Should We Subsidize Production or Investment Goods?

A Quantitative Analysis for the U.S. Electricity Sector

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Abstract

The U.S. reaffirmed funding for wind power by allocating a significant portion of the $386B climate package from the Inflation Reduction Act to the Production Tax Credit (PTC) and Investment Tax Credit (ITC). But given attitudes towards risk in light of wind intermittency, which subsidy is more cost-effective? I revisit the longstanding issue of output and investment subsidies' relative performance and address it from a new perspective. I do this by investigating how implicit risk attitudes from managerial decision-making influence the choice of subsidy type that minimizes public budgetary costs of meeting a given investment target. I show that unitary increments of the PTC provide significantly stronger incentives to invest in wind capacity than alternative percentage increases in ITC subsidy rates. Fixing the public budgetary cost of wind subsidies, I find average annual investment rates in wind capacity to be 7 percentage points higher under a prevalent and exclusive utilization of PTC in comparison to an alternative implementation of ITC. This is because wind project managers respond to unpredictable volatility in the flow of PTC benefits by over-investing in wind capacity (relative to ITC) to buffer potential losses in year-by-year PTC payments due to lower-than-expected capacity factor realizations.

JEL codes: H20, H23, Q48, Q58

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1 Introduction

Since enactment of the Energy Policy Act of 1992, the U.S. federal government has established a decades-long history of heavily subsidizing wind power. Its commitment went a step further when it allocated a major portion of the $386B climate package in the recently passed Inflation Reduction Act (henceforth, IRA) to incentivize investments in clean energy sources like wind. Two key components of this climate package are the extensions of the Production Tax Credit (PTC) and the Investment Tax Credit (ITC) in Section 45 and Section 48 of IRA, respectively. Under PTC, wind developers are eligible for up to $27.5/MWh over the course of 10 years after completion of the wind facility (in 2023 dollars). Alternatively, under ITC taxpayers qualify for a subsidy up to 30% of their investment costs in capital and equipment (e.g. wind turbines).

A fundamental distinction between both subsidy types is that PTC payments throughout the 10-year time frame of the policy are stochastic. This is because the PTC is an output-based subsidy and production at wind farms critically depends on exogenous weather conditions that are highly uncertain in the long run (e.g. due to changing patterns in spatial variation of air density, direction, and speed of wind). On the contrary, the one-time upfront payment under the ITC is known with absolute certainty when the wind developer builds the project. But given attitudes towards risk in light of wind intermittency, which subsidy is more cost-effective? In this paper, I investigate *how implicit risk attitudes in managerial decisions from wind developers influence the choice of subsidy type that minimizes public budgetary costs for meeting a given investment target.*

Since seminal work from Holmström (1999), economic literature has been interested in understanding how managers' risk aversion affects firm-level investment outcomes. Recent research has showed that managers hired by firms typically exhibit important degrees of risk aversion even in presence of unsystematic investment risk that could be diversified at the firm-level (e.g. Caliendo et al. (2024), Gormley and Matsa (2016), Jagannathan et al. (2016), and Brenner (2015)). This is largely driven by the fact that: i) managers receive compensation packages that are highly dependant on performance of investments specifically overseen by them, and ii) are considerably less able to mitigate downward investment risk relative to firms.

In the context of risk-averse agents, another salient feature of individual risk attitudes that is consistently observed in the data is prudent behavior. Recent literature has documented evidence of prudent behavior (i.e. convex *marginal* utility of state-dependent consumption) from risk-averse agents across a wide range of settings and how this feature leads them to self-insure against income risk (e.g. Boar (2021), Ameriks et al. (2020), He et al. (2018), Fagereng et al. (2017), Guerrieri and Lorenzoni (2017), Challe and Ragot (2016)). In the case of subsidies to commercial wind, accounting for risk aversion and prudence in managers' risk attitudes matters because investment income generated from wind projects under a PTC is subject to higher unpredictable volatility (i.e. relative to ITC). This is due PTC benefits being linked to uncertain production

outcomes that unfold gradually over time. Consequently, economic theory predicts that managers from wind developers under PTC payments should invest more intensively in wind capacity in order to buffer downward risk in the flow of PTC benefits from potentially lower-than-expected production outcomes. This allows the manager to self-insure herself against unexpectedly low compensation package payments due to productivity at overseen wind projects potentially falling below expectations. But what is the quantitative relevance of this mechanism? Can risk attitudes be a key driver of behavioral differences in investment decisions across subsidy types? What are the implications for cost-effectiveness of wind subsidies?

I answer these questions by developing a dynamic framework of optimal wind capacity *adoption* and *expansion* that models the intertemporal investment decisions from a risk-averse and prudent manager hired by a wind developer. At any period, the manager working for a wind developer makes investment decisions in wind capacity and financial assets in exchange for compensation package payments which are tied to the performance of her investments. On one hand, wind projects are risky investments undertaken by the manager due to prevalent uncertainty about future electricity prices and plant-level output realizations. On the other hand, because wind developers typically hold well-diversified investment portfolios outside of wind capacity, I account for this in the model by allowing the manager to invest in a risk-free asset with positive real rate of return. The return earned on the risk-free asset captures the implicit opportunity cost of wind investments that the manager considers when deciding how to allocate the developer's investments between wind capacity and alternative assets. Therefore, the model accommodates both extensive (i.e. whether or not to build the wind project) and intensive margins (i.e. how large to build the wind farm) of the manager's wind investment decision.

Subsequently, I augment this model to quantify how the effects of wind subsidies on investment outcomes vary based on the subsidy type. I do so by allowing wind developers to access a menu of subsidy types with the following two mutually exclusive alternatives: an output-based subsidy which is earned over time (akin to the PTC) and a one-time subsidy to investment costs of wind capacity additions (akin to the ITC)[1]. This policy extension allows the model to capture how the interaction between managers' risk attitudes and subsidy types matters, fundamentally and quantitatively, for investment outcomes in wind capacity. In addition, I explicitly account for the effects of monetization of tax benefits on investment decision-making.

I estimate structural parameters of the model by using survey data from the Texas electricity market. I consider Texas electricity market as the empirical study case for this paper because it is the U.S. power market that has experienced the largest increase in wind capacity additions during the last twenty years that the PTC and ITC have been active[2]. To this end, I draw upon plant-level wind data on net generation, installed capacity, overnight capital costs, and real-time market (RTM) electricity prices from the EIA-860

[1] In practice, a wind project may receive tax benefits either from PTC or ITC but not both. So these are mutually exclusive.

[2] ERCOT (Electric Reliability Council of Texas), serves ∼90% of Texas electricity demand and is actually the U.S. power market that has experienced the largest increase in wind power capacity during the last two decades.

and EIA-923 surveys, EIA Annual Energy Outlook, and ERCOT (Electric Reliability Council of Texas) databases on hourly real-time market (RTM) prices per MWh. In addition, I use CEO compensation data from the top 10 U.S. wind developers, specifically focusing on publicly traded companies[3]. The paper exploits data sourced from 2017 to 2021 and obtained from 10-K SEC filing forms.

For estimation purposes, I exploit time variation in installed wind farm capacity, net generation, RTM wholesale prices, and average CEO compensation to identify the vector of model parameters. Then, I implement a Simulated Method of Moments (SMM) to estimate the vector of structural parameters in order to match a set of moments conditions in ERCOT data that are relevant for investment decisions in wind capacity[4]. The estimated model is empirically validated by showing that it predicts the values in the data of key *untargeted* moments about installed wind capacity and generation output. Last, I use the estimated model to quantitatively evaluate the asymmetrical effects of different subsidy types on investment and electricity generation outcomes in the Texas wind power industry. To this end, the estimated model simulates exogenous variation in wind capacity factors in order to obtain numerical solutions under different policy parameters within an array of politically feasible counterfactual values of PTC and ITC subsidies. I draw upon numerical solutions of the simulation exercise to infer a ranking across subsidy types on the basis of cost-effectiveness.

I find that unitary increases of the PTC provide significantly stronger incentives to invest in wind capacity than alternative percentage increases in the subsidy rate of the ITC. This leads to quantitatively large differences in wind power output and total subsidy payments to wind developers at current policy parameters. For instance, I show that exclusive long-run implementation of a \$27/MWh PTC implies significantly higher average annual investment rates in wind capacity ($\sim$57%) when compared to exclusive reliance on an ITC at a 30% subsidy rate ($\sim$22%). Fixing the public budgetary cost of wind subsidies, I find average annual investment rates in wind capacity to be 7 percentage points higher under a prevalent and exclusive utilization of PTC in comparison to an alternative implementation of ITC. This is because wind project managers respond to unpredictable downward volatility in the flow of PTC benefits by over-investing in wind capacity (relative to ITC) in order to buffer potential losses in year-by-year subsidy payments due to unpredictable lower-than-average capacity factor realizations. These findings underscore the critical role that prudent behavior plays, as a salient feature of risk attitudes, on cost-effectiveness of subsidies to intermittent renewable sources like wind[5].

This paper advances our understanding of how attitudes towards risk matter for policy design of environmental subsidies. By doing this, it establishes a new link between literature on the implications of financial

[3]This list of wind developers is as follows: NextEra Energy, Avangrid, Orsted, Equinor, Enel Green Power, and E.ON SE.

[4]These statistical moments are: average CEO compensation growth, average investment rate in wind capacity; average, variance, and temporal autocorrelation of capacity factors, mean and variance of RTM wholesale electricity prices.

[5]In contrast, I use the model to show that for a *non-prudent* risk-averse wind developer, differences in long run capacity additions across subsidy types are, on average, zero – which implies subsidy types are equivalent. See Section 3.3.

incentives to intermittent renewables (i.e. solar and wind) with literature about the role of prudence on self-insuring behavior. On one hand, a major part of existing work on financial incentives to renewable energies focuses on studying the effects of subsidies on investment and generation outcomes (e.g. Aldy et al. (2023), Hagspiel et al. (2021), Gugler et al. (2021), De Groote and Verboven (2019), Murphy et al. (2014), Hitaj (2013)). Another important portion investigates the welfare and distributional implications of subsidies (e.g. Feger et al. (2022), Helm and Mier (2021), Abrell et al. (2019), Novan (2015), Cullen (2013)). On the other hand, literature on prudent behavior started with seminal work from Kimball (1990) on the microeconomic foundations of prudence and its connection to the Arrow-Pratt theory of risk aversion. However, recent literature has focused instead on providing empirical micro evidence of prudence and self-insuring behavior across a wide variety of different empirical settings (e.g. Boar (2021), Ameriks et al. (2020), He et al. (2018), Fagereng et al. (2017), Guerrieri and Lorenzoni (2017), Challe and Ragot (2016), Lise (2013), Krusell et al. (2010), Fuchs-Schundeln and Schundeln (2005), Parker and Preston (2005), Carroll et al. (2003), Banks et al. (2001)) to make the point that is a generalized salient feature of risk attitudes from risk averse agents.

Within these strands of literature, the closest work to this paper is that of Aldy et al. (2023) and De Groote and Verboven (2019). Both papers exploit natural experiments from different empirical settings to assess the relative performance of output and investment subsidies to intermittent energy sources on the basis of cost-effectiveness and arrive at mixed findings. On one hand, Aldy et al. (2023) place special emphasize studying this mechanism by assessing how policy effects on wind farm productivity vary based on the subsidy type. Alternatively, De Groote and Verboven (2019) focus on doing so by understanding the role of time discounting on public budgetary costs of output and investment subsidies.

