Queueing for Subsidies: Evidence from rooftop solar during a transient demand shock

Stephanie Hutson
University of California, San Diego
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Abstract

This paper exploits a temporary demand shock during the 2022-2023 California rooftop solar subsidy reform to understand firm entry and pricing dynamics in a market with queued demand and delayed delivery. I develop a theoretical model showing queueing demand as an optimal provision policy, and entering firms having a comparative advantage while their queue is empty. This is shown empirically through use of granular administrative data. I show that the semi-elasticity of months to delivery of service is -0.012, that during the demand shock very young firms are charging as much as 15% more than their older competitors, and finally that "jumping the queue" relative to other customers in the market is associated with paying 9.4% more. This shift in short-run market structure altered firm entry condition and potentially accelerated learning-by-doing or moral hazard for new firms. These results highlight how queueing mechanisms can reshape the transitional dynamics of subsidy reform, with implications for consumer and producer welfare.

1 Introduction

When subsidies are established to grow an infant industry, there is often an explicit assumption that someday those subsidies will go away. Because we typically subsidize industries that the government cares about, when it comes time for a subsidy to end, policymakers must decide how to wind down a subsidy while weighing the costs of the subsidy and the benefits to both consumers and the industry that the subsidy was designed to support. It is critical for policymakers to understand the role that a subsidy removal mechanism plays in both producer and consumer welfare, and it may be in their interest to dampen the immediate impacts of a subsidy reform. Common ways to end a subsidy include a hard deadline, an abrupt appeal, a quota, or a funding cap[1]. One politically palatable mechanism for ending a subsidy would be to allow demand for the subsidy to queue with suppliers up until a hard deadline but allow suppliers to serve their queue after the deadline. This is exactly what the California Public Utilities Commission decided to do when it reformed their rooftop solar net metering subsidy policy in late 2022.

The empirical context in the paper is the California rooftop solar market from 2021 to 2024. Rooftop solar has been one of the largest sources of government technology subsidy over the last few decades which individual consumers can choose to take direct advantage of. At the federal level, the US offers Investment Tax Credit of 30% of the total cost of an installation through 2032. In 2022 alone, the federal government spent nearly $7.5 billion on solar tax credits (US Energy Information Administration, 2024). While California currently has the most rooftop solar generation of any state, several other states are quickly building their solar infrastructures and over half of states in the U.S. have some financial incentive for residential or commercial solar (DSIRE). This paper focuses on a major policy reform, in 2023 known as the NEM 2.0 to NBT transition, which reduced the electricity generation subsidy by about 75% for new solar owners, adding several years to the pay-back period for the cost of an installation (Flannelly, 2024). Although the potential policy proposed 7 months before a final decision in December 2022, the roll-out mechanism of the policy was unanticipated. The mechanism allowed consumers to lock in the old subsidy if they signed a contract

[1] Abrupt Appeal: Louisiana Solar Tax Credit (2015),
Hard deadline: Section 1603 Treasury Grant Program (Dec 31 2011)
Quota: Electric Vehicle tax credit, manufacturer sales cap (2022)
Funding cap: "Cash for Clunkers" initially capped at $1 billion (July 2009)

with an installer and submitted an application to the Investor Owned Utility (IOU)[2] for grid interconnection by April 13 2023, without any requirements of project completion for an additional 3 years. Because of the degree of reform and the size of the California solar industry, the policy has received significant press. In observing the solar industry since the policy reform was finalized, Cart (2024) from CalMatters describes the policy change as a "job killer", while in the Berkeley Energy Institute blog, Borenstein (2025) argues that although the level of demand for rooftop solar has not returned to the peak pre-reform levels, after an initial harvesting period, they have returned to pre-2020 levels.

This paper leverages the policy reform and it's phase out mechanism to answer questions about the impact of queueing demand during a transient demand shock on industry profitability and firm entry. While the specific context appears narrow, subsidy removals and tax creations happen with some frequency and may easily create a demand structure similar to the one seen in this context. Because the removal of the subsidy is announced a few months ahead of time, we see a large temporary spike in demand followed by an anticipated drop in demand. We see a similar pattern with the anticipated arrival of tariffs in the United States in 2025 (MacDonald *et al.*, 2025; Confino, 2025) resulting in a spike in demand and in the US goods trade deficit (Mutikani, 2025). Queueing of demand by suppliers may happen in any industry where consumers are willing to trade off receiving a good tomorrow for a lower price, and suppliers face increasing costs. There are several reasons why this is an ideal case study. First, the California rooftop solar industry has been a major part of the renewable subsidy literature over the last decade. Second, the cost to the consumer of submitting an application - that is, of joining the queue - is between \$95 and \$145, or less than 0.5% the total cost of an average installation. Finally, while a consumer receives financial benefit from having solar installed, it is plausible to suggest that there is little to no non-monetary disutility from waiting in the queue for service.

The results of this paper are suggestive that allowing queueing of demand during a subsidy phase out can have a dramatic impact on firm entry and allow for greater quantity supplied at lower prices than a hard deadline without queueing. Through a simple theoretical model I show that 1) firms facing increasing costs and a consumer discount factor build queues without increasing their rate of output and as the time to delivery increases, prices decrease and 2) once incumbent firms have started to build

[2] e.g. Pacific Gas & Electric

a queue of demand, entering firms who have no queued demand are able to charge a price premium for earlier delivery, thereby offering consumers an opportunity to "jump the queue" by spending more money with a younger firm. Empirically, I am able to validate the theoretical findings. Through use of highly detailed installation data, I find that during the queueing period (which lasts 4 months) prior to the subsidy cliff, firms under 3 months in age charge on average 15% more than firms over 6 months in age. Across firms, during the treatment period, an additional month to delivery is associated with a 1.3% decrease in prices. Within firms, an additional month is associated with a 0.9% decrease in price. When considering the order with which a consumer is served, I find no evidence of price variation within a firm, however within a market during the queueing period, a consumer whose installation is completed in the order they arrived in the queue pays on average over 12% less than a consumer whose installation is completed immediately. These results give us insights into the short run outcomes of subsidy reform, specifically within the solar industry.

1.1 Contributions

This paper makes contributions to three different literatures. First, through use of granular data, it contributes to the subsidy reform literature. Although much has been written about the instance and size of subsidies, especially within the solar and renewable energy space, relatively few papers have explored the direct industry impacts of a major subsidy reduction. Secondly it contributes to the queueing literature. Much of the current queueing literature focuses on single server markets, for instance public health care. This paper adds to this by allowing endogenous pricing and entry and exit. Finally, this paper adds to the firm entry literature, especially through exploring the role of internal learning by doing otherwise known as internal or appropriable LBD. In this paper I explore how a transient demand shock and queueing induces a change in the entry condition, and I show how internal learning can be leveraged during queueing events which impacts the long-term outcomes of firms.

Several papers have worked to understand how subsidy design and reform plays a role in industry and economic health. Dewatripont and Roland (1995) explores different mechanisms of reform packages in the context of stimulating growth in former Soviet countries in Europe in the early 1990s. They compare "big-bang" approach verse a gradualist approach to economic reform finding that the gradualist approach is smoother and more successful. In extension, Bertocchi and Spagat (1997) reviews Dewatripont and Roland's findings while adding structural uncertainty from the perspective of the policy maker. They find that due to uncertainty, a policy maker may find it optimal to be more decisive, using the "big-bang" approach to reform. Since then, others have explored the macroeconomic impact of subsidy removal, especially in developing economies. Lin and Li (2012) each explore the long-term impacts of removing energy subsidies in China. Boyd and Doroodian (1999) explore the hypothetical impacts of removing a corn subsidy in Mexico in an effort to understand the potential impacts of the North Atlantic Free Trade Agreement. Energy subsidies in particular have received significant attention by researchers regarding their effectiveness (Calvo-Gonzalez *et al.*, 2015; Murray *et al.*, 2014; Lin and Zhang, 2023), and distributional impacts (Jiang *et al.*, 2015; Dauwalter and Harris, 2023; Dorsey and Wolfson, 2024). This paper adds to this literature by exploring a case study of the immediate economic impacts of subsidy removal in a narrowly defined industry.

The rooftop solar industry has been in the literature for the last couple decades, and several papers have been written about the optimal policy for subsidies to encourage technological growth and renewable energy adoption, and how much subsidy pass-through occurs. De Groote and Verboven (2019) and Bollinger *et al.* (2025) both explore the effects of time discounting and solar adoption, especially as it is a very durable good. This paper explores how these findings are relevant in periods of changing demand. Because I am able to exploit the sudden drop in subsidy, the option value of waiting that is a typical concern when estimating elasticities for durable goods drops considerably, thereby alleviating some concerns that Coase conjecture (Gul *et al.*, 1986) may apply.

Queueing, wait-lists and time-to-delivery have had a minor but steady presence in the economics literature since the late 1960s. Naor (1969) provides the framework for which many papers understand queues. Lindsay and Feigenbaum (1984) model and show through UK health queues how, when remaining in a queue is not costly, adding capacity does not decrease the length of the queue due to increased demand because of decreased wait-times. This paper differs from this by including equilibrium pricing. Chen and Frank (2001) finds the optimal policy for pricing given a demand function dependent on prices and wait times. Most similarly to this paper, Russo (2024) finds the value to veterans waiting in a queue for healthcare from the VA to be served more quickly and estimates the optimal policy for pricing and allocation of medical resources. The way this paper differs from most of the queueing literature is that while queues form naturally due to changing demand, they can be alleviated through changes in capacity both on the intensive and extensive margin.

On firm entry, this paper contributes a variation on the firm entry condition in the case of a transient demand shock with queueing. I build off the free-entry condition found in Hopenhayn (1992) and show that during a transient demand shock and a low labor supply elasticity, queuing of demand may increase the expected profitability of an entering firm. Several papers have shown the impact of subsidies on firm entry (Rotemberg, 2019; Siegloch *et al.*, 2025), however the model of queueing demand's during a subsidy cliff has to my knowledge not been explored. Bergin and Corsetti (2005) develop a theoretical model of monetary policy designed to stabilize firm entry's response to shocks and uncertainty finding that endogenous firm entry can reduce the inflationary consequences of monetary expansion. While Bergin and Corsetti use business cycles as their source of uncertainty and focus on the macro-economy, whereas this paper uses a short-term shock and a narrow industry, my findings of endogenous entry and smoothed provision of supply during a transitory demand shock through use of queueing are supportive of their argument. Finally, much of the learning-by-doing (LBD) literature is focused on passive learning, defined in Schank *et al.* (2013) as "an incidental and costless byproduct of a firm's production activities". When valuing the usefulness of a subsidy, the economic literature has been primarily focused on maturing industries Benkard (2000); Irwin and Klenow (1994) the spillovers which can incentivize subsidization (Nemet, 2012; Bollinger and Gillingham, 2019). This paper focuses on internal learning of the firm as is modeled by Arrow (1962). Entering firms which typically have a disadvantage due to no experience in an environmental with temporary queueing have a comparative advantage of having no wait time, which can be exploited to extract higher profits.

