure 3: Evidence of misreporting: Announced, Contracted and Observed CFs

Notes: The figure shows relative frequencies of reported (left) and realized (right) CFs. Bins are of 0.015 width. The figure uses the 41 projects which started operating before 1st January 2013.

5 Misreporting capacity factors: a simple model

This section analyzes the incentives for misreporting embedded in the PROINFA contracts. In order to quantify the distortions produced by the contract design and perform counterfactual exercises, we lay down a simple principal-agent model. The model mimics the key aspects of the contract and focuses on the announcement of capacity factors. We take as given some of the entrepreneurs' decisions. Specifically, we take as given the entrepreneurs' choices regarding factors affecting their true capacity factors, such as location, equipment and engineering choices. The current version of this model also ignores any uncertainty in electricity generation, assuming a risk-neutral entrepreneur.

A project i is characterized by a productivity parameter (capacity factor) $f_i \sim F(\cdot)$ with support in $[0,1]$. Each entrepreneur receives a signal s_i about his project's f_i, and must announce s_i to the principal. Denote by $\widehat{s}_i$ the announcement made by the entrepreneur about his signal s_i. For the sake of simplicity, we assume the entrepreneur's signal is fully informative of her project's productivity parameter, that is $s_i = f_i$.

We assume that entrepreneurs face a convex cost of untruthfully reporting their signals. In this scenario, the entrepreneur's payoff is given by

$$\pi(\hat{s}; f) = (1-\delta)p(\widehat{s})\widehat{s}K + \sum_{t=2}^{T} \delta^{t-1} p(f) f K - \frac{\beta}{2}(\widehat{s} - f)^2 + \epsilon, \tag{1}$$

where $\delta \in (0,1)$ represents how impatient the entrepreneur is and $\beta > 0$ represents the cost of lying (i.e., announcing $\widehat{s} \neq f$), and K represents the plant's installed capacity. The function $p(\cdot)$ is the price schedule entrepreneurs face, and is given by

$$p(s) = \begin{cases} \overline{p} & \text{if} \quad s \leq \underline{f} \\ \overline{p} - \alpha s & \text{if} \quad \underline{f} < s \leq \overline{f} \\ \underline{p} & \text{if} \quad s > \overline{f} \end{cases},$$

where $\alpha = (\overline{p} - \underline{p})/(\overline{f} - \underline{f}) > 0$, and $\overline{p} > \underline{p}, \overline{f} > \underline{f}$ are given thresholds. This price schedule subsidizes low-productivity projects by giving them a higher price per unit of output, and is precisely PROINFA's price schedule depicted in Figure 1. In period 1, the price schedule is a function of the reported capacity factor, whereas in subsequent periods it is a function of the realized (true) capacity factor. The term $p_2(f)fK - p_1(\widehat{s})\widehat{s}K$ represents the payment adjustment in period 2 due to discrepancies between $\widehat{s}$ and f in period 1.

The entrepreneur's problem is to choose a $\widehat{s}^*$ that maximizes (1). The first-order condition for this problem implies that

$$\widehat{s}^*(f|\delta, \beta, K, \overline{p}, \underline{p}, \overline{f}, \underline{f}) = \underset{\widehat{s} \in \{\widehat{s}_1^*, \widehat{s}_2^*, \widehat{s}_3^*\}}{\arg\max}\, \pi(\widehat{s}), \tag{2}$$

where

$$\widehat{s}_1^* = \begin{cases} f + \kappa\overline{p} & \text{if } f \leq \underline{f} - \kappa\overline{p}, \\ \underline{f} & \text{otherwise.} \end{cases}$$

$$\widehat{s}_2^* = \begin{cases} \underline{f} & \text{if } f \leq \underline{f}(1+2\alpha\kappa) - \kappa\overline{p} \\ \overline{f} & \text{if } f > \overline{f}(1+2\alpha\kappa) - \kappa\overline{p} \\ \frac{f+\kappa\overline{p}}{1+2\alpha\kappa} & \text{otherwise.} \end{cases}$$

$$\widehat{s}_3^* = \begin{cases} \overline{f} & \text{if } f \leq \overline{f} - \kappa\underline{p} \\ f + \kappa\underline{p} & \text{otherwise.} \end{cases}$$

where $\kappa = \frac{(1-\delta)K}{\beta}$. Equation (2) gives the optimal announcement in each region of the price schedule. Upon observing his true CF (f) and installed capacity K, the entrepreneur will choose the region of the price schedule that maximizes his profits. This clearly depends on the program's parameters $\underline{p}, \overline{p}, \underline{f}, \overline{f}$ as well as on the values of β, δ and K.