Despite extensive work in both literature fronts, progress in empirical research on the impact of risk attitudes on cost-effectiveness of clean energy subsidies remains notably limited. To a large extent, this is due to important data availability limitations concerning adequate sources of variation in management-level decisions that would allow clear understanding of how wind investment decisions vary based on salient traits of managerial risk preferences (e.g. degree of prudence). My paper addresses this gap in the literature by being the first to quantitatively evaluate how prudent behavior from risk averse management influences the asymmetrical effects of PTC and ITC payments on wind investments, wind farm output, and policy cost-effectiveness. Unlike Aldy et al. (2023) and De Groote and Verboven (2019), I show that prudent behavior plays a fundamentally and quantitatively relevant role on relative cost-effectiveness of output and investment subsidies to the wind power industry.

Additionally, I go beyond Aldy et al. (2023) and De Groote and Verboven (2019) by developing a quantitative framework that advances our understanding of the fundamental interplay between managerial risk preferences, wind investment decisions, and cost-effectiveness of environmental subsidies. This is important for two reasons. First, it allows me to circumvent existing data limitations that would otherwise critically

restrict the ability to link policy outcomes and wind investment decisions to risk preferences. Second, it enables me to quantify the impact that monetization of PTC benefits accrued over time has on capital accumulation in wind capacity. This is an important feature of the U.S. wind industry to account for in the analysis, as wind developers typically do not have sufficient tax liability to absorb their tax credits and instead rely on a tax-equity partner to do so[6].

The rest of the paper is structured as follows. Section 2 provides a description of the empirically-relevant institutional features where investment decisions from wind developers take place. This section provides a comprehensive overview of how monetization of wind tax credits works, what are the main risks for wind developers inherent to the stream of tax benefits, and why they always bear a quantitatively relevant portion of these risks even when they are not the ones directly absorbing such tax benefits (i.e. due to insufficient tax liabilities). Section 3 draws heavily on Section 2 to motivate and lay down the analytical model from this paper. Section 4 describes the policy experiment, identification, and estimation procedure. Section 5 reports key quantitative findings and elaborates on main connections to existing work. Last, Section 6 concludes.

2 The PTC and ITC in the Context of U.S. Commercial Wind

Wind power has consolidated itself as a key renewable energy source in U.S. power markets. As of 2022, roughly 10.3% of total electricity generation came from commercial wind according to EIA (2023a) data[7]. This figure was importantly larger than hydropower (6.0%), total solar (3.4%), or any other renewable energy source. Planned wind capacity additions by developers for 2023 amounted to 8.1GW – only to be surpassed by total solar (25.2GW) and battergy storage (9.6GW) according to EIA (2023b) statistics.

Within the U.S., ERCOT is the electricity market with the largest capital stock in installed wind capacity. As of Dec. 30th, 2022, ERCOT had 36,850 MW of installed wind capacity which generated ∼25% of the state's electricity production. This is due to a combination of extensive territory along with ideal wind conditions (i.e. wind speeds, air density, and wind direction) in the central, northern and southernmost parts of the state.

Under Section 45 and Section 48 of IRA, the federal government provided new extensions of the PTC and ITC until (at least) 2025. These subsidies have been a central catalyzing force behind wind investment dynamics in ERCOT as well as in other U.S. power markets. The PTC is a per MWh subsidy for electricity generated from wind, solar, and other non-fossil fuel facilities (up to $27.5/MWh in 2023 dollars depending on prevailing wage and apprenticeship requirements) for the first 10 years of the project's operation. Alternatively, the ITC is a subsidy that covers up to 30% (at the base rate for commercial wind projects above 1 MW of

[6] I elaborate on this issue in Section 2

[7] Commercial wind, as opposed to residential wind, is the process of generating electricity from large-scale wind turbines which is used by businesses, factories, or utilities to satisfy energy requirements. This means that electricity is sold in the wholesale market or through arranged bilateral transactions rather than consumed in-site.

capacity) of the project's investment costs. However, an important feature of these initiatives is that the subsidies are defined as tax credits rather than direct cash payments. Therefore, the vast majority of wind developers do not have sufficient tax liability (as determined by the IRS) to effectively claim the tax credits to which they would be entitled. These wind developers are investing firms that act as middlemen between land owners with significant wind resources and utilities that sell electricity in the retail market or other important power purchasers. Wind developers find adequate sites to build wind farms, secure financing for building the facility, manage its construction process and operate generation activities. As of 2022, data from the EIA Form 860 shows that utilities themselves only built and owned less than 15% of wind projects whereas the rest were built and operated by wind developers.

To address this limitation, wind developers have increasingly engaged in a type of financing contract called 'tax-equity partnerships'. Under these finance structures, the wind developer partners with an entity that has sufficiently large tax liabilities to absorb the tax credits that would be accrued by the wind project. Subsequently, the developer accepts to transfer most of the tax benefits to the tax-equity partner in exchange for a risk-adjusted upfront capital contribution in cash (i.e. adjusted in accordance to the internal rate of return required by the tax-equity partner). This capital investment is primarily determined by estimating the present value of the prospective stream of tax benefits earned by the wind facility over time and discounted at the target tax yield required by the tax-equity partner. As of 2022, suppliers of tax equity had typically been large financial institutions as well as some insurance companies[8]. Moreover, another reason why tax equity has assumed a central role as a funding source for developers is the fact that it also allows developers to monetize additional tax benefits due to capital depreciation from the wind project.

Under a tax-equity partnership, the wind project is held within a Limited Liability Company (LLC) and ownership of the LLC is mutually shared between the developer and the tax-equity partner. However, the roles performed by the wind developer and the tax-equity partner are not equivalent. This is because the developer acts as the active or managing investor and retains control of the operating facility. Therefore, the developer sponsors the project, stacks funding from different sources, oversees development, construction, and operation of the wind project. In contrast, the tax-equity partner is relegated to a passive investor role whose sole responsibility is to provide equity funding in exchange for a pre-negotiated return on investment. Even though wind developers raise capital from a combination of sponsor's (and private) equity, tax equity (between 35% and 65% of total project's cost according to data from ACORE (2023)), and debt, tax equity is senior to other forms of financing which means that the tax-equity partner transfers a major portion of the project's investment risk to the wind developer.

Due to its nature, the tax credit with an ITC can be claimed (and monetized) at the year of the commercial operations start date. However, this is not the case with a PTC given that it is earned over time as a

[8]E.g. domestic banks accounted for ∼80% of tax equity supply. See ACORE (2023) for details.

per MWh subsidy. Therefore, the most common tax equity contract in the wind industry for monetizing PTC benefits is the 'partnership flip'. In a typical contract, the tax-equity partner funds one third to two thirds of the total project's cost (through an upfront cash payment to the wind developer). In exchange, the tax-equity partner receives most of the stream of prospective tax credits as well as a minor portion of the stream of expected revenues to be generated by the wind project. During the pre-flip period, a typical allocation is 99% of the project's tax credits plus a 1%–5% of the project's prospective revenue payments to the tax-equity partner – i.e. the rest being allocated to the wind developer. This allocation changes permanently at the beginning of the post-flip period. A typical post-flip allocation is 95% of the tax benefits and project's revenues to the wind developer – i.e. with the rest being allocated to the tax-equity partner. The flip type can be a 'time-based flip' or a 'yield-based flip'. Under a yield-based flip, the allocation of tax benefits and project revenues flips after the tax-equity partner has achieved the target rate of return. In contrast, under a time flip, the allocation of tax benefits and project revenues flips at a pre-negotiated time after the commercial operations start date of the wind facility – usually close to the end of the 10-year term of the PTC[9]. By the flip date, the wind developer can exercise a right to buy the minority share of the LLC from the tax-equity investor at its market fair value.

In practice, tax-equity partners are reluctant to assume excessive risk associated to the uncertainty of future wind capacity factor realizations (i.e. production risk) that determine ex-post PTC payments. Therefore, tax-equity partnerships from projects receiving PTC payments typically incorporate PAYGO structures. This contract feature allows tax-equity partners to limit the downside production risk that they bear by deferring up to 25% of their total investment in the wind project contingent on production outcomes. This deferred investment is then scaled down if future output realizations at the wind facility fall sufficiently below forecasted output at the time the tax-equity partnership was formed (which occurs before the commercial operations start date). By doing so, the tax-equity partner *transfers a significant portion of the production risk to the wind developer even when it is the tax-equity partner the one absorbing PTC payments through decreases in its tax liability.*

Table 1 and Table 2 show how a typical PAYGO structure mitigates downward production risk for the tax-equity partner. Before the wind project becomes operational, the tax-equity partner forecasts the annual median output of the facility (typically labeled as 'P50'). Subsequently, it defers up to 25% of its total investment in the wind project to be contingent on actual output realizations. Then, the tax-equity partner transfers the deferred investment to the wind developer over time depending on how annual production outcomes compare relative to the P50 threshold. As indicated by Table 1 and Table 2, the actual (or realized) deferred investment may be lower than the initially deferred investment on the wind project. This is because the tax-equity partner scales down its deferred investment depending on the size of the output gap between actual annual generation and the P50 forecast when output falls below the threshold.

[9]The typical life span of a wind facility fluctuates between 20 and 30 years depending on maintenance schedule and other technological features.

Table 1: **An Example of a 5-year PAYGO Structure**

5-year PAYGO	**Total**	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Year 5**
P50 Forecast (*MWh*)	500,000	100,000	100,000	100,000	100,000	100,000
Actual Generation (*MWh*)	441,000	100,000	91,000	89,000	82,000	79,000
Generation as % of P50 forecast	88.2	100	91	89	82	79
Initial deferred investment (*MM of USD*)	25.00	5.00	5.00	5.00	5.00	5.00
Actual deferred investment (*MM of USD*)	17.25	5.00	4.50	4.00	3.75	0.00
Deferred investment payment rate (%)	69	100	90	80	75	0

Note: This table provides a hypothetical example of how a PAYGO structure mitigates production risk borne by the tax-equity partner. By doing so, it transfers a significant portion of the production risk to the wind developer. The annual payment rates in the bottom line have been directly pulled from Table 2.

Table 2: **An Example of a Deferred Investment Payment Rates Schedule**

Annual Generation (% of P50)	**Deferred Investment Payment Rate (%)**
Greater than or equal to 98%	100
Greater than or equal to 96%, but less than 98%	98
Greater than or equal to 93%, but less than 96%	96
Greater than or equal to 90%, but less than 93%	90
Greater than or equal to 85%, but less than 90%	80
Greater than or equal to 80%, but less than 85%	75
Less than 80%	0

Note: This table shows a hypothetical schedule of deferred investment payment rates under a PAYGO structure of a tax-equity partnership for a wind project. The payment rates in the rightmost column are expressed as a percentage of the initial deferred investment (which in this example is $25 million as indicated by Table 1).