2 Institutional Background

The solar industry has experienced rapid growth over the last two decades, buoyed by large government incentives at the state and federal level. The federal government subsidizes using an Investment Tax Credit of 30%, and has consistently with the exception of 2020 and 2021 (26% and 22% respectively) since 2008. Along with other states, California further incentivizes rooftop solar through net metering, which pays rooftop solar owners for the excess electricity generated and sent back to the grid during the day, partially to completely canceling out the households' energy consumption while the panels are not producing electricity. These incentives are paid out by the Investor Owned Utilities (IOU), of which there are three: Southern California Edison (SCE), Pacific Gas and Electric (PG&E) and San Diego Gas and Electric (SDG&E).

2.1 Policy Transition

In May 2022, a policy change in California was proposed to replace NEM 2.0 (Net Energy Metering), the current net metering policy, with a stricter net billing tariff hereafter NBT (Net Billing Tariff) (CPUC, 2022). This policy change would reduce the compensation to new solar installers by approximately 75%. The motivation behind the policy change was that the NEM 2.0 system, while highly advantageous to the consumers of rooftop solar, was detrimental to non-installers as the costs were passed onto other consumers on the grid Verdant Associates, LLC (2021). The distributional impacts of this are not to be undersold, as rooftop solar highly correlated with 1) owning one's home and 2) having access to capital, that is with high income. Feger *et al.* (2022) show that the distribution of rooftop solar adoption is inefficient, and Bollinger *et al.* (2025) show that households with lower income have a higher discount factor when it comes to adopting solar.

According to an IOU employee and a survey of the news at the time, prior to the finalization of the policy in December, there was a lot of uncertainty about how the policy would be put into place. When NEM 1.0 had been changed to NEM 2.0 in 2017, all installations had to have been completed prior to the policy cliff deadline. In fact as we see in Figure 1 in May 2022, when NBT was announced as a potential policy to be considered, there was an anticipatory rise in applications and completions. The peak month for completion was December 2022. This period between May 2022 and December 15th, 2022 will be henceforth referred to as the anticipation period.

In December 2022 the policy was voted to go into force on April 14th 2023 with an interesting, and not anticipated, loophole which allowed consumers to apply for their interconnection having signed a contract with an installer before April 14th, 2023, however are only required to have completed interconnection within 3 years of application submission.[3] An application received by the deadline holds in place a 20 year contract under the NEM 2.0 policy which is initialized when interconnection begins. As a result, in the months leading up to the April 2023 deadline, installers established queues

[3]According to the IOU employee, there had been about 90,000 applications submitted and in early 2025 about 15,000 were still outstanding.

of customers. Prior to the treatment period (Dec 2022-April 2023), the average wait time between when a permit was submitted for approval and when the installation was completed was about 35 days. The average wait time for an installation where the application was submitted in April 2023 was 146 days.

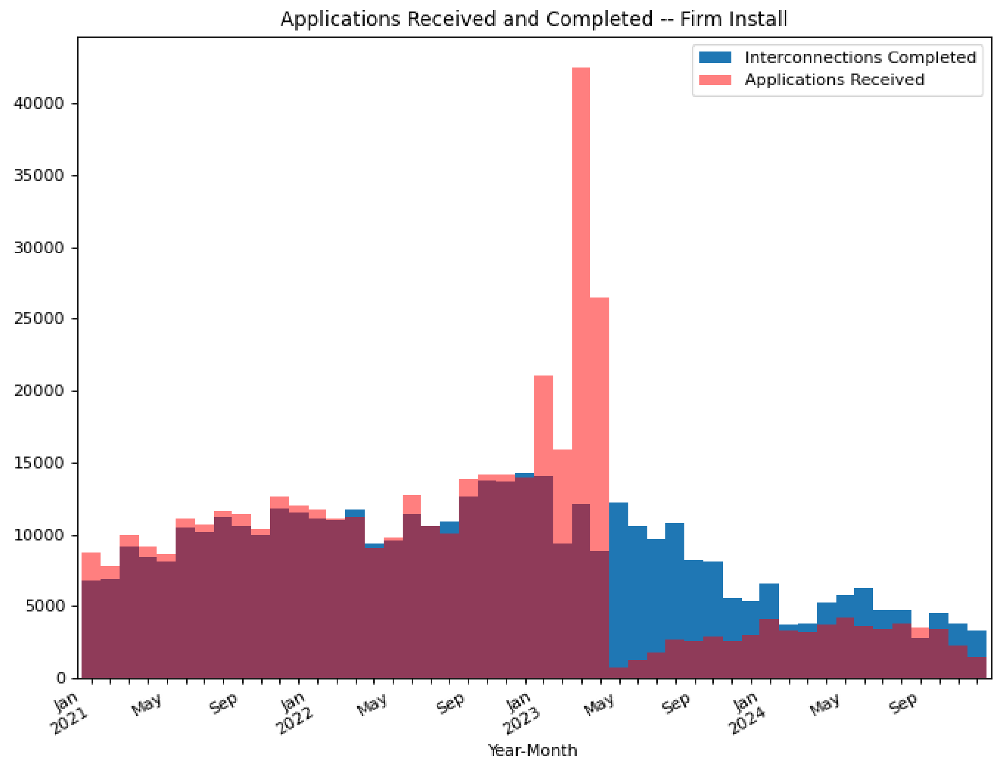


Figure 1: In red we see the number of applications for NEM 2.0 interconnection between 2021 and 2024. In blue we see the corresponding completion of installation of rooftop solar. We see that until January 2023, applications and completions kept pace with each other. Completion peaks in the anticipation period while both suppliers and consumers are uncertain about policy implementation.

Taking a look Figure 1, the left-hand panel shows the quantity of applications received by an IOU in a given month, and the right panel show the quantity of applications completed. There is gradual increase in applications between the announcement time in May 2022 and the final decision in December 2022, hereafter the "Anticipation Period", and a sharp increase in demand during the "Treatment Period", between

December 15th 2022 and April 2023, followed by a sharp drop off. There is evidence of some level of harvesting - perhaps people completing their paperwork earlier than they would have otherwise. The magnitude of the spike in demand relative to the lag in the period after the policy cliff is suggestive that this is not the primary mechanism behind the demand shock. This paper however does not take a stand on the behavioral economics of procrastination or what drove the magnitude of demand shock beyond the approaching policy cliff and drop in the financial payoff from installing rooftop solar.

In this paper a "queue" is measured as the number of applications at a given time that have been submitted to the IOU which refer to a specific firm, but that have a later completion date.[4] Figure A2 shows the distribution of queues for firms at the end of each month between January 2022 and April 2024. We see that until the policy parameters were finalized in December 2022, there was very little variation in the distribution of queues from month to month. Although I do not track here which firms have the longest queues and whether it changes, some spot analysis shows that the largest firms stay relatively consistent throughout the sample. Figure A3 shows the distribution of queues in April 2022 - before any announcement or anticipation in comparison to the distribution in April 2023, at the policy cliff.

2.2 Firm Entry

To understand effective firm entry and exit, I use the complete dataset of installations, which goes back to 2017, group by license number, and find the first date in which a firm enters the dataset and consider that the firm entry date. I then determine the last date that a firm's license number is associated with an installation and consider it the firm exit date. The dataset extends through December 2024, so to avoid suggesting that firms which only install solar once every few months have exited the market, I cut the dataset after doing the calculation to Jun 2024. The results are shown in Figure 2 for the state and county level. The county level may include firms which have already established themselves elsewhere in the state and first enter a new county.

We see that in the period prior to the December 2022 policy announcement, including during the anticipation period from May 2022, exits and entrances are relatively stable both at the county and the state level. We then see, after allowing for delayed delivery has been established by the policy first a growth in county entrants, suggestive

[4]This is not to be confused with interconnection queues which have to do with the administrative delay from the IOU and typically refers to utility scale generation applications.

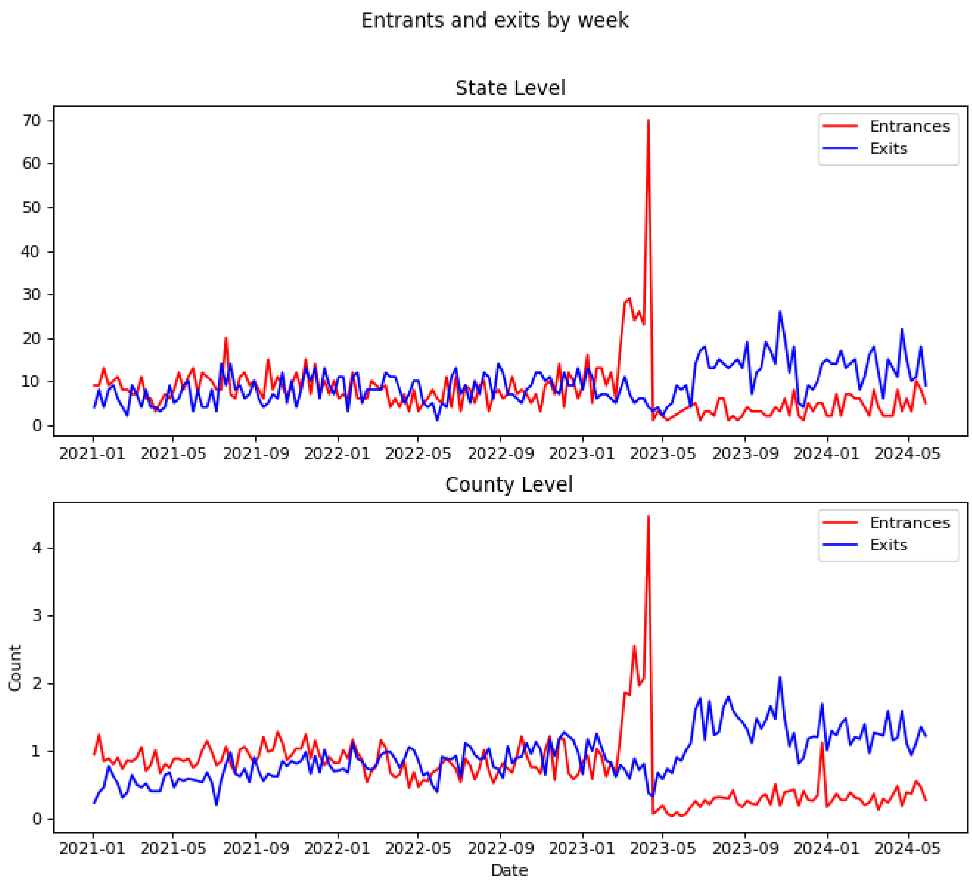


Figure 2: In the top panel I show the total number of firms entering an exiting in the state in any given week, and in the bottom panel I show the average number of entrants and exits in any given county.

of growth at the intensive margin, then growth at the state level suggestive of growth on the extensive margin. We then see that exits moderately increase and entrances decrease from their pre-period equilibrium, and have not yet re-entered a stead state where entries and exits are approximately equivalent.