To illustrate the model's prediction, Figure 4 plots the entrepreneur's optimal announcements as a function of his signal for given values of β, δ and K. The model has three predictions. First, the model predicts that all entrepreneurs find it optimal to "exaggerate" their signals: all announcements lie above the 45-degree line in the announcement-signal space. Second, there is bunching on the price schedule's first kink point: entrepreneurs with different signals find it optimal to announce their CFs at the first kink point. Third, the vertical line around the second kink point indicates that there will be a lack of announcements around that point.

6 Identification and Estimation

Our goal is to estimate β and δ of equation (1). We use the moment condition in (2) to map each project's true (that is, observed) capacity factor and installed capacity into its announced CF. By using one moment condition, we are able to identify only one parameter in our model. We therefore fix δ at different levels, and estimate the corresponding β using the procedure described below.

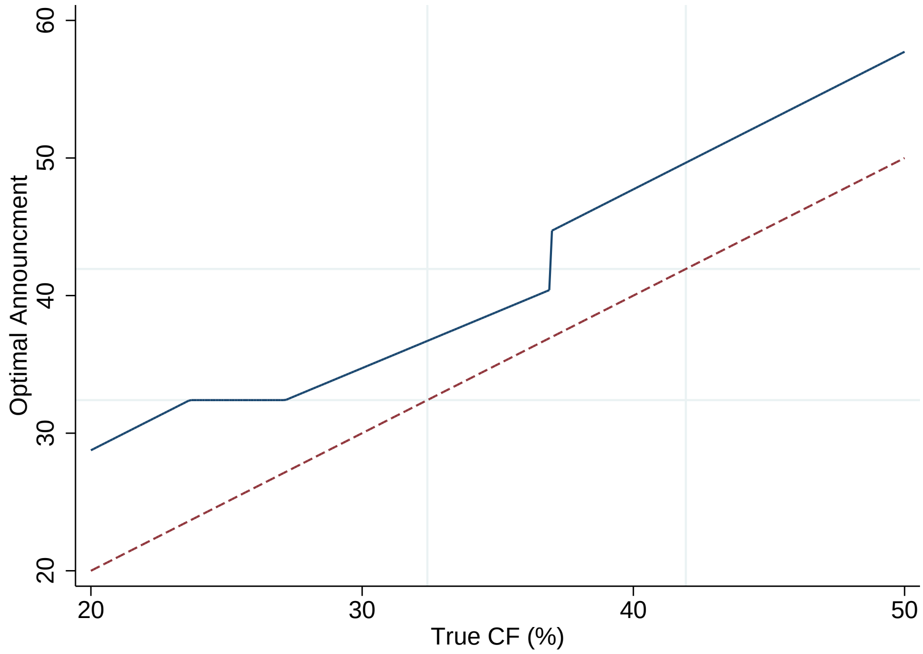

Figure 4: Model Solution: Illustration

Notes: The figure displays equation (2) for $\delta = 0.9$, $\beta = 14,000$ and $K = 30$. The remaining parameters are like in PROINFA: $\overline{p} = 205$, $\underline{p} = 180$, $\overline{f} = 41.9\%$, and $\underline{f} = 32.2\%$.

To estimate β, we use equation (2) to predict each projects' announced CFs. Denote the vector of predicted announcements as $\tilde{\mathbf{s}}(\beta;\delta,K,\theta)$, and the vector of observed announcements as $\widehat{\mathbf{s}}$. We then search for β that minimizes the distance between predicted and actual announced CF:

$$\widehat{\beta} = \arg\min_{\beta}(\widehat{\mathbf{s}} - \tilde{\mathbf{s}}(\beta;\delta,K,\theta))'W(\widehat{\mathbf{s}} - \tilde{\mathbf{s}}(\beta;\delta,K,\theta)) \tag{3}$$

We search for $\widehat{\beta}$ using a grid search associated with an optimization algorithm. We tested this estimation procedure in a Montecarlo exercise for several true values of β and δ. The Montecarlo results are reported in the appendix.

Table 2 presents the results for three different levels of δ. The minimized distance between the vector of predicted and actual announcements is 0.1408. In our model, β is interpreted as the marginal cost of lying.