For the case of tax-equity partnerships without a PAYGO structure, these contracts instead usually incorporate an accelerated cash payments structure that achieves the same goal. Table 3 shows how a typical accelerated cash payments structure mitigates downward production risk for the tax-equity partner. In this example, the tax-equity partner provides $93 million in capital funding to the wind developer before the commercial operations start date (i.e. year 0). Subsequently, the wind facility earns project revenues and PTC payments from year 1 through year 10. Within this period, the tax-equity partner earns the pre-flip tax benefits plus cash payments (i.e. 1% of the project revenues when no accelerated cash payments occur). However, if the wind facility performs poorly (e.g. due to incorrect wind forecasts or atmospheric conditions), then the tax-equity partner can activate the accelerated cash payments clause of the contract which increases the percentage of project revenues it earns from 1% to 11% in order to achieve the target tax yield (8.9%) by year 10 when the partnership flip takes place. This implies that the tax-equity partner usually transfers a quantitatively relevant portion of the production risk to the wind developer either through the use of a PAYGO structure or accelerated cash payments. Furthermore, this is the case even though the tax-equity partner is the one absorbing the tax credits due to its high tax liabilities.

Table 3: **Example of an Accelerated Cash Payments Structure** (in MM of USD)

	Yr 0	**Yr 1**	**Yr 2**	**Yr 3**	**Yr 4**	**Yr 5**	**Yr 6**	**Yr 7**	**Yr 8**	**Yr 9**	**Yr 10**
No accelerated cash payments											
Project revenues		11.7	13.0	12.6	11.0	11.5	11.1	10.5	10.7	10.2	10.1
PTC payments		10.5	11.7	11.3	9.9	10.4	10.0	9.5	9.6	9.2	9.1
Pre-flip tax benefits (99%)		10.4	11.6	11.2	9.8	10.2	9.9	9.4	9.5	9.1	9.0
Pre-flip cash payments (1%)		.1	.1	.1	.1	.1	.1	.1	.1	.1	.1
Total investment	-93										
Target tax yield (%)											8.9
With accelerated cash payments											
Project revenues		10.5	11.7	11.3	9.9	10.4	10.0	9.5	9.6	9.2	9.1
PTC payments		9.5	10.5	10.2	8.9	9.3	9.0	8.5	8.7	8.3	8.2
Pre-flip tax benefits (99%)		9.4	10.4	10.1	8.8	9.2	8.9	8.4	8.6	8.2	8.1
Pre-flip cash payments (11%)		1.2	1.3	1.2	1.1	1.1	1.1	1.0	1.1	1.0	1.0
Total investment	-93										
Target tax yield (%)											8.9

Note: This table provides an example of a hypothetical accelerated cash payments structure. In this example, the wind facility earns project revenues and PTC payments throughout its first 10 years of commercial operations. The tax-equity partner receives the pre-flip tax benefits and cash payments during this period after contributing $93 million in capital funding for the wind project. The accelerated cash payments feature mitigates production risk (which is transferred to the wind developer) for the tax-equity partner by allowing it to earn the target tax yield by year 10 independently of operational performance. All numbers are in millions of USD except for tax yield quantities. Moreover, numbers are rounded to the first decimal digit.

This section has described the basics of the institutional setting where investment decisions from wind developers take place. Most of the discussion has gravitated around a detailed description of how monetization of wind tax credits works, what are the main risk for developers and why they always bear a quantitatively relevant portion of this risk even when they are not the ones directly absorbing such tax credits. Therefore, the next section will draw heavily on the institutional setting's features described so far in order to motivate the modeling approach from this paper.

3 Model

3.1 Basic Framework

I begin laying down the model by considering an infinite horizon environment with discrete time and a set of risk neutral wind developers. Each wind developer consists of a firm which is operated by a risk averse manager that maximizes her lifetime utility over consumption streams and is in charge of managing investment projects for the wind developer. The assumption on the manager's risk attitudes follows a longstanding literature on managerial behavior and theory of the firm that has investigated and documented empirical evidence of managers exhibiting risk aversion even in presence of unsystematic investment risk that can be diversified by the firm (e.g. Caliendo et al. (2024), Gormley and Matsa (2016), Jagannathan et al. (2016), Brenner (2015) as well as earlier seminal work from Chevalier and Ellison (1999) and Holmström

(1999))[10]. Following Holmström (1999) and subsequent literature, this is because managers: i) receive compensation packages that are dependant on the performance of investments that they oversee, and ii) are significantly less able to mitigate downward investment risk relative to a well-diversified firm that hires their labor.

Wind projects are risky investments due to the inherent uncertainty associated with wind farm production realizations over long periods of time (i.e. around 20 to 30 years depending on the facility's life span) which: i) depend on atmospheric conditions (e.g. air density, direction and speed of wind), and ii) determine the project's stream of revenues. The fact that the manager's compensation package is typically tied to the performance of overseen wind investments means that the projects' investment risk matters for her managerial decisions. Moreover, this would be the case even if the project's risk can be diversified from the point of view of the wind developer's profits.

I account for the manager's risk attitudes by assuming that her preferences over consumption streams are described by an additively separable utility function,

$$\sum_{t=0}^{+\infty} \beta^t u(c_t) \tag{1}$$

where $\beta \in (0,1)$ represents the manager's annual discount factor and c_t stands for her compensation package in year t. Motivated by the previous discussion about manager's risk attitudes, I consider instant utility to be given by a C^3 function $u : \mathbb{R}_+ \to \mathbb{R}$ that satisfies $u' > 0$, $u'' < 0$, and $u''' > 0$. Concavity of instant utility (i.e. $u'' < 0$) accommodates the manager's degree of risk aversion to consumption risk due to variance in her compensation package payments c_t. Moreover, I allow for convex marginal utility of state-specific consumption (i.e. $u''' > 0$) in order to account for prudent behavior in managerial decision-making. This is a well-document salient trait of preferences towards risk at the individual level (e.g. Boar (2021), Ameriks et al. (2020), He et al. (2018), Fagereng et al. (2017), Guerrieri and Lorenzoni (2017), Challe and Ragot (2016)) and is also built in most standard classes of utility function representations for risk averse agents (e.g. CARA and CRRA utility classes).

The manager regards time-specific equity contributions e_t (i.e. dividends or proceeds to the firm's shareholders plus retained earnings) as exogenously given mandates determined from period-by-period gross income by the wind developer's board of directors. Firm-level resources of the wind developer that are not allocated to equity contributions or compensation package payments are allocated by the manager to investments that generate revenues to the wind developer. The manager oversees these investments by allocating them to new wind project developments or investments in an alternative one-period risk-free asset. This captures the fact

[10]For instance, Brenner (2015) uses option exercising data to infer risk attitudes of approximately 7,000 U.S. executives. He provides empirical evidence of moderate risk aversion among managers (average measures of relative risk aversion close to 3), with higher values of relative risk aversion disproportionately concentrated in non-senior managers.

that wind developers also own investment portfolios in other assets different from installed wind capacity that are typically well diversified. I assume that investing a_{t+1} units of the numeraire on the risk-free asset in year t pays Ra_{t+1} units of the numeraire in year $t+1$ (with gross return on investment equal to $R > 1$). Therefore, the risk-free asset accounts for the opportunity cost associated with allocating resources to wind investments. In particular, for a sufficiently high rate of return R, the manager would never choose to invest in wind capacity. This feature allows the model to accommodate the manager's one-time *extensive* margin (or adoption) decision in wind capacity.

Wind investments require that the manager chooses wind capacity levels m_{t+1} in year t which become available for operation at the beginning of the subsequent year given current capacity m_t. There are two types of costs associated with investing in wind capacity. First, the developer pays a fixed cost F per unit of capacity added by the manager. This represents the cost of buying machines and equipment necessary to build the wind facility. Second, there are equipment and capital installation costs $G\left(\frac{m_{t+1}}{m_t} - 1\right)$ that are strictly increasing and convex as a function of the investment size relative to existing capacity. The convexity of installation costs represents adjustment costs in capital accumulation borne by the wind developer. This assumption is empirically motivated by the fact that the typical wind developer is an extremely capital-intensive firm with lumpy investment schedules, i.e. large and infrequent adjustments to wind capacity portfolios rather than continuous changes over time. Therefore, lumpy investment schedules at the developer level are evidence of quantitatively relevant adjustment costs in capital accumulation which motivate the necessity to account for them by allowing installation costs at the firm-level to be strictly convex. These features that determine investment costs regulate the manager's year-by-year *intensive* margin decisions in wind capacity, i.e. how large to build the wind farm conditional on the adoption decision. I assume there is no depreciation.

Marginal production costs at the wind farm are zero since no fuel inputs are consumed for electricity generation and maintenance expenditures constitute fixed costs in production. Moreover, output realizations are regarded to be exogenous from the point of view of managerial decisions as they depend on atmospheric conditions (e.g. air density as well as direction and speed of wind). I model these features of the production process by considering output at the wind farm to be determined by an exogenously given capacity factor $\theta_t \in [0, 1]$ whose dynamics are dictated by the Markov process $J(\theta_{t+1}|\theta_t)$ with state space Θ and constant mean. This capacity factor is a plant-level productivity term that represents the proportion of a facility's capacity that is used in production given current atmospheric conditions[11]. Additionally, the time dependence of θ_{t+1} in the Markov process $J(\theta_{t+1}|\theta_t)$ captures persistence in atmospheric conditions that influence capacity factor realizations for subsequent years.

[11]For instance, a 2MW capacity wind turbine running at a 50% capacity factor for a given hourly period means that the turbine generated 1 MWh during that time frame. Therefore, θ_t indicates how fully a unit's capacity is used given weather conditions.

Each MWh of output produced at the wind farm is sold in the wholesale market at the market price p_t which is taken as given by the manager. I motivate the manager's price-taking behavior assumption on the fact that even for output of wind farms sold in wholesale markets through Power Purchase Agreements, the pre-negotiated prices are typically and largely informed by real time market prices which exist out of the manager's control. Therefore, I consider the wholesale market price p_t to evolve according to some stochastic process $H(p_{t+1}|p_t)$ with state space P and constant mean.