2.3 Market Concentration

Market power in rooftop solar has been examined many times. Pless and Van Benthem (2019) show unequivocally that the third-party owner (TPO) solar exhibit market power by showing that a change in solar subsidy results in a more than 1:1 price change. Gillingham *et al.* (2016) observe the county level Herfindahl-Hirschman Index (HHI) to be 0.1 at the county level in the state of California. Indeed, at the county level using the California Distributed Generation Statistics dataset I find an average HHI of 0.089 in the year preceding anticipation, and 0.096 in the year from May 2022 to May 2023. In the period after the cut off, when new demand for solar seriously declined, we see an increase in HHI to on average 0.109 at the county level. Despite the relatively low HHI when taken at the county level, Gillingham *et al.* argue that the price dispersion they observe and argued markups charged by the firms can be attributed to imperfect competition due to search and information costs.

3 Theoretical Model

Below I motivate my empirical findings with a few theoretical results. First, show that in an environment where there is an anticipated drop in demand, and queueing or delayed delivery is plausible, both monopolists and competitive firms, under certain conditions, find it optimal to construct a queue. Following that, I show that the firm entry condition in a competitive environment where incumbent firms have queues have a comparative advantage for impatient consumers and may charge a premium for the ability to serve arriving consumers sooner than incumbents. Finally, I explore two possible extensions through learning by doing and moral hazard.

3.1 Queueing as an optimal provision policy for firms

Here, I develop a simple two period (periods 0 and 1) monopoly model of supply and demand. Suppose the demand function is known to the firm.

- Period 0: $D_0 = F(p_0, p_1)$. Demand for given wait time for delivery τ, if there was not alternative delivery period is defined as $f(p, \tau)$. Thus, if people are perfectly elastic between period 0 and 1, $f(\bar{p}, 0) = f(\bar{p}, 1) = F(\bar{p}, \bar{p})$ for some $\bar{p}$.

    1. $\forall\ \tau\ \exists\ p > 0\ s.t.\ f(p, \tau) > 0$
    2. $\partial D_0/\partial p < 0$, $\partial D_0/\partial \tau < 0$

- Period 1: $D_1 = 0\ \forall\ p, \tau$

where D_t is new demand in time t. p_τ is price for delivery with wait time τ, or delivered in period τ, $F(p_0, p_1)$ is the total demand given prices across periods, and

$f(p,\tau)$ is the amount demanded at a given price p for wait time τ. The first condition states that demand does not go to zero for positive price and wait time, and the second condition is that demand is decreasing in price and decreasing in wait time.

Supply has convex marginal costs and discounts the future at rate β. This assumption about increasing marginal costs is important, and is contextually relevant. Within our empirical context, although the physical act of installing rooftop solar may have constant returns to scale, the operational efficiency of the back office and supply chain likely have decreasing returns to scale, and the tightness of the labor market may result in increasing costs. This assumption means that for a given price there is a unique most efficient size. The firm solves

$$\max_{p0,p1,q0,q1} p_0q_0 - c(q_0) + \beta\left(p_1q_1 - c(q_1)\right) \quad (1)$$
$$\text{s.t. } q_0 + q_1 \leq F(p_0, p_1)$$

where q_τ is the quantity supplied with wait time τ and $c(q)$ is the cost of supplying quantity q. We must make a further assumption to rule out that the firm chooses to increase capacity and provide everything in one period.

Assumption 1:
$$p^m q^m - c(q^m) \leq p_0q_0 - c(q_0) + \beta\left(p_1q_1 - c(q_1)\right)$$

This can be achieved by assuming marginal costs are increasing *fast enough*, or through assuming some pre-existing level of inputs combination convex cost and non-convex costs of changing or increasing inputs.[5]

Simplifying Assumption 2: Agents are heterogeneous in price preferences, but homogeneous in time preferences. That is $\exists$ some function $g(p,\tau)$ s.t. $f(p,\tau) = f(g(p,\tau), 0)$. For simplicity, let $g(p,\tau) = (\frac{1}{\gamma})^\tau p$.

Then $f(p_1, 1) = f(\gamma p_0, 0)$, and the marginal customer is indifferent between $p_0 = p$, $\tau =$

[5] A future version of this work will quantify the curvature necessary to achieve this. Also note that when taken to T periods, there will be some curvature which results in the firm choosing to maximize over a some $t < T$ periods.

0 and $p_1 = \gamma p,\ \tau = 1$. Thus our inequality becomes

$$q_0 + q_1 \leq f(p_0, 0)$$
$$q_0 + q_1 \leq f(p_1, 1)$$

Because consumers have homogeneous preferences over time to delivery and are utility maximizers, the only equilibrium p_0 and p_1 where consumers purchase for delivery in both time periods is where $p_1 = \gamma p_0$. This rules out certain inefficiencies from misallocation and rationing by creating a wait list (Breza *et al.*, 2021; Lindsay and Feigenbaum, 1984).

The firm now solves

$$\max_{p_0, p_1, q_0, q_1} p_0 q_0 - c(q_0) + \beta\left(p_1 q_1 - c(q_1)\right) \tag{2}$$

$$s.t.\ q_0 + q_1 \leq f(p_0, 0)$$
$$q_0 + q_1 \leq f(p_1, 1)$$

Let $Q = q_0 + q_1$, and $Q' = \frac{\partial f(p_0, p_1)}{\partial p_0}$. See Appendix B for how I obtain these results.

$$p_0(1 - \beta\gamma) = c'(q_0) - \beta c'(q_1) \tag{3}$$

$$\beta\gamma p_0 - \beta c'(q_1) + \frac{Q}{Q'} - \frac{(1 - \beta\gamma q_1)}{Q'} = 0 \tag{4}$$

Equations (3) and (4) are key in our theoretical result.

Suppose we take $\beta \to 1$ and $\gamma \to 1$. Then $p_0(1-1) = c'(q_0) - c'(q_1)$, which implies by strict concavity of the cost function, that $q_1 = q_2$. Then $p_0 - c'(q_0) + \frac{q_1}{f'(p_1)}$ Allow $\varepsilon = \frac{p}{Q}\frac{\partial q_\tau}{\partial p_\tau}$ to be the price elasticity of demand. Then equation (4) simplifies to a Cournot competition duopoly result:

$$p_0\left(1 + \frac{1}{2\varepsilon}\right) = MC$$

The implications of this result are that a firm facing sufficiently increasing costs and can delay deliver, upon an anticipated drop in demand will increase their total supply by decreasing their price and providing quantities spread across periods. The firm is able to take advantage of being further down on their cost curve and queuing their consumers, while consumers are able to take advantage of lower prices.

Under the same preference assumptions, Table 1 shows what is the optimal policy for the firm.

Table 1: Policy for Queueing given demand patterns.

$D_0 = F(p_0, p_1); D_1 = 0$	$p_1 = \gamma p_0$ $p_0(1-\beta\gamma) = c'(q_0) - \beta c'(q_1)$	Queueing
$D_0(p) = D_1(p)$	$q_0 = q_1$ Standard monopolist price	No queueing
$D_0(p) > D_1(p) > 0$		Ambiguous

Competitive Market Suppose instead that firms, with increasing costs take prices as given and behave competitively. The demand function follows the same policy, and the firm faces the same production function. Then the firm solves:

$$\max_{q_0, q_1} p_0 q_0 - c(q_0) + \beta \left(p_1 q_1 - c(q_1)\right)$$

The first order condition quickly gives us our results:

$$q_0 = \frac{c'(q_0)}{p_0}$$
$$q_1 = \frac{c'(q_1)}{p_1}$$

Supposing that $p_1 = \gamma p_1$, then we find

$$\frac{q_0}{q_1} = \gamma \frac{c'(q_0)}{c'(q_1)}$$

As $\gamma \to 1$ because we have assumed that $c(q)$ is a strictly convex function, $q_1 \to q_0$.

Both the competitive and monopolistic models can be taken to multiple periods. In both cases, for $\gamma < 1$, we have that as τ increases, the market clearing q_τ and p_τ both decrease.

3.2 Firm Entry

Let's start with a Hopenhayn (1992) style set of assumptions and firms. Assume that firms are profit maximizing and there is free entry of firm and let f^e be the fixed cost of entry. Suppose we have perfect competition and decreasing returns to scale. A standard free-entry condition is

$$\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\pi_t\right] = f^e \tag{5}$$

where π_t is profit in time t. For this example, we consider the discrete time scenario, although this could easily be extended to continuous time.

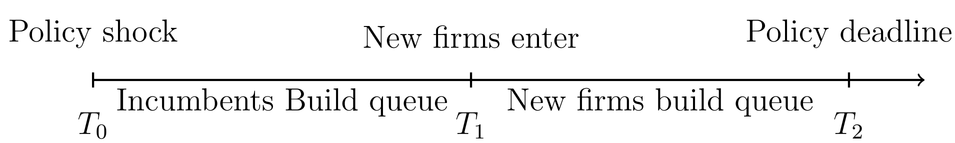
Let the production function in each period t and firm j be

$$q_{jt} = \varphi_{jt}\ell_t^{\alpha}$$

for some $\alpha < 1$ and costs be $c_t = w_t\ell_t$. In our empirical setting, the main capital expenditure is the good itself rather than an input to production. If we assume that firms perfectly pass through the direct costs of the physical good and consumers consider the price of the installation service separately from the price the panels we can allow p_t to be the price of the service after accounting for the price of the panels.

Let demand be an exogenous function $q_t^d(p_t, \tau)$ of price p_t and delay of delivery τ. Assume, as we did above, that there exists some γ such that at time t for any price p, $q_t^d(p, 0) = q_t^d(\gamma^\tau p, \tau)$.