Table 2: Model Estimates

δ	$\widehat{\beta}$
0.90	14050
0.95	7025
0.99	1405

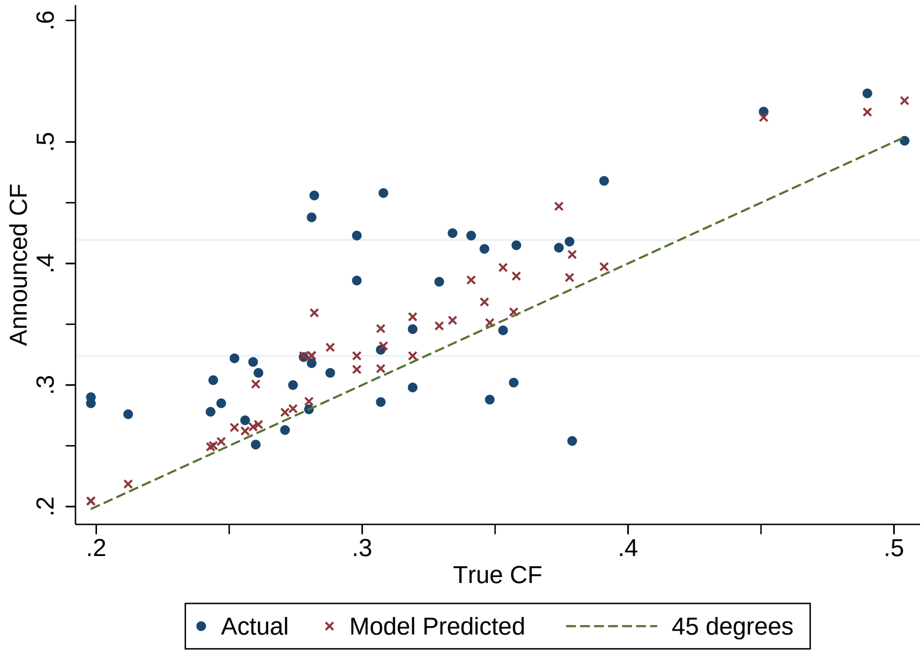

Figure 5: Model Fit: Reported vs Model Predicted CFs

Notes: Model predictions were obtained by plugging the estimate obtained in (3) into the profit function (1). The minimized distance between the vector of predicted and actual announcements is 0.1408.

We assess our model's goodness of fit by confronting its predictions with actual data. The results are presented in Figure 5. Our model clearly captures the main empirical regularity of PROINFA, namely, the bunching at the price schedule's kink point. The model overpredicts this bunching, but we believe the model's performance can be improved, as discussed at the beginning of Section 5.

7 Counterfactual exercises

We now perform counterfactual policy experiments to study the effects of alternative PROINFA contract designs. The first exercise is to assess what would have happened under a linear price schedule. In our model, this amounts to setting $\overline{p} = \underline{p}$. We predict announced CFs assuming a unique price per MWh set at the midpoint of the price schedule (R$ 192).

The results are displayed in Figure 6. We can see that the predicted announced CFs do not bunch at any particular values. We also see that many firms move closer to truthful announcement, particularly those firms with true CFs at the low end of the distribution.

However, all predicted points lie above the 45-degree line, indicating that all firms now over-report their CFs. This is because there are no price gains from under-reporting under linear pricing. Moreover, firms with true CFs at the high end of the distribution are the ones that profit the most from over-reporting under linear pricing. As a result, the net effect is that over-reporting actually goes up: the gap between expected and actual energy output increases from 14 to 28.5 percent.