The previously described structure of the economic environment implies that the manager's decisions are bounded by the following firm-level accounting identity,

$$\underbrace{p_t\theta_t m_t + Ra_t}_{\text{Gross income}} - \underbrace{\left[c_t + F\cdot(m_{t+1}-m_t) + G\left(\frac{m_{t+1}}{m_t}-1\right) + a_{t+1}\right]}_{\text{Operating expenses}} \quad = \quad \underbrace{e_t.}_{\text{equity contributions}} \tag{2}$$

The manager's intra-period decision timeline is as follows. First, the wind developer enters current year t with assets a_t and wind capacity m_t carried over from manager's decisions in year $t-1$. Upon realization of gross income, a mandate from the board of directors is received by the manager regarding how much of the firm's resources are to be allocated towards equity contributions (i.e. either dividends to shareholders or retained earnings). Subsequently, remaining resources are invested by the manager either on wind investments or additional purchases of the risk-free asset. The manager's compensation package in year t is determined as a residual outcome from gross income after equity contributions and investments. To formalize this decision-making process, I assume that the manager maximizes the expected discounted value of her lifetime utility flow by solving the following problem,

$$\begin{cases} \max\limits_{\{c_t, m_{t+1}, a_{t+1}\}_{t=0}^{\infty}} & \mathbb{E}_0 \sum\limits_{t=0}^{+\infty} \beta^t u(c_t) \\ \text{s.t.} & c_t + F\cdot(m_{t+1}-m_t) + G\left(\frac{m_{t+1}}{m_t}-1\right) + a_{t+1} = p_t\theta_t m_t + Ra_t - e_t,\ \forall t \\ & c_t, m_{t+1} \geq 0,\ \forall t \\ & m_0, a_0 \text{ — given.} \end{cases} \tag{3}$$

In problem (3), gross income is a given value for the wind developer (and manager) at year t since it depends only on past choices. Upon receiving the equity contributions mandate issued by the board, the manager allocates firm resources to revenue-generating investments. Therefore, by making investment decisions in wind capacity and asset purchases, the manager realizes that she residually determines her compensation package for current year t. This has two important implications. First, outcomes on investment and compensation package payments are bounded above by current year gross income (after equity contributions) by the time

managerial decisions have to be made. Second, the manager also realizes that her compensation package payments are tied to the performance of investment decisions made in previous periods. This is because higher realizations of gross income for the wind developer lead to more firm-level resources than can be residually allocated to compensation package payments to the manager. However, by doing so the manager understands that she is also diverting resources from revenue-generating investments which decreases growth of future compensation package payments. This introduces a dynamic trade-off in managerial decision-making that will lead her to deviate from corner solutions where all resources of the wind developer are fully allocated either to investment or compensation package payments.

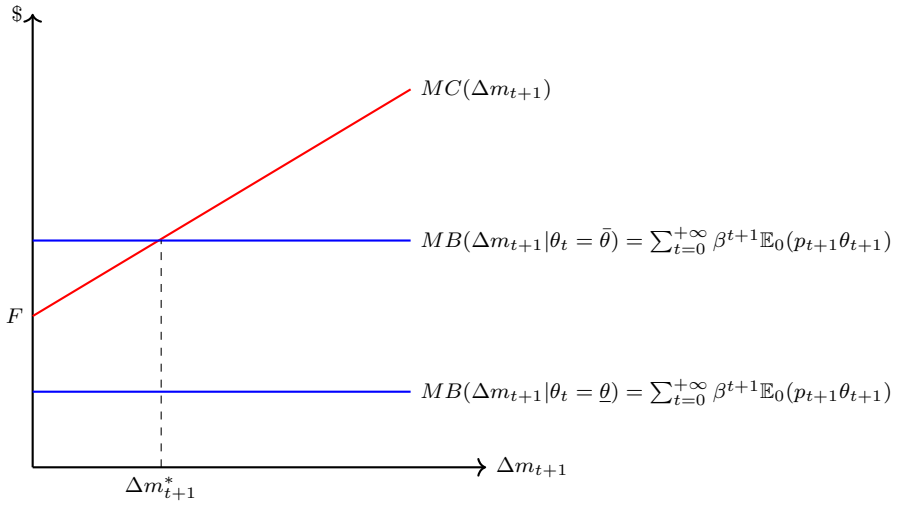


Figure 1: **The Role of Investment Costs – A Graphical Interpretation**

Note: This figure provides a graphical representation of how the assumptions regarding investment costs determine period-by-period levels capacity additions. The MC curve represents the marginal cost of capacity additions. The MB line represents the marginal benefits (in terms of additional expected revenues) of capacity additions. With a high capacity factor realization $\bar{\theta}$, the manager chooses in year t a level Δm^*_{t+1} of wind capacity additions that become available for year $t+1$. However, with a low capacity factor realization $\underline{\theta}$, the manager decides not invest in subsequent capacity additions.

Figure 1 provides a graphical interpretation of how investment costs determine the dynamics of wind capacity additions. The MC curve represents the marginal cost of capacity additions. The MB line represents the marginal benefits (in terms of additional expected revenues) of capacity additions. As previously explained, there are two components that make up investment costs in this model. First, the per MW fixed cost F which represents the effort associated with buying machines and equipment (e.g. wind turbines). Second, the convex installation costs which are an increasing function of investment size Δm_{t+1} relative to current capacity m_t. Convexity of installation costs implies that the marginal cost of capacity additions is monotonically increasing. These two assumptions together rationalize the empirical fact that wind developers typically display lumpy investment schedules, i.e. large and infrequent increases in wind capacity rather than continuous gradual adjustments. To explain how this is the case, I represent in Figure 1 two alternative scenarios. On one hand, a high capacity factor realization $\bar{\theta}$ implies large marginal benefits to the developer

of capacity additions due to the time persistence of the Markov process that regulates the evolution of wind projects' productivity over time. However, whenever atmospheric conditions eventually align with a sufficiently low capacity factor realization $\underline{\theta}$, the marginal benefits of capacity additions to the wind developer can fall below the per MW fixed cost F. In such case, the manager will not expand current capacity because it is not profitable. Moreover, due to time persistence of capacity factor realizations, the wind developer will experience a time window of (potentially) several yearly periods before observing again a sufficiently high capacity factor that makes capacity additions profitable. This rationalizes the fact that wind investments are lumpy rather than gradual or continuous.

Figure 1 underscores the importance of the convexity assumption regarding installation costs. In absence of convex installation costs, marginal costs of capacity additions would be constant and the manager's decisions about wind investments would be characterized by a period-by-period bang-bang solution, i.e. no investments if marginal costs exceed marginal benefits of capacity additions, and unbounded investment if marginal benefits of wind capacity additions surpass marginal costs. Therefore, the convexity assumption is necessary to guarantee interior solutions and rationalize empirical trends of lumpy and finite wind investments over time.

3.2 Incorporating Effects of Tax Credits

Production Tax Credit — Following the description in Section 2 about the nature of tax credit payments, the PTC is a per MWh subsidy for electricity generated at the wind facility built, operated, and overseen by the developer. When wind investment decisions are being made by the manager, the uncertainty surrounding PTC payments arises from the inherent production risk associated with wind-generated electricity. This risk stems from the uncertainty of future plant-level capacity factor realizations, which are heavily influenced by unpredictable volatility in atmospheric conditions such as air density, wind speed, and direction. Additionally, uncertainty in the flow of PTC payments matters for wind investment decisions of the risk-averse manager because PTC benefits, as per policy design, are earned gradually over the course of the wind facility's first 10 years of operation. This decade-long policy horizon makes it difficult for managerial decisions to accurately predict long-run wind patters and how they would affect the flow of PTC benefits.

In addition, the wind developer always bears a quantitatively relevant portion of the uncertainty in the flow of PTC benefits. As explained in Section 2, wind developers typically do not have enough tax liability to monetize the tax credits earned over time under PTC. Therefore, they partner with a financial entity with sufficiently high tax liabilities to fully absorb the tax credits (through decreases in tax liability) that will be earned by the wind project during its first 10 years of operation. In this way, the wind developer accepts to transfer most of the PTC benefits to the tax equity partner in exchange for an equivalent upfront capital contribution – in terms of *expected present value* at a discount rate equal to the tax yield required by the tax-equity partner. However, tax-equity partners also exhibit reluctance to assume excessive risk associated with

the uncertainty of future wind capacity factor realizations that determine ex-post PTC payments. Therefore, tax-equity partnerships typically incorporate PAYGO and accelerated cash payment structures (see Section 2 for details) that allow tax-equity partners to transfer risk in the flow of PTC benefits to the developer should the wind project under-perform relative to production forecasts at the moment wind investment (and financing) decisions were made.

From the model's perspective, the previous discussion means that the risk-averse manager cares about the inherent uncertainty in the flow of PTC payments due to production risk from the wind project. I model the impact of these policy features on the manager's investment decision by assuming that the wind developer receives a subsidy $S > 0$ per unit of electricity produced at the wind farm. Therefore, the manager's decisions in wind capacity are now bounded by the following firm-level accounting identity,

$$\underbrace{(p_t + S) \cdot \theta_t m_t + R a_t}_{\text{Gross income}} - \underbrace{\left[c_t + F \cdot (m_{t+1} - m_t) + G\left(\frac{m_{t+1}}{m_t} - 1\right) + a_{t+1} + T_t \right]}_{\text{After-tax operating expenses}} = \underbrace{e_t.}_{\text{equity contributions}} \tag{4}$$

This formulation captures the fact that period-by-period PTC benefits are inherently stochastic because they depend on output realizations which are random – i.e. on the realization of the period-specific capacity factor θ_t. Additionally, I allow the model to account for effects of lump-sum taxes T_t to accommodate the possibility of revenue-neutral or non-neutral subsidization design. This sequence of lump-sum tax payments is assumed to be exogenously determined by the government and publicly announced at period $t = 0$.

However, it is important to account in this modeling approach for the effect of monetization of PTC benefits. As explained in Section 2, wind developers associate themselves with tax-equity partners who do have sufficient tax liability to fully absorb the PTC benefits. Subsequently, the wind developer agrees to give all PTC benefits to the tax-equity partner in exchange for an equivalent and upfront cash contribution to support the project's funding requirements. This cash contribution is 'equivalent' in terms of expected present value where the flow of PTC benefits is discounted at a rate equal to the target tax yield required by the tax-equity partner.

To account for the monetization effects of PTC benefits on the manager's investment decision, it is necessary to rewrite (4) in terms of expected present value. Let $\delta = \frac{1}{R}$ be the wind developer's discount factor and $\tau = \frac{1}{1+\kappa}$ be the discount factor applied to PTC benefits earned over time where κ represents the target tax yield required by the tax-equity partner. Therefore, equation (4) implies that the expected present value of equity contributions must equal the expected present value of the difference between gross income and (after-tax) operating expenses. This is summarized in the intertemporal accounting identity given by equation (5), i.e.

$$\sum_{t=0}^{+\infty} \delta^t \left[c_t + F \cdot (m_{t+1} - m_t) + G\left(\frac{m_{t+1}}{m_t} - 1\right) + a_{t+1} + T_t \right] = \sum_{t=0}^{+\infty} \delta^t \left[p_t \theta_t m_t + R a_t - e_t \right] + \sum_{t=0}^{+\infty} \tau^t S \cdot \theta_t m_t. \tag{5}$$

Investment Tax Credit — As explained in Section 2, the ITC is a one-time upfront subsidy that covers up to 30% of the project's cost of buying machines and equipment (e.g. wind turbines). A key fact that differentiates it from the PTC is that due to its nature, it is independent of any source of production risk that might affect the flow of revenues from the wind project. This implies that the total value of ITC benefits is essentially known with certainty by the manager at the moment wind investment decisions are made. Put differently, there is no uncertainty in the present value of the flow of ITC benefits per MW of capacity additions as it was for the case with PTC payments.

To capture this in the model, I assume that the government issues a one-time upfront payment equivalent to a fixed proportion $s \in [0, 1]$ of investment costs in machines and equipment due to new capacity additions. Therefore, the manager's decisions in wind capacity are bounded instead by the following firm-level accounting identity,

$$\underbrace{p_t \theta_t m_t + R a_t}_{\text{Gross income}} - \underbrace{\left[c_t + (1 - s \cdot (1 - \kappa)) \cdot F \cdot (m_{t+1} - m_t) + G\left(\frac{m_{t+1}}{m_t} - 1\right) + a_{t+1} + T_t \right]}_{\text{After-tax operating expenses}} = \underbrace{e_t}_{\text{equity contributions}}. \tag{6}$$

In this case, the upfront subsidy payment to the wind developer is known with certainty by the time investment decisions are made. This is because the size of the subsidy payment depends only on the contemporaneous decision about new capacity additions rather than on future (and random) output realizations. Similarly to the case of PTC benefits, κ represents the target tax yield required by the tax-equity partner due to monetization of ITC benefits. However, since ITC benefits are not earned over time but instead constitute an upfront payment, constraint (6) already in sequential form is sufficient to describe the set of decisions available to the manager.