Suppose there are three periods:



Because the value option of waiting for consumers of the durable good has been reduced, this induces an immediate positive shock to demand during period T_0 and T_1 and an anticipated negative, persistent reduction in demand beginning in period T_2. Suppose prior to T_0, demand is stable and predictable. Demand that is queued during the $t \in T_0, T_1$ is served at some point $t + \tau$ without penalty or uncertainty. Firm profits from the period they build their queue are described as

$$\pi_t = \sum_{s=0}^{\tau_f} \beta^s \left(\gamma^s p_t \varphi_{ft+s} \ell_{t+s}^{\alpha} - w_{t+s}\ell_{t+s}\right) \tag{6}$$

They solve a profit maximization problem to determine the quantity they can provide in each period and thus how large their queue should be. In each period $t+s$:

$$\ell_{t+s} = \left(\frac{\alpha\gamma^s \hat{p}\varphi}{w}\right)^{1/(1-\alpha)}$$

$$q_{t+s} = \varphi^{1/(1-\alpha)} \left(\frac{\alpha\gamma^s \hat{p}}{w}\right)^{\alpha/(1-\alpha)}$$

As we showed above, in the period before T_0, there is no incentive for firms to queue their demand. Thus, the free entry for T_0 equation resembles equation 5. Now consider T_0. An incumbent firm finds it optimal to queue demand, thus the firm has a time delay of τ_f. If period fixed costs are homogeneous across firms, then all firms build their queue such that $\tau_f = \tau^M$, a market level delay. The maximum level of τ^M is such that $\gamma^{\tau^M} p_{T_0} = p^{post}$ for p^{post}, the market price after the subsidy drops.

A firm, entering in period $t = T_1$ has no queue. New demand in period t is such that the marginal consumer is indifferent between paying $\gamma^{\tau^M} p_t$ with incumbent firms with a delay of τ^M or $p_t > \gamma^{\tau^M} p_t$ for immediate delivery. Thus, the new firm builds their queue, with a one period profit function as in equation 6. Now, the free entry condition becomes

$$\begin{aligned}\mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \pi_t\right] &= \sum_{s=0}^{\tau_f} \beta^t \left(\gamma^s p_t \varphi \ell_{t+s}^{\alpha} - w_{t+s}\ell_{t+s}\right) + \sum_{s=\tau}^{\infty} \beta^s \pi_{t+s} \\ &= f^e\end{aligned}$$

If f^e stays persistent between periods, then the change in profitability between an queueing and non-queueing scenario dependent on labor elasticity in the market and demand elasticity during the shock. Consider a no queue profit scenario where the expected profits π_t^{NQ}. Then there will be an increase in entry relative to the no-queuing scenario if the following condition holds:

$$\sum_{s=0}^{\tau_f} \beta^t \left(\gamma^s p_t \varphi \ell_{t+s}^{\alpha} - w_{t+s}\ell_{t+s}\right) > \pi_{T_0+1}^{NQ} + \sum_{s=T_1}^{\tau^f} \beta^s \pi_s^{NQ} \tag{7}$$

Learning by Doing Extension Now consider, instead of the standard Markov process for firm productivity φ_f', with $\varphi_f' = F(\varphi_f'|\varphi_f)$ but rather one of internal learning by doing in similar to the learning curve described in Arrow (1962).

$$\varphi_{ft} = \varphi_f(1 - \frac{b}{Q_t^n}) \tag{8}$$

for $n > 0$, $b \in (0, 1)$ and $Q = \sum_{s=0}^{t} q_s$, the cumulative number of projects completed since the firm began operating.

In Hopenhayn (1992), there is an equilibrium "zero-profit cutoff" productivity level, φ^{ZPC} where for any firm where $\varphi_f < \varphi^{ZPC}$, they exit at the end of the period because their expected future profits are less than zero. If you include this learning by doing evolution of productivity, this φ^{ZPC} becomes dynamic with firm age. In a world without queueing, by period T_1, the demand has dropped, and new entrants are partially along their learning curve, with low productivity. With queueing, firms face the lower demand levels in period $T_1 + \tau^M$, having progressed further along their learning curve before facing lower demand. This has the potential to increase the expected value on the left-hand side of equation 7 and decrease the expected value on the right-hand side. Further work on this topic could be done to quantify this change and to determine a difference in rates of convergence to the new, post subsidy drop, φ^{ZPC}.

Moral Hazard Extension Firms give consumers an estimated date of delivery when they create a contract. Lewis and Bajari (2014) show moral hazard within the construction industry and mechanisms to reduce it's prevalence.

Moral hazard for a firm can be thought of as a second price auction where the firm that wins with a set price and proposed delivery date is then maximizing their profit relative to the consumer's next best option. Suppose for simplicity, the supplier informs the consumer in the next period when they will actually deliver service, which may or may not be the reported time, and in the current period there is some deposit D the consumer must pay the firm to retain the contract.

$$\tau^* = \arg\max_{\tau_j} \beta^\tau \left((p_0 - D) - MC_\tau\right)$$
$$s.t. \;\; \gamma^\tau V_0 - (D + \gamma^\tau (p_0 - D)) \geq D + \gamma(V_1 - p_1)$$

where MC is marginal cost of the project given the intensity with which the firm chooses to provide service. The condition can be rearranged to

$$\gamma^{\tau-1}(V_0 - p_0 + D) \geq V_1 - p_1$$

If we assume sufficiently increasing marginal costs and $\beta \geq \gamma$ then firm optimizes τ to make the inequality an equality. Then, the optimal condition for τ^* is

$$\tau^* = \frac{\ln(V_1 - p_1) - \ln(V_0 - p_0 + D)}{\ln \gamma} + 1$$

If the expectation of V_1 is approximately V_0 and the aggregate demand in the economy stays the same, thus $p_0 \approx p_1$, then the optimality condition is dependent mostly on D and γ. Thus, the extent of moral hazard in a competitive market may be limited.

On the other hand, suppose $V_0 > V_1$, for instance due to a removal of a subsidy in period 1. Then, if we assume $\gamma \in (0, 1)$, we have $\frac{\partial \tau^*}{\partial V_1} > 0$, and V_1 is going down in this scenario, moral hazard is greater. This will be true for the last person is a firm's queue. Given a greater mass of consumers in a firm's queue, the firm is now optimizing over marginal costs as they work through their queue. In this case, the τ_i for consumer i interior of the queue may be such that the IC condition is binding as before, or the profit condition is binding.

The key takeaway is that if entering firms internalize the possibility for moral hazard in their entry condition, then a transient positive demand shock will encourage entry. Unlike in the learn by doing scenario, where the entry from the queueing scenario has a clear positive benefit to the industry and overall welfare by improving the aggregate productivity in the market when the demand drops, if firms enter due to their ability to take advantage of moral hazard this may have net negative welfare implications.

4 Data

I use data from the California Distributed Generation Statistics on residential solar permits. This includes complete permit information about the project, including size, battery, mount, panel model, as well as the installer name and location, license number, and the installation location at the zip code level. I limit the dataset to begin with applications submitted since January 1, 2021 though December 31, 2024. I then remove projects that are under 1kW and over 12kW. 1kW as the lower bound, because some projects are just amendments of earlier projects, and over 12kW because that is the threshold to qualify for the NEM 2.0 tariff that we are interested in. I also remove projects whose listed price is blank or under $1000, which removes several projects where an application was submitted without full details about the project[6]. Due to difficulties in understanding pricing, I remove self-installed and third-party owned installations. After filtering I am left with about 315,000 firm installed permits. Table A1 includes summary statistics for the installation attributes of installations which remain after filtering.

Each interconnection application in the data holds information about the date received by the IOU, the date the application was considered "complete" and the approval date. The "complete" date is uninformative, as all it describes is the completeness of the paperwork, not the installation. The approval date, which is the date when the IOU approves interconnection is what I use in my analysis to indicate a job complete. Each IOU is responsible for reviewing each application, inspecting and approving interconnection, and by CPUC Electric Rule 21 they are mandated to limit their time with each application and since 2021 have reported their monthly averages for time with application. Figure A1 shows us the amount of time that the IOU spends with an application officially between application submission and approval. The total interconnection time during between January 2021 and October 2022 stands out as irregular for SDG&E. They appear to have had very large delays in approving interconnection, despite the IOU time in contact with the application appearing low.[7] Unlike in Johnston *et al.* (2023) where the time to interconnection is the main hold up of large generation projects, during the treatment period in particular, the main driver of long periods

[6]A representative from one of the IOUs expressed that they and the other IOUs were somewhat lenient about allowing such applications to be submitted during the policy transition. Depending on the information submitted, the application may or may not have been updated

[7]As a robustness check, I validate my results using the other two IOUs only, found in Appendix C

before interconnection is approved seems to be the installer.

I use the monthly US consumer price index, for urban areas in Western United States from the FRED Economic Data. All prices are adjusted by the national consumer price index from the Bureau of Labor Statistics centered on May 2022.

5 Methods

To understand the role of patience and firm age on pricing during a period of market queuing, I do a first difference heterogeneity analysis of four different metrics. The treatment period is broken into two time periods - first the Anticipation Period between May 15th and December 14th, second the Queueing period, which falls between December 15th and April 13th. The uncertainty period has effectively no change in queueing patterns (see figure A2), however rates of completion where had increased. During this period neither consumers nor installers knew how the policy transition would be implemented in terms of deadline for application submission or installation completion. The Queuing Period is the period in which most firms are taking on more clients than they are able to delivery to as their usual rate of delivery, with the explicit and communicated intention of delivering service at a later date. The four metrics I use in separate regressions are as follows: first, I use the time to completion from application submission to approval, second, I construct a novel metric to measure the degree to which a project follows a queue, third, I use firm age, finally I use the nth complete installation by the firm.

The second metric is what I call the "FIFO Score" which is the degree to which a project follows a first in first out model (FIFO) for delivery. This is done both at the firm-county level and at the county level. The score is constructed in the following way: *1 - the portion of projects that were received before a given project's receive date that were completed after said project's approval date.*

The reason to use the firm-county level is to answer is to understand the degree of FIFO queueing within a given firm in a given market (county). By looking at the county-level we observe the degree to which a market in aggregate is following a FIFO pattern. This method should capture the degree to which people are willing to pay to be serviced out of the order of arrival. The summary statistics are shown in Table A2. We note the high level of FIFO-ness at both the county and the county-firm level. This is suggestive of two things, 1) that within firm, there is very little evidence of queue jumping and 2) within a market (county), although the degree to which projects follow first-in-first-out is marginally lower, it is still extremely high, this may mean that once a firm enters a market, they are quick to fill their queue. In the whole sample, selecting a random project i, 92% of the projects in the same county that were completed between the time that the project application was received and interconnection occurred had been received by the IOU prior to the time project i's application was received.