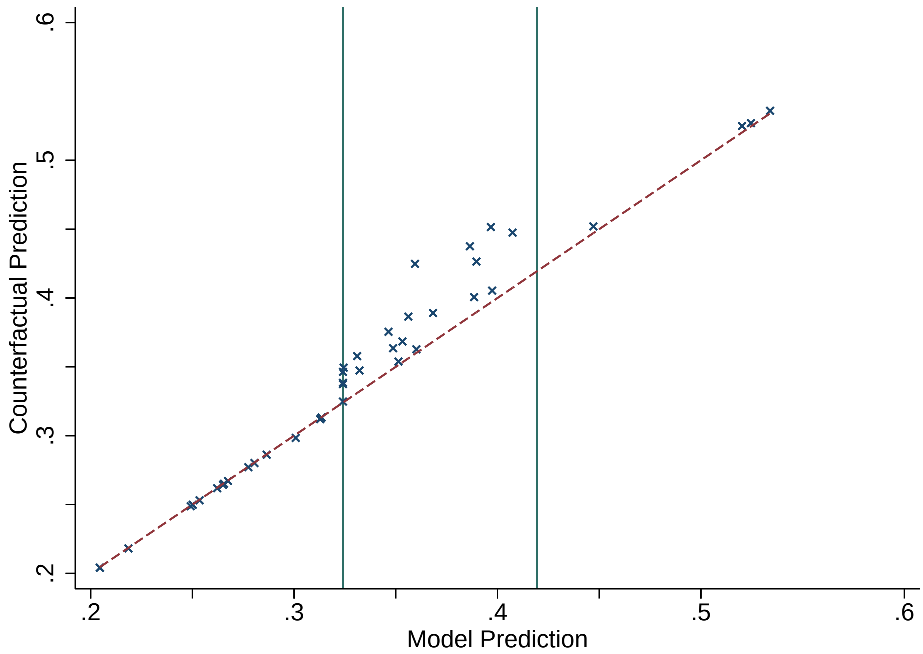

Figure 6: Optimal CF Announcements under Linear Pricing

Notes: Predicted announcements were made under the assumption of a single unit price set at R$192, which is the midpoint of the original price schedule. The vertical distances from points to the 45-degree line, weighted by the respective installed capacity, give the difference between expected and observed energy output.

The main conclusion from this counterfactual exercise is that the non-linear price schedule appears to have played an important role in PROINFA for unanticipated reasons. Together with state quotas, the aim of non-linear pricing was to incentivize the development of wind farms on non-prime locations. Yet, only three states reached (in fact, exceeded) their quota and together they account for 95% of the capacity contracted by PROINFA. Not surprisingly, those three states are the ones with the best wind conditions. We find evidence that PROINFA's non-linear pricing schedule, while giving incentives to firms' to report CFs at its kink points, prevented larger discrepancies between expected and realized electricity output.

In the second counterfactual exercise we study the effects of charging interest in payment adjustments. In our model, this amounts to including interest payments in the firms' payoff function (1). We then predict announced CFs for various interest rates. The results are displayed in Figure 7. We find that charging 1% interest on overpayments practically offsets any incentives to misreport CFs. Lower rates are not enough, while higher rates give firms incentives to under-report their CFs and earn interest on under-payments. It is interesting to note that the rate of 1% is close to the subsidized real interest rate at which entrepreneurs could borrow from the government.

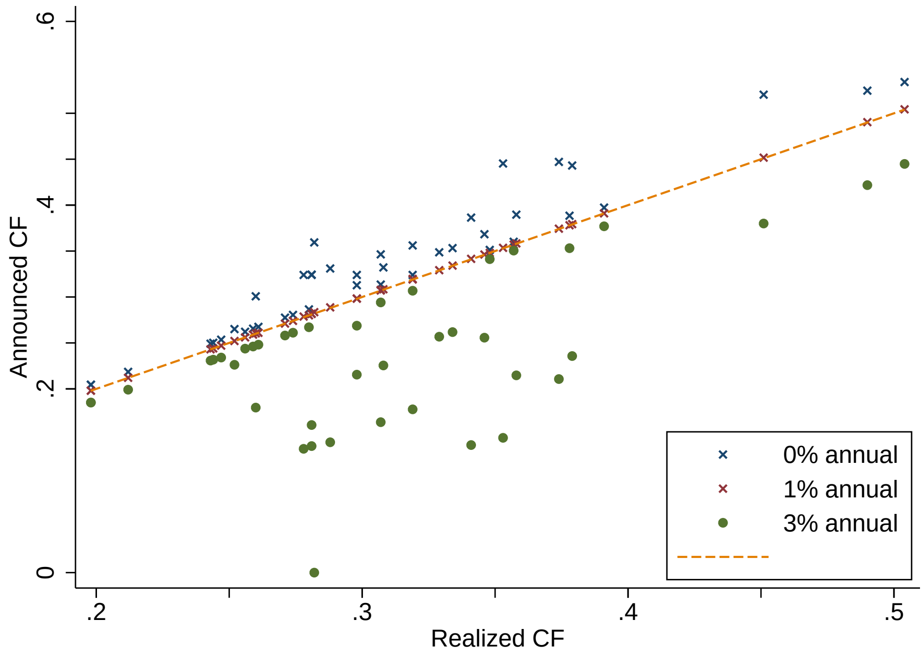

Figure 7: Optimal CF Announcements with Interest Payments

The main conclusion from this second exercise is that a properly set penalty for misreporting would offset any effects accruing from imperfect monitoring and the resulting asymmetric information. We interpret the lack of an interest payment as a contract design flaw which exacerbated the imperfect monitoring of wind conditions on specific sites.[10]

It is important to point out the limitations of these counterfactual exercises. In our model, we do not take into account the entrepreneur's participation constraints. Therefore, throughout the counterfactual exercises we implicitly assume that all firms would still apply to

[10]Of course, there are other possible contract designs which could potentially solve the problem of misreporting without the need of costly monitoring. For example, wind farms could be paid on a monthly basis strictly for the electricity they generated. Such design could be undesirable however, for it introduces more uncertainty in the wind farm's cash flow.