3.3 Characterization of the Optimal Investment Rule

Production Tax Credit — For a wind developer that receives PTC benefits, the manager makes investment decisions in order to maximize (1) subject to (5), i.e.

$$
\begin{cases}
\max\limits_{\{c_t, m_{t+1}, a_{t+1}\}_{t=0}^{\infty}} & \mathbb{E}_0 \sum\limits_{t=0}^{+\infty} \beta^t u(c_t) \\
\text{s.t.} & \sum\limits_{t=0}^{+\infty} \delta^t \left[c_t + F \cdot (m_{t+1} - m_t) + G\left(\frac{m_{t+1}}{m_t} - 1 \right) + a_{t+1} + T_t \right] = \\
& \qquad \sum\limits_{t=0}^{+\infty} \delta^t \left[p_t \theta_t m_t + R a_t - e_t \right] + \sum\limits_{t=0}^{+\infty} \tau^t S \cdot \theta_t m_t \\
& c_t, m_{t+1} \geq 0, \ \forall t \\
& m_0, a_0 \text{ — given.}
\end{cases} \tag{7}
$$

The solution to this managerial decision-making problem is characterized by the accounting identity (4) and Euler equations (8) and (9). These 3 conditions jointly describe optimal transition dynamics of: i) net holdings of the risk-free asset owned by the wind developer, ii) installed wind capacity, and iii) compensation package payments to the manager (respectively),

$$
(p_t + S) \cdot \theta_t m_t + R a_t - \left[c_t + F \cdot (m_{t+1} - m_t) + G\left(\frac{m_{t+1}}{m_t} - 1 \right) + a_{t+1} + T_t \right] = e_t
$$

$$
\underbrace{u'(c_t) \left[G'\left(\frac{m_{t+1}}{m_t} - 1 \right) \frac{1}{m_t} + F \right]}_{\substack{\text{Utility value of consumption forgone in } t \text{ to increase capacity in 1 MW}}} = \tag{8}
$$

$$
\underbrace{\beta \cdot \mathbb{E}_t \left\{ u'(c_{t+1}) \left[\theta_{t+1} p_{t+1} + G'\left(\frac{m_{t+2}}{m_{t+1}} - 1 \right) \frac{m_{t+2}}{m_{t+1}^2} + F + \left(\frac{R}{1+\kappa} \right)^{t+1} S \theta_{t+1} \right] \right\}}_{\substack{\text{Expected utility value of extra consumption in } t+1 \text{ due to increase in capacity}}}
$$

$$
u'(c_t) = \beta R \cdot \mathbb{E}_t \{ u'(c_{t+1}) \}. \tag{9}
$$

Equation (8) captures the effect of monetization of tax benefits. The impact of monetization on period-by-period investment decisions originates due to the wedge between the developer's return on its diversified portfolio, R, and the target tax yield required by the tax-equity partner, κ. As later shown in the estimation step from Section 4, it is the case in the data that $1 + \kappa > R$. This means that the need to monetize tax benefits increases the rate at which the effects of PTC payments fade over time. This is because a hypothetical case where the wind developer were able to fully absorb the tax benefits would be equivalent to discounting tax benefits earned over time at the risk free rate (i.e. $1 + \kappa = R$).

Investment Tax Credit — Alternatively, for a wind developer that receives ITC benefits, the manager makes investment decisions in order to maximize (1) subject to (6), i.e.

$$
\begin{cases}
\max\limits_{\{c_t, m_{t+1}, a_{t+1}\}_{t=0}^{\infty}} & \mathbb{E}_0 \sum\limits_{t=0}^{+\infty} \beta^t u(c_t) \\
\text{s.t.} & c_t + (1 - s \cdot (1-\kappa)) \cdot F \cdot (m_{t+1} - m_t) + G\left(\frac{m_{t+1}}{m_t} - 1\right) + a_{t+1} + T_t = \\
& \qquad p_t \theta_t m_t + R a_t - e_t, \ \forall t \\
& c_t, m_{t+1} \geq 0, \ \forall t \\
& m_0, a_0 \text{ — given.}
\end{cases}
\tag{10}
$$

The solution to this managerial problem is characterized by the accounting identity (6) and Euler equations (11) and (9). Analogously to the previous case, these 3 conditions jointly describe optimal transition dynamics of: i) net holdings of the risk-free asset owned by the wind developer, ii) installed wind capacity, and iii) compensation package payments to the manager (respectively),

$$
p_t \theta_t m_t + R a_t - \left[c_t + (1 - s \cdot (1-\kappa)) \cdot F \cdot (m_{t+1} - m_t) + G\left(\frac{m_{t+1}}{m_t} - 1\right) + a_{t+1} + T_t \right] = e_t
$$

$$
\begin{aligned}
&\underbrace{u'(c_t)\left[G'\left(\frac{m_{t+1}}{m_t} - 1\right)\frac{1}{m_t} + (1 - s \cdot (1-\kappa))F\right]}_{\text{Utility value of consumption forgone in } t \text{ to increase capacity in 1 MW}} = \\
&\qquad \underbrace{\beta \cdot \mathbb{E}_t\left\{u'(c_{t+1})\left[\theta_{t+1} p_{t+1} + G'\left(\frac{m_{t+2}}{m_{t+1}} - 1\right)\frac{m_{t+2}}{m_{t+1}^2} + (1-s)F\right]\right\}}_{\text{Expected utility value of extra consumption in } t+1 \text{ due to marginal increase in capacity}}
\end{aligned}
\tag{11}
$$

$$
u'(c_t) = \beta R \cdot \mathbb{E}_t\{u'(c_{t+1})\}.
$$

Equations (8) and (11) formalize the key difference regarding how subsidy types modify incentives at the margin. The PTC increases the return (in consumption units) of a marginal increment in wind capacity while leaving its cost unchanged. This return is uncertain as it depends on future realizations of the (unobserved) capacity factor. Alternatively, the ITC is a direct reduction to contemporaneous investment costs which are always known by the entrepreneur at the time investment decisions in capacity take place.

To understand how prudent behavior from the risk-averse manager drives differences in investment outcomes based on the subsidy type, consider the stream of PTC payments from an additional MW of wind capacity as a mean-preserving spread of a present-value equivalent ITC subsidy. This is always the case because for each subsidy rate $s \in [0, 1]$, there exists a per-unit subsidy $S > 0$ that satisfies,

$$\underbrace{s \cdot F}_{\text{ITC subsidy of an additional MW}} = \underbrace{\mathbb{E}_t \left[\sum_{j=t+1}^{+\infty} \beta^{j-t} \cdot S \cdot \theta_j \right], \ \forall t.}_{\text{Expected present-value of PTC payments of an additional MW}} \tag{12}$$

However, it is also the case that,

$$var_t(s \cdot F) = 0 \ \text{ and } \ var_t \left(\sum_{j=t+1}^{+\infty} \beta^{j-t} \cdot S \cdot \theta_j \right) > 0, \ \forall t. \tag{13}$$

Therefore, conditions (12) and (13) formalize the fact that PTC payments are inherently riskier than equivalent ITC payments. This excess risk matters to the manager whose compensation package payments are tied to the performance of wind investments through equation (4). Therefore, prudent behavior will lead managers from wind developers under PTC payments to over-invest in wind capacity (i.e. relative to those under equivalent ITC payments) to self-insure against downward variance in compensation package payments due to lower-than-expected capacity factor realizations (which affect both flows of revenues and PTC benefits).

To show that this is the case, consider the second-order Taylor approximation of u' centered at c_t and write (9) as follows,

$$u'(c_t) \approx \beta R \cdot \mathbb{E}_t \left[u'(c_t) + u''(c_t)(c_{t+1} - c_t) + \frac{1}{2} u'''(c_t)(c_{t+1} - c_t)^2 \right]$$

$$\implies 1 \approx \beta R \cdot \mathbb{E}_t \left[1 + c_t \frac{u''(c_t)}{u'(c_t)} \frac{(c_{t+1} - c_t)}{c_t} + \frac{1}{2} \cdot c_t \frac{u'''(c_t)}{u''(c_t)} c_t \cdot \frac{u''(c_t)}{u'(c_t)} \cdot \left(\frac{c_{t+1} - c_t}{c_t} \right)^2 \right]$$

Such second-order Taylor expansion of u' at c_t exists given that $u''' > 0$. Define $\gamma_t = -c_t \frac{u''(c_t)}{u'(c_t)} > 0$ and $\psi_t = -c_t \frac{u'''(c_t)}{u''(c_t)} > 0$ as the coefficients of relative risk aversion and relative prudence, respectively. These time-dependant parameters are well-defined because $u' > 0$ and $u'' < 0$. Using these definitions and rearranging terms in the previous expression yields,

$$\underbrace{\mathbb{E}_t \left[\frac{c_{t+1} - c_t}{c_t} \right]}_{\text{Expected growth in manager's compensation}} \approx \underbrace{\frac{1}{\gamma_t} \frac{\beta R - 1}{\beta R}}_{\text{Impatience motive}} + \underbrace{\frac{1}{2} \psi_t \mathbb{V}_t \left[\frac{c_{t+1} - c_t}{c_t} \right]}_{\text{Self-insurance motive}} \tag{14}$$

where I have used the fact that $\mathbb{E}_t [c_{t+1}] \approx c_t$ in an open ball centered at c_t when c_{t+1} is arbitrarily close to c_t. If $u''' = 0$ (i.e. no prudent behavior), then from (14) we would have that the expected growth in manager's

compensation is independent of subsidy type because there is no tendency to self-insure when receiving PTC payments (i.e. the self-insurance term in (14) is zero). In this case, differences in cumulative wind capacity across subsidy types would be, on average, zero. However, since $u''' > 0$ (i.e. manager is prudent), then from (14) we know that the expected growth in manager's compensation is higher under PTC payments. This is because the manager's compensation under PTC benefits (which is tied to performance of wind investments) exhibits higher variance due to PTC payments being riskier than equivalent ITC benefits (i.e. the value of the self-insurance term in (14) is higher under PTC). As previously explained, the manager responds to higher variance in the flow of tax benefits under PTC by over-investing in wind capacity to create a buffer against lower-than-expected output realizations in comparison to an equivalent ITC. Consequently, this tendency to self-insure through larger wind investments leads to a steeper growth profile of her compensation payments over time.