To test the theory that younger firms are taking advantage of the queuing and a consumer's elasticity of waiting, I interact firm age with the treatment period. To understand the relationship between firm age and price, I bin by age, where firm age is calculated as the time since the first time a firm shows up associated with an application for interconnection. The bins are *Younger than 1 month*, *1-3 months*, *3-6 months*, *6-12 months*, *12-24 months* while using firms older than 2 years as the control. I have described the size of each bin for each period in table A3. Finally, because firms deliver at variable rates, I have order firm installations by completion date and grouped by their rank. I do this both at the county level and the state level to understand the difference between new firms and firms expanding their territory. The installation bins are *First 10*, *Installations 11-20*, *Installations 21-50*, *Installations 51-100* and *Installations 101-1000*, while using installations 1001 and above for a firm as the control.

To establish the relationship between price and firm and installation properties, I run a first difference heterogeneity analysis of price on during the treatment on firm age, wait time, cumulative count of installations by a firm, and finally on the FIFO score. The treatment periods - anticipation and queueing are plausibly exogenous shocks to the market. Although the policy change being proposed several months before it was finalized may have resulted in some harvesting of demand into the anticipation period, the policy which allows demand to be queued was unanticipated. In our setting, there are no units that are untreated by the policy, however each installation is differentially exposed to firm age, time to completion, and market demand. While one may make the case that the timing of arrival of any individual consumer to a market is effectively random given some temporal flow, time to completion is clearly endogenous as firms select their rate of service provision through profit maximizing behavior given prices. An incumbent firm's age is exogenous, however because market pricing impacts the firm entry decision, consumer exposure to young firms during the treatment period is endogenous. Among these variables, the market level FIFO score best approximates an exogenous continuous treatment in the sense of Callaway, Goodman-Bacon and Sant'Anna (2024), however the exogeneity depends on whether prices impacts firm's willingness to move people up the queue can only be observed after analysis. Due to the embedded endogeneity, I refrain from making causal claims beyond the policy causing a market shift, and instead will use the results as correlative evidence which motivates the theoretical findings.

The regression I run is as follows:

$$\log y_{itc} = \alpha + \xi\, \mathrm{d_i} + \beta \mathbf{D}_t + \phi\, \mathrm{d_i} \times D_t + \gamma_c + \delta' X_i + \epsilon_{itc} \tag{9}$$

with y_{itc} as the total cost of installation, $\mathrm{d_i}$ as the metric (one of time to completion, FIFO score, and firm age), $\mathbf{D}_t$ as a vector of treatment periods: anticipation and queueing. X_i are installation attributes, and γ_c is fixed effects. For each metric I run two regressions. One regression using county fixed effects, where county how a market is defined (Gillingham and Tsvetanov, 2019), and the second using firm-county fixed effects to understand the within-firm dynamics. I then cluster the error terms using county and firm-county clusters respectively.

Installation firms are traditionally in charge to submitting the application to the IOU. As a result, an individual firm may have bunching of applications received by the IOU on the same day. This may also mean that installers and customers may have entered an agreement an unknown period of time before the application was submitted to the IOU. Prior to the uncertainty period, when there was no universal deadline (with uncertainty during the uncertainty period, and with certainty during the treatment period), there may be no incentive for firms to file paperwork quickly before starting an installation, however during in particular the treatment period, and potentially during the uncertainty period, the firms may be more careful to fill out paperwork quickly. This could bias the time to completion results toward zero during the treatment period.

Similarly, we do not have the date that a consumer initiates a contract with a supplier, nor when the contract is signed. While there appears to be the sharpest increase in applications in the final weeks prior to the application deadline, we cannot be certain the prices were not agreed upon weeks before. Thus, rather than doing time series analysis to understand the impact of the closeness to the deadline, I use a single indicator for each Anticipation and Treatment (Queueing) periods.

Table 2: Time to Completion on Price

	Log Installation Price					
	(1)	(2)	(3)	(4)	(5)	(6)
Months to Completion	-0.000	0.001	0.008***	-0.002**	-0.001	0.004***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Treatment		-0.023**	0.011		-0.023***	-0.002
		(0.011)	(0.009)		(0.006)	(0.006)
Anticipation		-0.009*	-0.011**		-0.020***	-0.016***
		(0.005)	(0.005)		(0.003)	(0.004)
MTC $\times$ Treatment			-0.013***			-0.009***
			(0.002)			(0.001)
MTC $\times$ Anticipation			0.001			-0.003*
			(0.002)			(0.002)
Size (kW)	0.138***	0.138***	0.138***	0.135***	0.135***	0.135***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Has Battery	0.209***	0.207***	0.208***	0.328***	0.326***	0.326***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Output Monitoring	0.012	0.010	0.012	0.052***	0.049***	0.051***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)
Battery Size (kWh/1000)	0.034***	0.034***	0.034***	0.029***	0.029***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
County	x	x	x	-	-	-
Firm-County	-	-	-	x	x	x
Observations	315,542	315,542	315,542	315,542	315,542	315542
R^2	0.463	0.463	0.465	0.643	0.644	0.644
R^2 Within	0.450	0.450	0.451	0.485	0.485	0.486

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Here I measure the impact of months to completion (MTC) on the log of the total cost in 2022 dollars. The first three columns are at the county or market level, and the last three columns are at the firm-county level.

6 Results

6.1 Days to completion

Table 2 shows the results from the regressions for equation 9. We find that throughout the who period (columns 2 and 4), there is a weakly positive relationship between time to completion and price, with the exception of column (5) where we see that when accounting for price changes at the firm level during the treatment and anticipation period, there is a very weakly negative relationship. If we interact the time to completion with the treatment period, we find that at the county level (column 3), during the treatment period an additional month (30 days) to installation completion is associated with a 1.3% reduction in price and at the firm-county level (column 6) is it associated with a 0.9% reduction in price. In addition, at the firm level, an additional month to completion during the anticipation period is associated with a 0.3% decrease in price. We see clear evidence that during the treatment and anticipation period prices are higher than in the pre-period. When we account for the impact of time to completion on price, we see that the treatment period is associated with higher prices than the anticipation period, however the average time to completion during the Anticipation period was statistically no different from the pre-period, whereas the time to completion during the Treatment period was approximately 110 days greater on average.

6.2 FIFO scores

In table 3 we see the results from looking at people's willingness to pay to jump the queue. We find in column (1) at the county level, during the treatment period, prices were weakly higher, however because the majority of installations have a FIFO score near 1, this is canceled out by the FIFO $\times$ Treatment term. During the pre-period, changing the order with which a consumer received service was not associated with a change in price, however during the treatment period, a 10% move up the queue associated with an increase in a 1.25% increase in price. Column (2) tells us a slightly different story by using firm-county fixed effects. In the pre-period whether a consumer jumps the line or not has little impact on price. During the treatment period jumping the queue is associated with statistically zero price change. In contrast, during the anticipation period, we so no significant effect of FIFO score on price at the county level, but we see that within firm, queue jumping cost approximately 0.3% for a 10% movement. The interpretation of this may be that within a firm, the projects that moved quickly during the pre-period are the easier projects, though as we know from A2, the firm FIFO score are very left skewed during all periods.

6.3 Firm Age

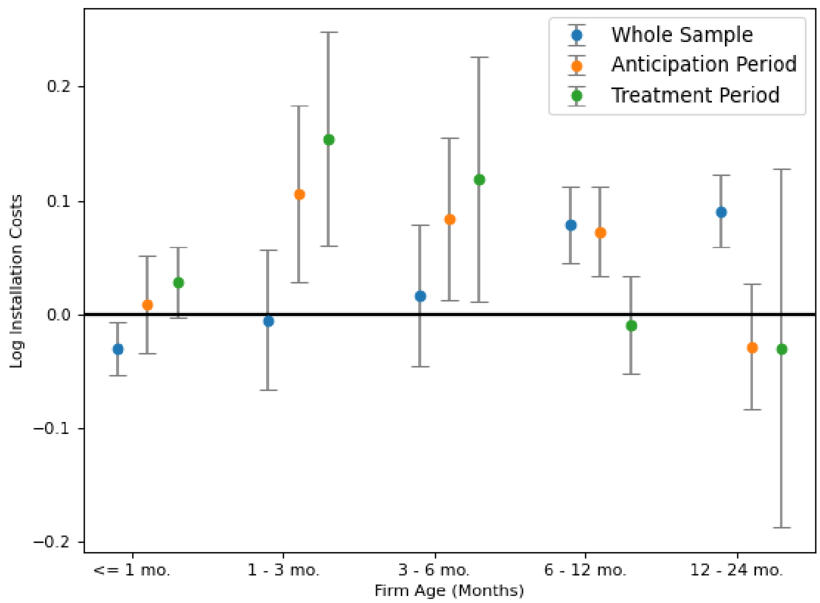
I test for the relationships between firm age and price during the treatment and anticipation periods. I bin firm age, where firm age is calculated as the time since the first time a firm shows up associated with an application for interconnection. The bins are *under 1 month*, *1-3 months*, *3-6 months*, *6-12 months*, *12-24 months* while using firms

Table 3: FIFO Score on Price

	Log Installation Price	
	(1)	(2)
Treatment	0.097	-0.010
	(0.063)	(0.019)
Anticipation	0.079	0.011
	(0.056)	(0.014)
FIFO Score	0.018	0.014
	(0.033)	(0.009)
Treatment × FIFO Score	-0.125*	-0.019
	(0.068)	(0.019)
Anticipation × FIFO Score	-0.094	-0.033**
	(0.060)	(0.014)
Size (kW)	0.138***	0.135***
	(0.004)	(0.002)
Battery Size (kWh/1000)	0.034***	0.029***
	(0.005)	(0.005)
Has Battery	0.208***	0.325***
	(0.020)	(0.020)
Output Monitoring	0.011	0.048***
	(0.012)	(0.011)
County	x	-
Firm-County	-	x
Observations	315,601	315,601
R^2	0.463	0.644
R^2 Within	0.450	0.485

Significance levels: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.
Using a score for the degree to which a project follows a "First in first out" I regress the log price on the treatment period interacted with the FIFO score along with other project attributes.

Figure 3: Relationship between firm age and price



older than 2 years as the control.