PROINFA after the policy changes. In the linear pricing exercise, we implicitly assumed that all firms would be willing to participate in PROINFA if the unit price was R$ 192. To illustrate this point, imagine we chose half of the minimum original price, R$ 92. It is likely that some firms would choose not to apply to PROINFA altogether, in which case our counterfactual would yield misleading results. In the second exercise, it may be the case that some firms needed the insurance against wind variation implicitly provided in PROINFA's contracts. To the extent that those firms could not find insurance without this feature of the contracts, our exercise would again miss an important point.

8 Concluding Remarks

In this paper, we analyze the design of PROINFA – a FiT scheme used to deploy renewable energy in Brazil. We use a unique dataset of wind projects in our analysis, and show that PROINFA contained flaws in its contract design which gave incentives for misreporting of capacity factors. We first document such misreporting and then analyze PROINFA's selection mechanism. We find that both the contract design and the selection mechanism created distortions, which are important for cost-effectiveness, energy planning, and security.

Our analysis underlines the more general point that the details of policy design and implementation, rather than the choice of actual policy type, are of first-order importance to renewable energy policy. As such, it is in line with recent trends in policy making arenas (see, for instance, IEA (2011) and IRENA, 2012). In particular, our findings suggest that rewarding projects on the basis of estimated CFs can create perverse incentives for firms to concentrate their efforts on this particular parameter, in detriment of other performance measures. In turn, this may have serious implications for planning of electricity supply and energy security.

References

Agnolucci, P. (2007). The importance and the policy impacts of post-contractual opportunism and competition in the English and Welsh non-fossil fuel obligation. *Energy Policy*, 35(1):475 – 486.

Becker, B. and Fischer, D. (2012). Promoting renewable electricity generation in emerging economies. Technical report, Deutsches Institut fur Entwicklungspolitik.

Blanco, M. I. (2009). The economics of wind energy. *Renewable and Sustainable Energy Reviews*, 13(6-7):1372–1382.

Boccard, N. (2009). Capacity factor of wind power realized values vs. estimates. *Energy Policy*, 37(7):2679 – 2688.

Butler, L. and Neuhoff, K. (2008). Comparison of feed-in tariff, quota and auction mechanisms to support wind power development. *Renewable Energy*, 33(8):1854 – 1867.

Canton, J. and Linden, A. J. (2010). Support schemes for renewable electricity in the eu. Technical report, European Commission.

Carley, S. (2009). State renewable energy electricity policies: An empirical evaluation of effectiveness. *Energy Policy*, 37(8):3071 – 3081.

del Rio, P. and Tarancon, M.-A. (2012). Analysing the determinants of on-shore wind capacity additions in the EU: An econometric study. *Applied Energy*, 95(0):12 – 21.

Dong, C. (2012). Feed-in tariff vs. renewable portfolio standard: An empirical test of their relative effectiveness in promoting wind capacity development. *Energy Policy*, 42(0):476 – 485.

Dutra, R. M. and Szklo, A. S. (2008). Incentive policies for promoting wind power production in Brazil: Scenarios for the Alternative Energy Sources Incentive Program (PROINFA) under the new Brazilian electric power sector regulation. *Renewable Energy*, 33(1):65–76.

IEA (2011). Deploying renewables. best and future policy practice. Technical report, OECD/IEA, Paris.

International Renewable Energy Agency (IRENA) (2012). Evaluating policies in support of the deployment of renewable power. Technical report, IRENA.

Jenner, S. (2012). Did feed-in tariffs work? an econometric assessment. Available at SSRN: http://ssrn.com/abstract=2121261. or http://dx.doi.org/10.2139/ssrn.2121261.

Kissel, J. M. and Krauter, S. C. (2006). Adaptations of renewable energy policies to unstable macroeconomic situations–case study: Wind power in brazil. *Energy Policy*, 34(18):3591–3598.

Kitzing, L., Mitchell, C., and Morthorst, P. E. (2012). Renewable energy policies in Europe: Converging or diverging? *Energy Policy*, 51(0):192–201.

Miguel Mendonça, David Jacobs, B. S. (2010). *Power the Green Economy. The feed-in tariff handbook*. Earthscane.

Ragwitz, M., Winkler, J., Klessmann, C., Gephart, M., and Resch, G. (2012). Recent developments of feed-in systems in the eu. Technical report, International Feed-In Cooperation.

REN21 (2012). Renewables 2012 global status report. Technical report, REN21 Secretariat, Paris.

Schmalensee, R. (2012). Evaluating policies to increase the generation of electricity from renewable energy. *Review of Environmental Economics and Policy*, 6:45–64.