4 Policy Experiment

4.1 Experiment Design

The previous section showed that attitudes towards risk from managers matter for wind investment outcomes because PTC payments are inherently riskier. Moreover, the excess risk of PTC benefits (i.e. relative to ITC) is relevant for managerial decisions because the tax-equity partner is always able to transfer an important portion of this risk to the wind developer through contractual provisions like PAYGO structures or advanced cash payments. Therefore, the aim of the policy experiment in this paper is to use the estimated model to quantify how wind investments change depending on the subsidy type (i.e. PTC and ITC). By fixing the expected level of total subsidy payments to wind developers (i.e. the public budgetary cost), I estimate the previous model with ERCOT data and use it to evaluate the difference in wind power investment and generation outcomes across alternative subsidy types. This allows to determine the quantitative relevance of risk attitues (i.e. risk aversion and prudence) as a driver of differences in policy effects from alternative subsidization modes.

The basic steps for implementing the policy experiment are as follows:

1. Simulate a set of histories for capacity factor realizations and electricity prices for a 20-year period in yearly time blocks.

2. Define a set of values $\{s_k\}_{k=1}^{K}$ for the proportional subsidy to capital expenses under the ITC. At each s_k, solve the manager's problem (i.e. problem (10) for all histories of electricity price and capacity factor realizations. Compute the expected annual investment rate, wind power output, and ITC benefits.

3. For each s_k, find the per unit subsidy S by solving the manager's problem under the PTC (i.e. problem

(7) for all histories such that subsidy payments are equivalent (on expectation) across subsidy types. ompute the expected annual investment rate, wind power output, and PTC benefits.

4. For each level of expected subsidy payments, compare annual investment rate, wind power output, and tax benefits across subsidy types.

4.2 Data

ERCOT, which manages $\sim 90\%$ of Texas electricity generation, is the U.S. power market that has experienced the largest increase in wind power capacity over the last two decades. This, in part, makes it an ideal empirical study case for this paper. I use several main data sources in the quantitative analysis. First, I draw upon 1996-2021 survey data from the EIA-860 Annual Electric Generator Report to collect information on net generation by type of producer and energy source in Texas. Second, I use survey data from the EIA-923 Power Plant Operations Report on existing nameplate capacity by producer type, energy source, and state from 1996-2021. Third, I collect 2017–2021 CEO compensation data from the top 10 U.S. wind developers, specifically focusing on publicly traded companies and obtained from their 10-K SEC filing forms[12]. Next, I use historical data on overnight capital costs for new electricity generating plants from the 2023 EIA Annual Energy Outlook. Last, I use 2011-2021 ERCOT data on hourly real-time market (RTM) prices per MWh at the zonal level (i.e. North, North Central, South, South Central, and West zones) which I aggregate at the system level.

4.3 Identification and Estimation

To estimate structural parameters, I adopt necessary functional and distributional assumptions regarding model primitives. First, I consider the following cubic form for the convex installation costs G described in Section 3,

$$G\left(\frac{m_{t+1}-m_t}{m_t}\right)=\frac{\alpha}{3}\left(\frac{m_{t+1}-m_t}{m_t}\right)^3,\ m_t>0. \tag{15}$$

Next, since the average annual capacity factor θ_t follows a first order Markov chain, I parametrize this data generating process by assuming an AR(1) process for wind plant productivity levels,

$$\theta_{t+1}=\rho_0+\rho_1\theta_t+\varepsilon_{t+1},\ \varepsilon_{t+1}\sim \mathrm{N}(0,\sigma^2). \tag{16}$$

As explained in Section 3, this assumption captures time persistence in fluctuating atmospheric conditions over long periods of time that determine the project's evolving productivity. In contrast, wholesale electricity

[12]This list of wind developers is as follows: NextEra Energy, Avangrid, Orsted, Equinor, Enel Green Power, and E.ON SE.

prices are determined on an extremely high-frequency basis (i.e. typically every 15 min.) with current price realizations having little to no effect in the long run. Therefore, I parametrize the wholesale price process with the following i.i.d. distributional assumption,

$$p_t \sim \text{gamma}[k, \gamma]. \tag{17}$$

This gamma process replicates not only the mean and variance of annual average prices, but also the skewness of the pdf, with potentially heavy tails towards the upper end of the support[13].

Last, I assume log preferences to characterize how managers rank streams of compensation payments over time as follows,

$$u(c_t) = \log(c_t). \tag{18}$$

The assumption about preferences captures attitudes towards risk both in terms of risk aversion (i.e. $\gamma_t = -c_t \frac{u''(c_t)}{u'(c_t)} = 1 > 0$) and prudence (i.e. $\psi_t = -c_t \frac{u'''(c_t)}{u''(c_t)} = \frac{2}{c_t} > 0$). This structural assumption is a special case of the CRRA specification when the relative risk aversion equals 1 which is in line with the median relative risk aversion across U.S. executives from empirical evidence documented by Brenner (2015).

I estimate the model in two steps. First, I discipline the discount factor β, time horizon T, per-unit output subsidy S, and per-unit cost of capacity additions F through direct calibration. Then, I use a Simulated Method of Moments (SMM) to estimate the installation costs parameter α, the rate of return R, AR parameters $(\rho_0, \rho_1, \sigma^2)$, and shape-scale parameters of the distribution of wholesale prices (k, γ). Last, I use the estimated model to implement the policy experiment outlined in Section 4.1.

4.3.1 Identification

I identify 7 parameters grouped into 3 categories and discuss their identification group-wise. First, parameters $(\rho_0, \rho_1, \sigma^2)$ are identified from plant-level capacity factor data. The assumption that capacity factors follow a stationary AR processes directly implies that there exists a unique set of parameters that can be determined from observable data. Similarly, parameters (k, γ) from the process that regulates wholesale electricity prices are identified from RTM hourly ERCOT prices. The mapping from observable data to the parametric space being single-valued is a consequence of electricity prices following a gamma process.

Second, I identify the rate of return R from Euler equation (9) for compensation package payments which relies on the assumption of log preferences,

[13] These tails represent average price realizations during years that experience abnormally high electricity demand, for instance, due to prolonged and frequent heat waves or below-freezing temperatures.

$$\beta \cdot \mathbb{E}_t \left\{ \frac{c_t}{c_{t+1}} \right\} = \frac{1}{R}.$$

The LHS depends on a previously calibrated parameter and consumption decisions which I treat as observable as they can be estimated from solving the economic model consistently with compensation pay growth in the data. Hence, the rate of return R is identified from Euler equation (9) and observable data on CEO compensation payments.

Last, identification of installation costs parameter α is based on the manager's Euler equation (8) for installed capacity decisions,

$$\alpha \cdot \left\{ \frac{1}{c_t} \left(\frac{m_{t+1}}{m_t} - 1 \right)^2 \frac{1}{m_t} - \beta \mathbb{E}_t \left[\frac{1}{c_{t+1}} \left(\frac{m_{t+2}}{m_{t+1}} - 1 \right)^2 \frac{m_{t+2}}{m_{t+1}} \right] \right\}$$
$$= \beta \cdot \mathbb{E}_t \left\{ \frac{1}{c_{t+1}} \left[\theta_{t+1}(p_{t+1} + S) + F \right] \right\} - \frac{F}{c_t}$$

which relies on the assumption of cubic installation costs and log preferences for purposes of identification. Both RHS and LHS are determined by endogenous investment outcomes consistent with manager's utility maximization that depend on previously calibrated and estimated parameters. I treat investment decisions as observable since they can be estimated by directly solving the economic model consistently with observed growth in installed wind capacity. Distributional assumptions about p_t and θ_t allow using observed data to estimate expectation terms. This means that α is identified from Euler equation (8) and observable data on installed wind capacity.

4.3.2 Step 1: Calibration

I report externally calibrated parameters in Table 4. I set the annual discount factor at $\beta = .98$ in line with commonly used values in macro literature (e.g. Guner et al. (2023)). Additionally, I choose the value for the time horizon T consistently with the expected life span of a typical wind project in the data. Third, I set the per-unit output PTC subsidy S consistently with the full PTC when the policy was renewed in 2013. Last, I directly calibrate the average per MW cost of nameplate wind capacity F using historical EIA data on overnight capital costs for new electricity generating plants.

Table 4: **Calibrated Parameters**

Parameter	Definition	Value	Source
β	**Discount factor**	.98	Standard
T	**Time horizon**	20	Wind project avg. lifespan
S	**Per-unit subsidy**	23	PTC, 2013 renewal
F	**Per-unit capacity cost**	800,000	Annual Energy Outlook
κ	**Target tax yield**	.08	Aldy et al. (2023)

Note: This table reports values of externally calibrated parameters. The time horizon is measured in calendar years. The per-unit output subsidy is expressed in $/MWh. Last, units for the cost of installed capacity are in $/MW of nameplate capacity.

4.3.3 Step 2: Estimation

I use a SMM strategy to estimate the rest of structural parameters and report estimation results in Table 5. To do so, I start by defining a set of key moments that inform the estimation of each parameter of interest. The number of moments is equal to the number of parameters to estimate which means this is a case of exact identification. Then, I simulate the history of innovations in capacity factors and wholesale electricity prices to compute estimated moments obtained from the numerical solution of the economic model. Subsequently, I find parameters that allow matching each of these model-dependent moments to those observed the data.

Table 5: **SMM Estimation Results**

Parameter	Definition	Estimate	Target	Moment	
				Model	*Data*
R	**Real rate of return**	1.03 (0.01)	Avg. CEO compensation growth	0.11	0.11
α	**Installation cost parameter**	2.0687×10^{8} (4.3506×10^{7})	Avg. investment rate	0.32	0.32
ρ_0	**Autoregression intercept**	0.24 (0.02)	Avg. capacity factor	0.35	0.35
ρ_1	**Autocorrelation parameter**	0.31 (0.04)	Autocorrelation capacity factor	0.31	0.31
σ^2	**Error term variance**	1.8×10^{-3} (2.0×10^{-7})	Variance capacity factor	2.0×10^{-3}	2.0×10^{-3}
k	**Shape parameter**	41.03 (2.21)	Avg. electricity price	31.95	31.95
γ	**Scale parameter**	0.78 (0.05)	Variance electricity price	24.88	24.88

Note: This table reports SMM estimation results for structural parameters that were not calibrated in Step 1. Empirical moments are directly calculated from data described in Section 4.2. Average values for investment rate, capacity factor, and compensation growth are on an annual basis and reported in percentage terms. Autocorrelation moments correspond to first-order autocorrelation from annual capacity factors. Moments for electricity prices are computed on an annual basis and measured in $/MWh. Standard errors are in parenthesis. Average annual CEO compensation growth is expressed in real terms, i.e. after accounting for a 2% annual inflation rate.

I rely on a SMM approach given that it is not possible to compute analytical solutions of the key moments used to inform the estimation of (α, R). To jointly estimate (α, R), I use time variation in installed wind

capacity and CEO average annual compensation growth to match the model-dependent averages of annual investment rates in wind capacity and consumption growth rates to their empirical values in the data, respectively. Additionally, I estimate structural parameters of the stochastic processes for the capacity factor and wholesale electricity prices using the following procedure. First, I exploit time variation in annual net generation and installed wind capacity to infer capacity factor realizations. Then, I use these data to jointly estimate $(\rho_0, \rho_1, \sigma^2)$ in order to match the: i) average (annual) capacity factor, ii) variance of (annual) capacity factors, and iii) first-order autocorrelation of (annual) capacity factor realizations. Additionally, I use time variation in ERCOT RTM electricity prices to jointly estimate (k, γ) in order to match: i) annual mean of hourly electricity prices, and ii) variance of (annual) average electricity prices.