Table A4 shows the complete results, and figure 3 shows the coefficients on the interaction term with treatment periods and firm age. Column 1 uses market level fixed effects and column 2 uses firm-market level fixed effects. We see that at the market level, very young firms throughout the sample charge about 3% lower prices than their older peers. We find that firms 6-24 months old are charging higher prices than firms older than 24 months, which does not have a clear interpretation. During the queuing treatment period, we find that firms under 6 months in age are charging more, in particular firms that are 1-3 months old, meaning that they either entered the market either during or just before the queueing period, are charging on average 15% more than their older peers. Firms that have been in a market 3-6 months during the treatment periods are charging nearly 11% more than their older peers. During the anticipation period, I find that firms between 1 and 12 months are charging 7-10% more than their peers at the same time. We see relatively little evidence that within a firm, firms charge significantly different prices at different ages, although it appears that firms charge slightly more when then are less than a year old than they do later in their life.

When we look at the relationship between age of firm at the state level and the price, the picture is much less clear. We see in column (4) of table 3 has virtually no significant relationship between the within firm age and price. This is is a similar result to the county level. Column (3) which examines age of firms within a state using county fixed effects shows us that firms in their first month of existence tend to charge less than their peers in the market, and ages 3-24 months they charge as much as 9% more than their older and younger peers. During the treatment period, we only see a change from this where firms 1-3 months in age adjust their prices during the treatment by 15% more than their peers, which have no significant heterogeneous results during the treatment period.

6.4 Cumulative Completions

Table 4 shows us the relationship between the nth completion by the firm and the price. Columns 1 and 2 measure the nth completion within a county, and columns 3 and 4 show us the nth completion by the firm in the state. These results are somewhat noisy. Columns 1 and 3 use County fixed effects and columns 2 and 4 use Firm-County fixed effects. We find that throughout the whole sample, when a firm enters the state, they charge lower rates than other firms in the county they are servicing for their first 100 installs, but this relationship does not persist either when looking at the within-firm prices nor when an existing firm enters the county. During the Treatment period we find virtually no relationship between price and number of installations, and during the Anticipation period we find noisy results when a firm enters the county, and no significant results when a firm enters the state.

Because, by our theory, the entering firms are considering a different firm-entry condition during the treatment period, I limit the sample to the treatment period only and report the results in table 5. Here we see a clearer story. We continue to see that when a firm enters the state (column 3), they charge less than their competitors for their first 100 installations. When a firm enters a county, we see in column 1 that there is no clear difference between the prices they charge and their competitors within the county for any subset of their cumulative installations. In Column 2 however we from using firm-county fixed effects see that firms are charging more for their first installations relative to their later installations.

All of the regressions consistently show that an additional kW of solar capacity increases the price by about 13.7%, additional battery increases prices in the market by

Table 4: Relationship between cumulative installations and price

	Log Installation Price			
	County Level		State Level	
	(1)	(2)	(3)	(4)
Treatment	-0.024**	-0.026***	-0.016*	-0.029***
	(0.009)	(0.009)	(0.009)	(0.006)
Anticipation	-0.025***	-0.012*	-0.006	-0.018***
	(0.009)	(0.007)	(0.006)	(0.004)
Installations ≤10	0.006	0.015	-0.141***	-0.020
	(0.019)	(0.017)	(0.020)	(0.023)
Installations 11-20	0.020	0.022	-0.108***	-0.000
	(0.016)	(0.016)	(0.017)	(0.024)
Installations 21-50	0.035*	0.030**	-0.078***	0.013
	(0.020)	(0.015)	(0.014)	(0.020)
Installations 51-100	0.029	0.023*	-0.066***	0.012
	(0.021)	(0.013)	(0.017)	(0.017)
Installations 101-1000	0.030*	0.018	-0.016	-0.001
	(0.017)	(0.011)	(0.013)	(0.008)
Treatment × Installations ≤10	-0.022*	0.028**	-0.029*	0.036
	(0.013)	(0.014)	(0.017)	(0.025)
Treatment × Installations 11-20	0.005	0.017	-0.022	0.031
	(0.014)	(0.013)	(0.023)	(0.022)
Treatment × Installations 21-50	-0.004	0.004	-0.035*	0.019
	(0.010)	(0.012)	(0.019)	(0.015)
Treatment × Installations 51-100	0.018	0.004	-0.031	0.018
	(0.023)	(0.013)	(0.024)	(0.013)
Treatment × Installations 101-1000	0.016	-0.002	-0.017	0.001
	(0.021)	(0.011)	(0.027)	(0.010)
Anticipation × Installations ≤10	0.025*	-0.005	-0.032	0.007
	(0.014)	(0.011)	(0.024)	(0.021)
Anticipation × Installations 11-20	0.043***	-0.004	0.028	0.026
	(0.014)	(0.011)	(0.021)	(0.021)
Anticipation × Installations 21-50	0.018	-0.023**	-0.001	-0.013
	(0.015)	(0.010)	(0.015)	(0.013)
Anticipation × Installations 51-100	0.039**	-0.014	0.028	-0.003
	(0.016)	(0.010)	(0.023)	(0.011)
Anticipation × Installations 101-1000	0.025	-0.006	-0.026	-0.006
	(0.015)	(0.009)	(0.017)	(0.008)
Size (kW)	0.137***	0.135***	0.139***	0.135***
	(0.005)	(0.002)	(0.004)	(0.002)
Battery Size (kWh/1000)	0.031***	0.029***	0.034***	0.029***
	(0.004)	(0.005)	(0.005)	(0.005)
Has Battery	0.217***	0.325***	0.199***	0.325***
	(0.019)	(0.020)	(0.020)	(0.020)
Output Monitoring	0.018	0.049***	-0.001	0.048***
	(0.012)	(0.012)	(0.012)	(0.012)
County	x	-	x	-
Firm-County	-	x	-	x
Observations	315,542	315,542	315,542	315,542
R^2	0.465	0.644	0.467	0.644
R^2 Within	0.451	0.485	0.453	0.485

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Here we show the relationship between the nth project completed by a firm and the price faced to the consumer. Columns 1-2 look at the nth completed installation within a county, columns 3-4 look at the nth completed installation in the entire state.

Table 5: Relationship between cumulative installations and price during Treatment Period

	Log Installation Price			
	County Level		State Level	
	(1)	(2)	(3)	(4)
Installations ≤10	-0.015	0.138***	-0.171***	0.020
	(0.022)	(0.037)	(0.017)	(0.032)
Installations 11-20	0.027	0.135***	-0.130***	0.041
	(0.025)	(0.034)	(0.017)	(0.029)
Installations 21-50	0.034	0.110***	-0.113***	0.055**
	(0.023)	(0.033)	(0.024)	(0.024)
Installations 51-100	0.047*	0.100***	-0.094***	0.024
	(0.028)	(0.028)	(0.020)	(0.022)
Installations 101-1000	0.048	0.061**	-0.033	0.017
	(0.038)	(0.024)	(0.033)	(0.014)
Size (kW)	0.129***	0.128***	0.132***	0.128***
	(0.005)	(0.003)	(0.004)	(0.003)
Battery Size (kWh/1000)	0.026***	0.025***	0.032***	0.025***
	(0.004)	(0.010)	(0.004)	(0.010)
Has Battery	0.220***	0.309***	0.200***	0.308***
	(0.020)	(0.023)	(0.019)	(0.023)
Output Monitoring	-0.014*	0.024**	-0.033***	0.022**
	(0.007)	(0.010)	(0.006)	(0.010)
County	x	-	x	-
Firm-County	-	x	-	x
Observations	91,848	91,848	91,848	91,848
R^2	0.426	0.623	0.429	0.623
R^2 Within	0.416	0.443	0.419	0.443

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Here we show the relationship between the nth project completed by a firm and the price faced to the consumer during the treatment period only. Columns 1-2 look at the nth completed installation within a county, columns 3-4 look at the nth completed installation in the entire state.

about 20% and within a firm by about 33%. Battery size has a statistically significant, but economically insignificant impact on price , and output monitoring has no significant relationship with price at the market level, but adds about 5% to the price within a firm.

7 Discussion

It is encouraging to our theory to see from table 3 that, potentially for reputational reasons, during the treatment individual firms do not appear to be accelerating individual installations for a price premium, although we do see some of this during the anticipation period. Due to the risk of moral hazard and that the estimated delivery times increased on average throughout the treatment period, the time to completion metric may not be informative about how consumers discount delayed arrival, (γ from our theoretical section). On the other hand, the FIFO score at the market level, if you are willing to accept the propensity to act on moral hazard is essentially random, shows a truer metric for how consumers trade off receiving solar earlier. Future research in this area may use Bollinger *et al.* (2025)'s estimates for discount rates with the expected rate of income from an individual installation to estimate the degree of moral hazard during this period of time.

Consistent with our theoretical predictions, we see from the empirical results that consumers pay a premium for faster delivery of service, that individual firms do not have a policy of allowing people to pay a premium to jump their queue, and therefore when consumers receive earlier delivery, it is from firms that have a shorter wait time. We also see that during the treatment period, young, entering firms are charging more than firms that have been around for a long time. This result is fairly noisy and we see that firms who have been in a county for 1-2 years are also charging more than firms that are older. There is also quite a bit of movement during the anticipation period which does not see a rise in entry, or queueing of demand, although demand itself had increased. This could be suggestive that young firms have characteristics and strategies that take advantage of demand shocks differently from their older peers that is unrelated to queueing.

We find strong evidence to suggest that firms are charging more within a county for their earlier installations during the treatment period than for their later installations within the county. Tables 4 and 5 show that consistently brand-new firms in the state charge less than their competition in the county throughout the entire sample period, specifically this does not go away during the treatment or anticipation periods. When compared against their own prices, using firm-county fixed effects, there appears to be no directional relationship between the number of installations a firm has performed in a state and their price. A potential interpretation for this is that a brand-new firm within a state has benefit from accumulating experience. Two plausible benefits of experience are from 1) brand recognition and 2) internal learning-by-doing. If brand recognition were the main driver, we would expect to see a similar, although perhaps smaller relationship at the county level as they build their reputation and recognition within a market. This is not something we see however, which may suggest that internal learning at the operational level drives firms to lower their price and increase their experience. Learning at the operational level here is key, because installers are generally confined to a specific market, therefore increased productivity at the installation level would show up in the county-level cumulative installation statistics. This difference seems to reflect the idea that firms while they are early on their learning curve will charge lower than marginal cost as discussed in Benkard (2000). If that is the case, this suggests the significant learning is be done at the operational level, rather than the installation level.

As we see from table 5, an existing firm that grows on their intensive margin by entering a new county is charging more for earlier installations during the treatment period relative to their later installations. It's possible this is completely described by the fact that as a firm builds its queue, the first completed installations have the lowest time to completion and therefore the price is not discounted.

In figure A4, I show the age bins of active firms in the state in the first quarter of 2022, 2023 and 2024. Notably, the firms aged 12-15 months are the firms which are aged 0-3 months in the previous year's graph. In 2024 we see that the rate of entry is significantly down from previous years' rate of entry. The total number of firms over 15 months old is about half what it was in the previous years. Interestingly, the cohort of firms that are 12-15 months old, or that showed up in the data during the treatment period is higher than in previous years, and the count is roughly the same. Future work can examine the properties of firms which survived, and whether the portion of surviving firms from the entry spike is fundamentally different from those that would have survived using a different policy removal mechanism.

Overall, the empirical evidence generally supports the main theories outlined in the paper and encourages future work to estimate how firm entry and industry health vary under queueing during a subsidy removal vs. other mechanisms.

8 Conclusion

This paper explores the role of queue formation during a transitory demand shock caused by a major subsidy reform. Although this paper empirically focuses on reforms to solar subsidies, the concept of a sudden positive demand shock followed by an anticipated drop in demand can be extended to any scenario where there are deadlines after which a consumers' utility drops. The paper finds that allowing queueing of demand beyond the deadline which allows consumers to take advantage of the pre-deadline returns results in an increase in overall production and lower prices than the same deadline but without queueing. It also finds that where a first-in-first-out pattern of provision to consumers is followed by firms, new entrants to a market who have an empty queue may enter, charging higher prices, earning greater short-run profits while providing weakly greater surplus to consumers. This dynamic changes the profit free-entry condition. If new firms experience internal learning, this has the compounding effect of new firms being further along their learning curve once the new, lower, demand is being satisfied than if the deadline remained the same but queueing was not allowed.

There are many ways in which this work can be extended from the empirical analysis done above. First one could develop a structural model for firm entry and queue formation using estimated demand elasticities during the period. There are two key counterfactuals which may inform the impact on consumer and producer welfare that allowing queueing has. First, consider the scenario where the deadline stays the same, but instead of it being a deadline for an application submission, it is a deadline for installations to be completed. Secondly, suppose we take the total number of additional installations after the beginning of the treatment period as a quota without a deadline. Future versions of this work will consider these counterfactuals and assess the costs of different subsidy removal mechanisms.

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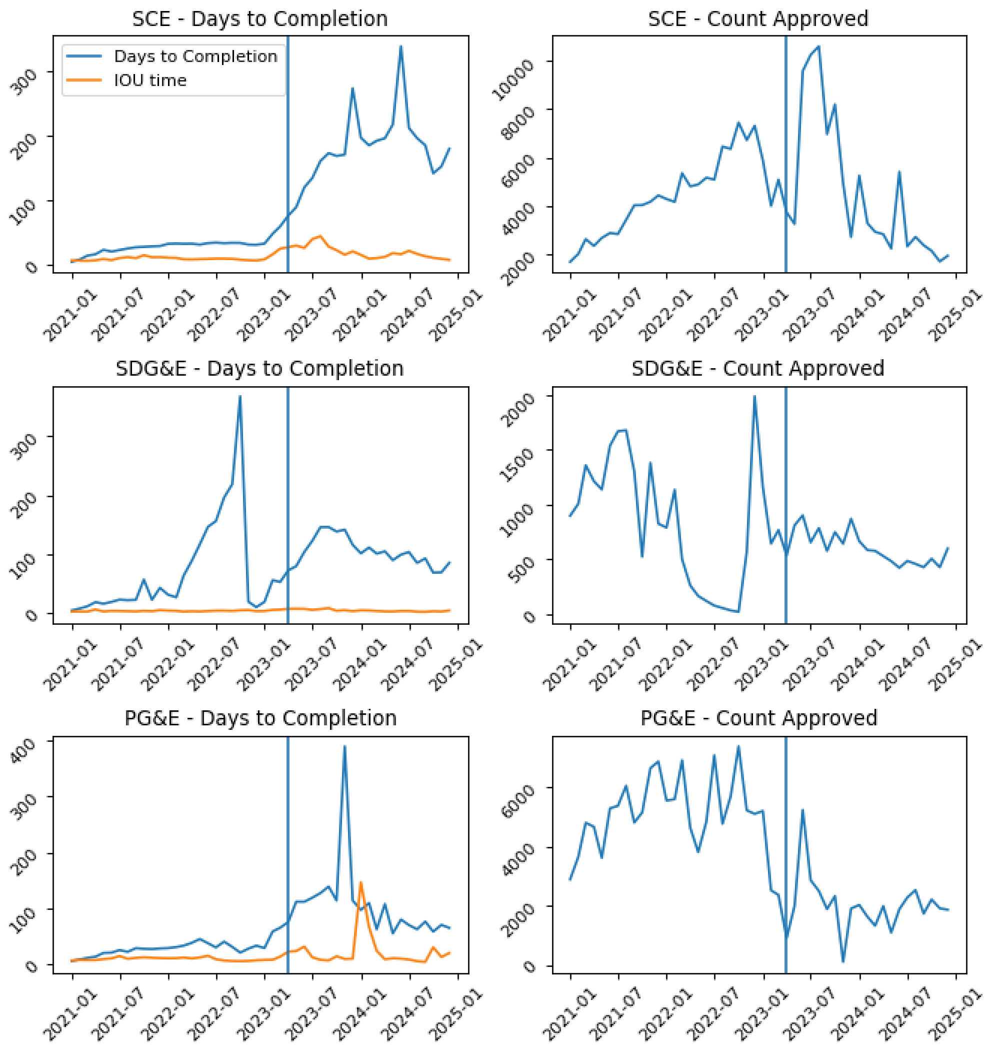
Appendix A

Figure A1: Time IOU in contact with application vs. Days to Delivery



Here we see the time to deliver in each IOU territory and the amount of time the IOU recognizes as having been “in contact” with the application. The vertical like is on December 15th, 2022 to represent the start of the treatment period.

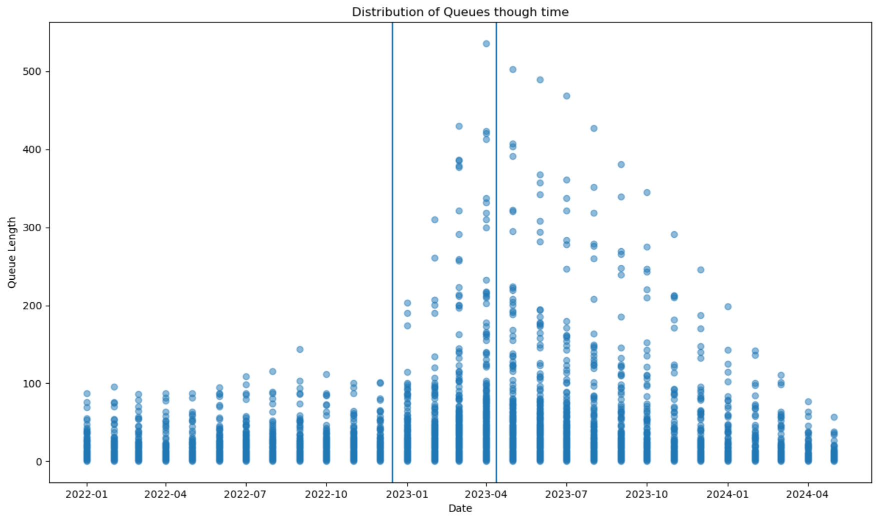


Figure A2: The distribution of queues by month where each dot represents a firm

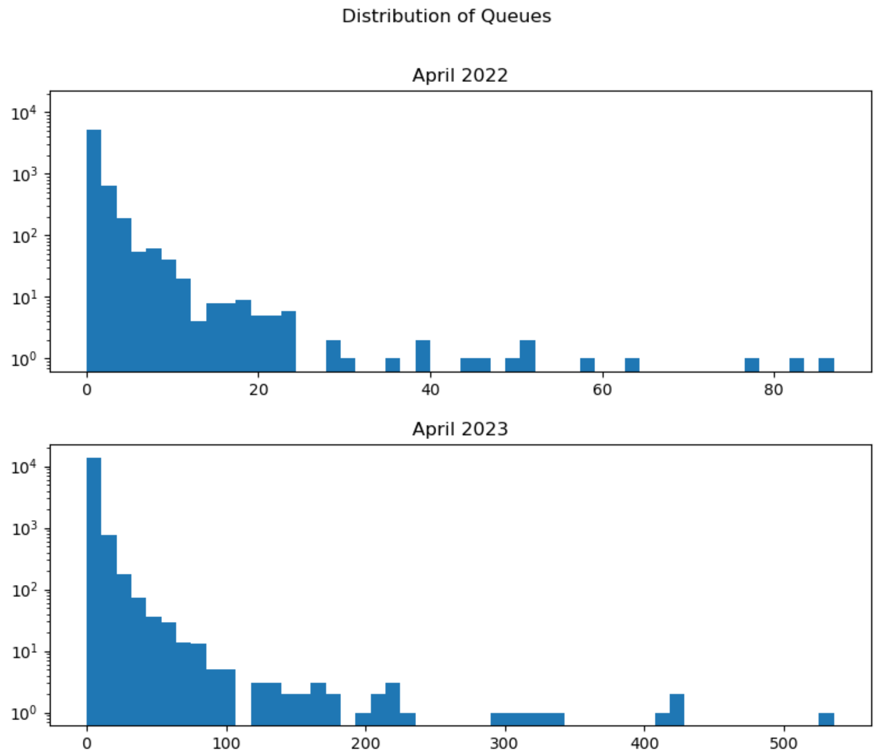


Figure A3: Here we have a snapshot of queue lengths going into April 2022—before the anticipation period—and April 2023—at the policy cliff. Note the x-axis on each graph is very different. We see that in both points in time there is a very large cluster (about 1,000) firms who maintain a queue length of zero. Notably, the shape of the two distributions is quite similar, despite the support of x-axis on the top panel being about 1/6th the support of the bottom panel.

Table A1: Attribute Summary Statistics

	Mean	St.Dev	Min	Max
Total cost (2022 dollars)	29,585.4	15,741.0	965.48	483,378.89
Months to Completion	2.25	3.43	0.0	46.27
Size (kW)	6.52	2.43	1.01	12.0
Battery Size (kWh)	0.0	0.17	0.0	19.2
Has Battery	0.07	0.25	0.0	1.0
Output Monitoring	0.86	0.35	0.0	1.0

Table A2: FIFO Score Data description

	Whole Sample	Pre-trend	Anticipation	Treatment Period
	(1)	(2)	(3)	(4)
County Level				
Mean	0.9242	0.9182	0.9200	0.9379
Std	0.0697	0.0735	0.0828	0.0458
Kurtosis	21.0293	18.795	18.409	2.989
Skew	-3.21	-2.89	-3.44	-1.35
County-Firm Level				
Mean	0.9312	0.9284	0.9300	0.9366
Std	0.1152	0.12054	0.1165	0.1048
Kurtosis	23.3259	22.1238	21.915	28.585
Skew	-4.09	-4.03	-3.98	-4.27
Observations	336850	157086	80856	98908

This table presents a few summary statistics about the degree to which a project is First-In-First-Out (FIFO) relative to other contemporaneous projects at the firm-county level and the county level.