Table 6: **Empirical Validation with Untargeted Moments**

99% CI	**Avg. annual capacity** (MW)	**Avg. annual output** (MWh)
Lower bound	7,882.7	2.4172×10^7
Upper bound	11,787	3.6142×10^7
Empirical value	10,263	2.8936×10^7

Note: This table shows how model-dependent untargeted moments compare to their empirical analogues in the data. Line 1 defines the relevant untargeted moments. Lines 2 and 3 provide the lower and upper bounds for the 99% confidence intervals, respectively. Line 3 reports the empirical value for each moment.

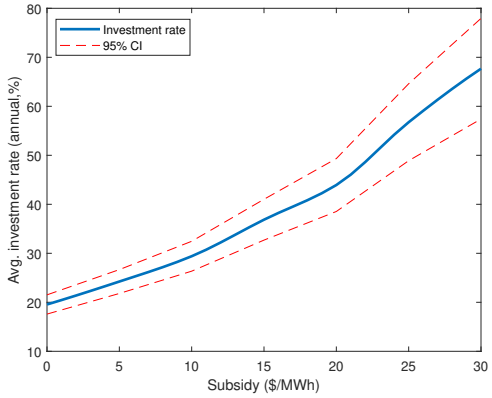
Last, I draw upon the Simulated Method of Moments strategy developed in this section to provide empirical validation of the model from Section 3. I do this in two separate steps. First, in Table 5, I provide results on how well my estimated model replicates the targeted empirical moments from the data that are used for informing the estimation of the vector of structural parameters. These results go beyond assessing goodness-of-fit because they play a critical role in the computation of the J-statistic which serves as a diagnostic tool for empirical validation of the model. When dealing with exact identification, where the number of moments equals the number of parameters as in this application, the model should exactly match each targeted moment *conditional on the model not being misspecified*. Therefore, since my estimated model is able to exactly replicate all targeted moments, the J-statistic is zero, indicating a strong alignment between the model and the data, and thus, minimal grounds for rejecting the model based on the observed moments.

As with any statistical test, there is always a non-zero probability of not rejecting a false hypothesis. In the case of the J-test, this means not rejecting a model that is misspecified. To address this concern, I also report in Table 6 how well the estimated model performs when replicating *untargeted moments* that are relevant for validity of the counterfactual analysis results in Section 5. These constitute untargeted moments because they were not used for informing the SMM estimation procedure. Table 6 shows that the empirical values observed in the data for the untargeted moments fall within the 99% confidence intervals generated from solving the economic model under the vector of estimated parameters. This provides further empirical support that concerns of model misspecification (*i.e. the model not being appropriate for rationalizing the true data generating process*) are minimal given statistical evidence from the data.

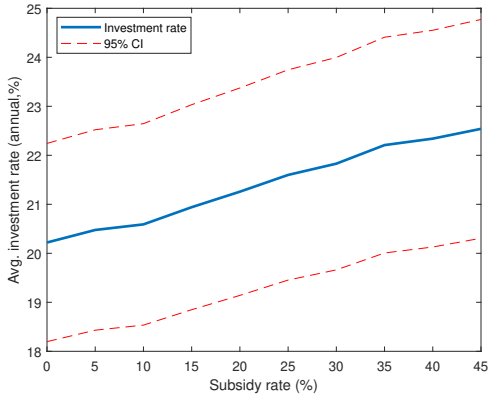
5 Results

5.1 Main findings

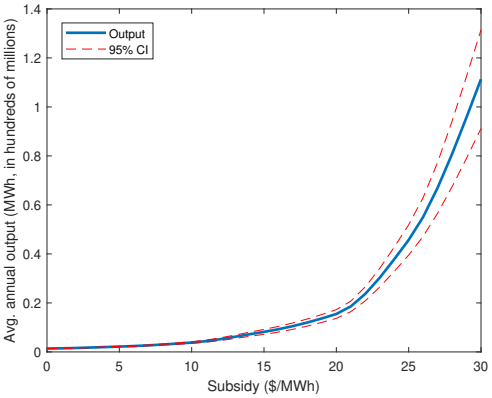
I report simulation results in Figure 2, Figure 3, Figure 4, and Figure 5. In Figure 2, I use panel a) and panel b) to show results of estimated wind investment rates by subsidy type. Additionally, I use panel c) and panel d) to provide results of estimated wind power output by subsidy regime. Results are reported as functions of the subsidy level which constitutes the policy parameter. For the case of the PTC, the policy parameter corresponds to the dollar amount of the subsidy per MWh of wind power output. Alternatively, for the ITC the policy parameter is defined as a percentage of capital costs per MW of nameplate capacity additions that is covered by the subsidy.



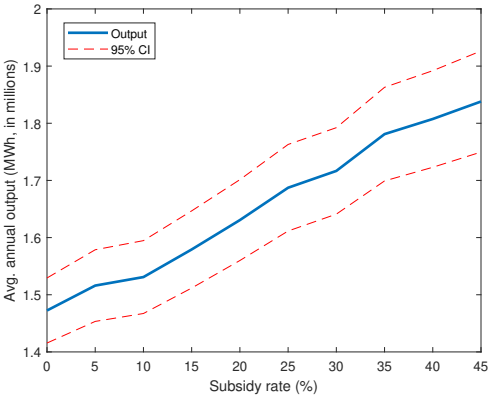
(a) **Investment rate under PTC**



(b) **Investment rate under ITC**



(c) **Wind power output under PTC**

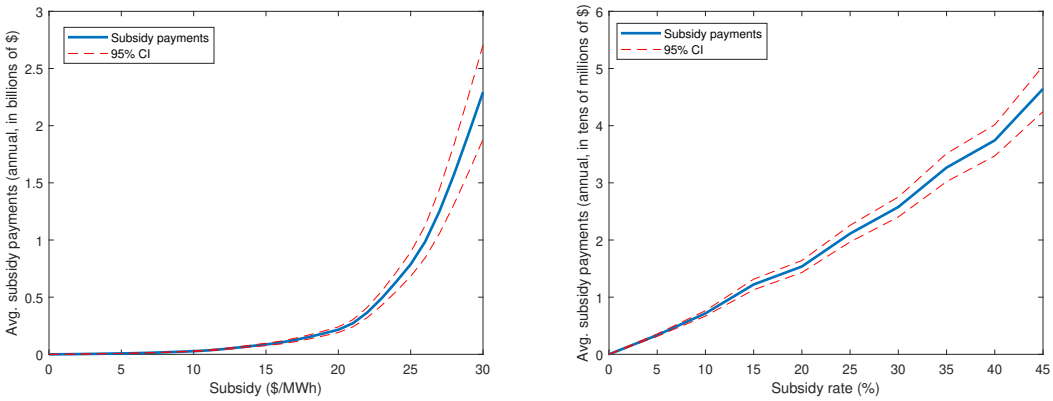


(d) **Wind power output under ITC**

Figure 2: **Simulation Results on Wind Investment Rates and Output**

Note: This figure shows simulation results for wind investment rates and wind power output. Panels a) and b) show results for average annual investment rates in wind capacity under PTC and ITC, respectively. Panels c) and d) show results on average annual wind power output under PTC and ITC, respectively. For the case of ITC, subsidy rates represent the percentage of installation costs that is covered by the policy.

Panels a) and b) in Figure 2 show that unitary increases in the per-unit subsidy of the PTC provide significantly stronger incentives to invest in wind capacity than alternative percentage increases in the subsidy rate of the ITC. For instance, at current policy parameters a PTC leads to a ∼57% average annual investment rate in wind capacity, whereas the ITC yields just ∼22%. This result is driven by the interaction of managerial risk attitudes with the additional uncertainty from PTC payments (i.e. relative to ITC). Managers optimally respond to unpredictable downward volatility in the flow of PTC benefits (which affects performance of wind investments) by over-investing in wind capacity relative to ITC. This allows them to insure their stream of compensation package payments (which depends on performance of wind investments) by creating a buffer against potentially lower-than-expected output realizations in the future at overseen wind projects. That managerial response does not take place with an ITC because the one-time subsidy payment to contemporaneous investment decisions is independent of capacity factor uncertainty. Panels c) and panel d) show that this leads to important quantitative differences in wind power output across subsidy types.



(a) **Subsidy payments under PTC** (b) **Subsidy payments under ITC**

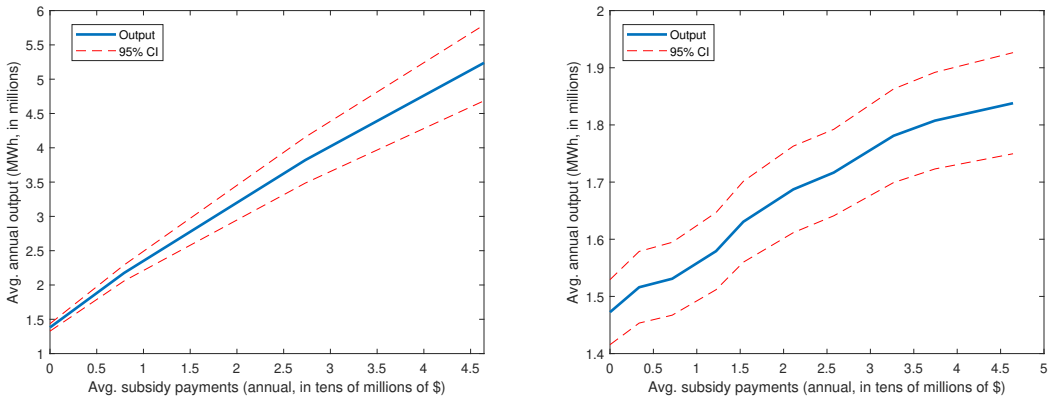
Figure 3: **Simulation Results on Total Subsidy Payments**

Note: This figure shows simulation results on aggregate subsidy payments allocated to wind developers. Panels a) and b) show average annual subsidy payments under PTC and ITC, respectively. For the case of ITC, subsidy rates represent the percentage of capital costs that is covered by the policy.

Figure 3 reports estimates of average annual subsidy payments to wind developers during the 20-year time frame of the policy experiment as a function of the per-unit subsidy and subsidy rate, respectively. The fact that unitary increases in the PTC drive higher investment rates than alternative percentage increments of the ITC also implies higher installed capacity and wind power output under a PTC (see Figure 2). This output gap explains the quantitatively large differences in aggregate subsidy payments to wind developers across subsidy types.

To use these findings for ranking subsidy types on the basis of cost-effectiveness, it is necessary to establish the comparison across them while 'fixing' the public budgetary cost of the subsidy. This allows addressing

the central question of this paper by directly answering '*Given an arbitrary level of average annual subsidy payments to wind developers, which is the subsidy type that maximizes wind power output?*'. I address this issue by showing results on Figure 4 and Figure 5. Panel a) of Figure 4 provides estimates of average annual wind power output within the 20-year time frame of the policy experiment as a function of annual mean PTC payments to developers. Panel b) shows analogous estimates for the case of an ITC.



(a) **Wind power output under PTC** (b) **Wind power output under ITC**

Figure 4: **Wind Power Output by Level of Public Expenditures in Subsidy Payments**

Note: This figure shows simulation results on average annual wind power output given a level of average annual public expenditures in terms of subsidy payments allocated to wind developers. Panels a) and b) show wind power generation outcomes under PTC and ITC, respectively.

Results in Figure 4 show that for any given level of public budgetary cost, the PTC implements significantly higher wind generation outcomes than an equivalent ITC[14]. To explain this finding, Figure 5 shows that investment rates are importantly higher under uncertain PTC benefits when compared to an equivalent (in expectation) but certain ITC subsidy. For instance, at current policy parameters the ITC covers 30% of capital costs from new wind projects. Panel b) in Figure 3 shows that this translates into ∼$25 million in average annual subsidy payments. However, results in Figure 4 (panel b) and Figure 5 indicate that this would imply just 1.7 millions of MWh in average annual wind output and a 22% average annual investment rate in wind capacity additions, respectively. In contrast, the average annual subsidy payments of $25 million to wind developers through the PTC result in approximately 3.5 million MWh of average annual output (shown in panel a) of Figure 4) and a 29% average annual investment rate in wind capacity. This indicates a doubling of output and a 7 percentage point higher investment rate under a prevalent and exclusive utilization of PTC in contrast to an alternative and analogous ITC implementation. Therefore, my results underscore the crucial role that risk aversion and prudence together have on cost-effectiveness of subsidies for intermittent renewable sources like wind.

[14]Given a PTC with an arbitrary and fixed per-unit subsidy, the equivalent ITC allocates exactly the same annual subsidy payments to wind developers **in expectation**.

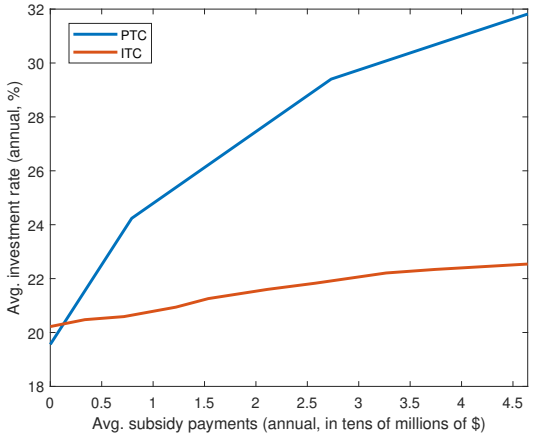


Figure 5: **Investment Rates by Level of Public Expenditures in Subsidy Payments**

Note: This figure shows simulation results on average annual investment rates in wind capacity as a function of mean annual subsidy payments to developers. The red line provides estimates of the investment rate under a PTC while the blue line reports estimates of the investment rate under an alternative ITC.

These results are tightly related to those from Aldy et al. (2023) and De Groote and Verboven (2019). Both studies assess the performance of output and investment subsidies on the basis of cost-effectivess. On one hand, De Groote and Verboven (2019) exploit data from a 2006–2012 natural experiment that subsidized residential solar photovoltaic systems in Belgium. Focusing on modeling the solar *adoption* decision (i.e. the extensive margin of investment decisions) and local market heterogeneity, they find that investment subsidies had been more cost-effective.

Alternatively, Aldy et al. (2023) investigate the issue of relative cost-effectiveness between output and investment subsidies in the context of the U.S. wind power industry. Their work exploits data from a 2009–2012 natural experiment in which wind developers were *temporarily* able to choose between: i) a $23/MWh subsidy for the first 10 years of the wind plant under the PTC, or ii) an upfront cash payment of 30% of total investment costs in wind capacity under the Section 1603 grant of the 2009 American Recovery and Reinvestment Act. Consistently with findings in this paper, Aldy et al. (2023) also observe that after accounting for extensive margin effects and selection into subsidy types, developers with the investment subsidy were significantly less productive and, therefore, the PTC had been more cost-effective over a wide range of output targets. Their empirical analysis focuses on two technological channels through which the PTC can increase wind farm production at the margin. One is by incentivizing developers to invest more in costly turbine maintenance in order to reduce the frequency of technical shut downs. Another is by moving wind farms up in the merit order which increases their probability of getting selected to produce during off peak hours.

The quantitative results from this paper extend the analysis and empirical findings from Aldy et al. (2023) and De Groote and Verboven (2019) in two important ways. On one hand, this is the first paper to empirically evaluate how attitudes towards risk influence the effects of PTC and ITC payments on wind

investments, wind farm output, and policy cost-effectiveness. Unlike Aldy et al. (2023) and De Groote and Verboven (2019), I show that risk attitudes play a quantitatively relevant role on relative cost-effectiveness of output and investment subsidies to the wind power industry. This is important considering the extensive empirical evidence that has been documented regarding risk aversion exhibited by managers (e.g. Caliendo et al. (2024), Gormley and Matsa (2016), Jagannathan et al. (2016), and Brenner (2015)) and the broader prudent behavior typically observed among risk-averse agents (e.g. Boar (2021), Ameriks et al. (2020), He et al. (2018), Fagereng et al. (2017), Guerrieri and Lorenzoni (2017), Challe and Ragot (2016)). The significant quantitative implications of prudence as a salient feature of managerial risk attitudes yield contrasting results regarding the ranking of output and investment subsidies in ERCOT, as compared to the ranking established by De Groote and Verboven (2019) for the solar industry in Belgium. On the other hand and in contrast with the approach taken by Aldy et al. (2023), my analysis develops and estimates an analytical model for understanding both *extensive* and *intensive* margins of managerial wind investment decisions. This is important for two reasons. First, it allows a thorough examination and quantification of the *long-term* effects of prevalent subsidies (i.e. like the PTC and ITC) on wind investments, generation outcomes, and public budgetary costs[15]. Second, my approach explicitly models the effect of PTC benefits monetization on optimal capital accumulation in wind capacity. Both extensions explain why my estimates of differences in wind power production and public budgetary costs across subsidy types are notably larger than the short-term effects in Aldy et al. (2023).

5.2 Climate Change, Global Weather Patterns, and Limits to Diversification

In the context of ERCOT commercial wind, the strategic selection of project locations plays a crucial role in managing production risk associated with variable wind patterns. This is because wind developers often leverage geographic diversity to mitigate unsystematic production risk by capitalizing on regional differences in wind conditions. However, it is important to recognize that certain aspects of production risk, particularly those stemming from broader systematic climate factors, cannot be entirely diversified through location choices alone. Therefore, the key findings from my quantitative analysis highlight the importance of explicitly accounting for the systematic component of production risk that persists across wind project sites when assessing the performance and consequences of wind subsidies. Specifically, there are two sources of systematic production risk that are empirically relevant in the context of the ERCOT wind industry: climate change and global climate patterns as, for instance, El Niño and La Niña.

First, the effect of uncertain climate change dynamics on global wind patterns is a key source of systematic production risk. This is because winds originate primarily due to temperature differentials across the Earth's surface. The imbalance in temperatures between the cold poles and warm tropics creates a stark contrast

[15]Long lead times of wind farm development and the short time window of the natural experiment in Aldy et al. (2023) may potentially exclude long run entry decision dynamics of new wind projects that underestimate the asymmetry between policy effects of subsidy types on new developments.

that drives the movement of air masses and generates wind patterns. Warm air rising from the equator and cooler air sinking towards the poles establish pressure gradients that set the stage for air circulation on a global scale. This fundamental principle of atmospheric dynamics, known as the Hadley cell circulation, shapes the circulation patterns that govern wind flows across the planet. As climate change accelerates and the poles warm at a faster pace than the tropics, the diminishing temperature contrast weakens the driving force behind wind formation. The Arctic's rapid warming relative to other regions intensifies this imbalance, further impacting global wind systems by inducing weaker and stiller winds over time (see, for instance, Rantanen et al. (2022) and Abell et al. (2021)). Since this constitutes a global climate phenomenon, its effects on wind farm productivity in ERCOT – or anywhere else – cannot be diversified by exploiting spatial variation in wind patterns within Texas for location choice of wind projects.

In addition, El Niño and La Niña climate patterns, collectively known as the El Niño-Southern Oscillation (ENSO), also constitute an important source of systematic production risk for wind production. This is because these climate patterns exert significant influence on the global circulation of winds by disrupting ocean temperatures and atmospheric pressure gradients. During El Niño events, warmer-than-average sea surface temperatures in the central and eastern tropical Pacific Ocean lead to changes in atmospheric pressure patterns, altering the distribution of heat and moisture around the globe. This disrupts wind patterns, particularly in the equatorial Pacific region, and can trigger shifts in the position of the jet stream and the development of anomalous weather patterns worldwide. In contrast, La Niña events are characterized by cooler-than-average sea surface temperatures in the same region, resulting in contrasting atmospheric pressure anomalies and impacting global wind circulation in an opposite manner. Therefore, the interplay between El Niño and La Niña events influences the strength and direction of prevailing winds, affecting weather systems, precipitation patterns, and storm activity across the globe, particularly in non-landlocked regions like Texas. Similarly to climate change, these climate patterns with inherent unpredictable intensity constitute global climatic phenomena that affects global wind circulation and average and wind project capacity factors beyond the scope of diversification through spatial variation in wind patterns within ERCOT.

The previously outlined explanation underscores two key ideas in the context of the quantitative findings in Section 5. First, it explains why diversification of production risk by exploiting geographic variation in wind resources throughout Texas is limited and leaves a quantitatively relevant component of systematic production risk for wind developers unmitigated. Second, it establishes a direct link between the model's framework and the specific sources of systematic production risk prevalent in the ERCOT commercial wind industry. This connection enhances the transparency and relevance of the estimated model's quantitative findings in capturing fundamental decision-making dynamics underlying wind investments.

6 Concluding Remarks

The U.S. federal government has stepped up its commitment to subsidize the wind power industry by allocating a major portion of the $386B climate package of the Inflation Reduction Act to output and investment subsidies like the PTC and ITC. But which subsidy type is more cost-effective? In this paper, I investigated *how implicit risk attitudes in managerial decisions from wind developers influence the choice of subsidy type that minimizes public budgetary costs for meeting a given investment target.* Using plant-level data of wind facilities from the Texas electricity market, I showed that unitary increases of the PTC provide significantly stronger incentives to invest in wind capacity than alternative percentage increases in the subsidy rate of the ITC. This leads to quantitatively large differences in wind power output and total subsidy payments to wind developers at current policy parameters. For instance, an exclusive long-run implementation of a $27/MWh PTC would imply significantly higher average annual investment rates in wind capacity (∼57%) when compared to a counterfactual setting with exclusive reliance on an ITC at the current 30% subsidy rate (∼22%). Fixing public budgetary costs, these disparities in investment rates between subsidy regimes result in a twofold increase in wind output and a 7 percentage point higher wind investment rate under a prevalent and exclusive utilization of PTC in contrast to an alternative and analogous ITC implementation. This is because managers respond to unpredictable downward volatility in the flow of PTC benefits (which affect performance of wind investments) by over-investing in wind capacity relative to ITC. This allows them to insure the stream of their compensation package payments over time (which depends on performance of wind investments) by creating a buffer against potentially lower-than-expected output realizations in the future at overseen wind projects. My quantitative findings underscore the crucial role that managerial risk attitudes play on cost-effectiveness of prevalent subsidies to intermittent renewable sources like wind.

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