Table A3: Firm Age data description

	Whole Sample	Pre-trend	Anticipation	Treatment Period
	(1)	(2)	(3)	(4)
Num. Applications				
Age $\leq$ 1 mo.	6,942	3,363	1,429	2,097
Age 1-3 mo.	3,533	1,674	742	1,095
Age 3-6 mo.	5,247	2,827	1,115	1,266
Age 6-12 mo.	11,301	5,905	3,177	2,169
Age 12-24 mo.	23,321	12,005	5,870	5,398
Age $\geq$ 24 mo.	287,005	130,105	70,106	84,293
*Num. County-License pairs**				
Age $\leq$ 1 mo.	1,822	1,134	568	694
Age 1-3 mo.	501	310	143	163
Age 3-6 mo.	514	338	179	153
Age 6-12 mo.	619	417	232	207
Age 12-24 mo.	804	560	339	338
Age $\geq$ 24 mo.	1,548	1,268	1,074	1,131

* Firms are counted in each bin they are present. Eg. if a firm opens at the beginning of the 2.5 sample period and provides service every month, in column (1) representing the whole sample, they will be counted once for each bin.

Table A4: Relationship between firm age and prices

	Log Installation Price			
	County Level		State Level	
	(1)	(2)	(3)	(4)
Anticipation	-0.011**	-0.020***	-0.009*	-0.020***
	(0.005)	(0.004)	(0.005)	(0.004)
Treatment	-0.018**	-0.027***	-0.021**	-0.028***
	(0.007)	(0.005)	(0.008)	(0.005)
Age $\leq$1 mo.	-0.030**	0.042*	-0.082***	0.012
	(0.012)	(0.025)	(0.027)	(0.023)
Age 1-3 mo.	-0.005	0.026*	0.015	0.007
	(0.032)	(0.015)	(0.024)	(0.019)
Age 3-6 mo.	0.017	0.008	0.076***	0.020
	(0.032)	(0.014)	(0.022)	(0.018)
Age 6-12 mo.	0.079***	0.019*	0.040***	0.022
	(0.017)	(0.010)	(0.013)	(0.014)
Age 12-24 mo.	0.091***	0.004	0.091***	0.005
	(0.016)	(0.008)	(0.018)	(0.015)
Anticipation $\times$ Age $\leq$1 mo.	0.009	-0.051	-0.062	-0.064
	(0.022)	(0.043)	(0.040)	(0.046)
Anticipation $\times$ Age 1-3 mo.	0.106**	-0.005	0.075**	-0.008
	(0.041)	(0.027)	(0.032)	(0.029)
Anticipation $\times$ Age 3-6 mo.	0.084**	0.024	0.043	0.010
	(0.037)	(0.024)	(0.036)	(0.022)
Anticipation $\times$ Age 6-12 mo.	0.073***	0.006	0.105***	0.005
	(0.021)	(0.019)	(0.030)	(0.015)
Anticipation $\times$ Age 12-24 mo.	-0.028	0.021*	-0.021	0.025*
	(0.029)	(0.011)	(0.021)	(0.015)
Treatment $\times$ Age $\leq$1 mo.	0.028*	-0.040	0.017	-0.019
	(0.016)	(0.059)	(0.034)	(0.069)
Treatment $\times$ Age 1-3 mo.	0.154***	-0.001	0.150***	0.068
	(0.049)	(0.045)	(0.036)	(0.056)
Treatment $\times$ Age 3-6 mo.	0.118**	0.034	-0.020	0.012
	(0.056)	(0.032)	(0.054)	(0.036)
Treatment $\times$ Age 6-12 mo.	-0.010	0.015	0.025	0.009
	(0.022)	(0.024)	(0.026)	(0.024)
Treatment $\times$ Age 12-24 mo.	-0.030	0.001	0.048*	0.032
	(0.082)	(0.038)	(0.027)	(0.019)
Size (kW)	0.137***	0.135***	0.137***	0.135***
	(0.004)	(0.002)	(0.004)	(0.002)
Battery Size (kWh/1000)	0.034***	0.029***	0.033***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)
Has Battery	0.215***	0.325***	0.214***	0.325***
	(0.020)	(0.020)	(0.020)	(0.020)
Output Monitoring	0.012	0.048***	0.011	0.048***
	(0.011)	(0.012)	(0.011)	(0.012)
County	x	-	x	-
Firm-County	-	x	-	x
Observations	315378	315378	315378	315378
R^2	0.467	0.643	0.467	0.643
R^2 Within	0.454	0.485	0.454	0.485

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Here we regress the log installation cost of the project on firm log firm age by bins with firms greater than 2 years old as the control, the treatment period, and months to completion. Columns (1-2) are age within a county, columns (3-4) are age within the state. Column (1) and (3) uses county fixed effects, columns (2) and (4) use firm-county fixed effects.

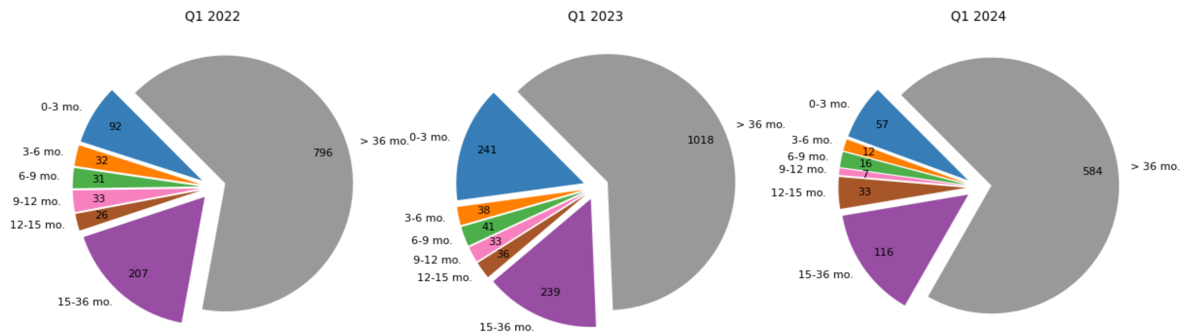


Figure A4: Here we see the number of firms that were active (submitting applications for interconnection) in the state of California during Q1 of 2022, 2023 and 2024. Each age group is broken into bins. Notably, the bin 12-15 months consists of the firms which were started during Q1 of the pervious period. Specifically, 12-15 months in Q1 2024 aligns with the firms that started during a three month period in the treatment period.

Appendix B

Here I show the math for the theoretical result.

The firm solves

$$\max_{p_0,p_1,q_0,q_1} p_0q_0 - c(q_0) + \beta\left(p_1q_1 - c(q_1)\right) \tag{10}$$

$$\begin{aligned} s.t.\ q_0 + q_1 &\leq f(p_0, 0) \\ q_0 + q_1 &\leq f(p_1, 1) \end{aligned}$$

Lagrangian:

$$\begin{aligned} \mathcal{L} =& p_0q_0 - c(q_0) + \beta\left(\gamma p_1 q_1 - c(q_1)\right) \\ &+ \lambda\left(f\left(p_0, 0\right) - q_0 - q_1\right) \\ &+ \mu\left(f\left(p_1, 1\right) - q_0 - q_1\right) \end{aligned}$$

Taking the First order conditions:

$$\begin{aligned} &\text{F. O. C.} \\ &\qquad p_0 - c'(q_0) - \lambda - \mu = 0 \\ &\qquad \beta(p_1 - c'(q_1)) - \lambda - \mu = 0 \\ &\qquad q_0 + \lambda\frac{\partial f(p_0, 0)}{\partial p} = 0 \\ &\qquad \beta q_1 + \mu\frac{\partial f(p_1, 0)}{\partial p} = 0 \end{aligned}$$

Let $f(p) = f(p, 0)$, $g(p) = f(p, 1)$ by our simplifying assumption, $f(p) = g(\gamma p)$, then $h'(p) = \gamma g'(\gamma p)$ so $\frac{\partial f(p,1)}{\partial p} = \frac{1}{\gamma} f(p)$. This leads to

$\beta q_1 + \frac{\lambda}{\gamma} f'(\frac{1}{\gamma} p_1) = 0$

$$\lambda = -\frac{\gamma \beta q_1}{f'(\frac{1}{\gamma} p_1)}$$
$$\mu = -\frac{q_0}{f'(p_0)}$$

If $p_0 = \frac{1}{\gamma} p_1$ then agents are indifferent between receiving the good in period 0 versus period 1. $\implies \lambda = \frac{\gamma \beta q_1}{f'(p_0)}$

Let $Q = q_0 + q_1$, and $Q' = \frac{\partial f(p_0, p_1)}{\partial p_0} = \frac{1}{\gamma} \frac{\partial f(p_0, p_1)}{\partial p_1}$ at equilibrium prices.

After some algebra we get the conditions

$$p_0(1 - \beta\gamma) = c'(q_0) - \beta c'(q_1)$$
$$\beta\gamma p_0 - \beta c'(q_1) + \frac{Q}{Q'} - \frac{(1 - \beta\gamma q_1)}{Q'} = 0$$

Appendix C

To validate that the unusual behavior in days to completion in the pre-preiod of SDG&E, I have re-run the regressions using just SCE and PG&E. I find that none of the results vary considerably from including SDG&E.

Table C1: Time to Completion on Price – SCE and PG&E only

	Log Installation Price					
	(1)	(2)	(3)	(4)	(5)	(6)
Months to Completion	-0.000	0.000	0.007***	-0.002**	-0.002	0.004***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Treatment		-0.016*	0.018**		-0.019***	0.002
		(0.009)	(0.008)		(0.006)	(0.006)
Anticipation		-0.006	-0.009*		-0.019***	-0.015***
		(0.005)	(0.005)		(0.003)	(0.004)
MTC $\times$ Treatment			-0.012***			-0.009***
			(0.002)			(0.001)
MTC $\times$ Anticipation			0.002			-0.003*
			(0.002)			(0.002)
Size (kW)	0.137***	0.137***	0.137***	0.134***	0.134***	0.134***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Has Battery	0.211***	0.210***	0.211***	0.332***	0.330***	0.330***
	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
Output Monitoring	0.011	0.010	0.012	0.054***	0.051***	0.054***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
Battery Size (kWh/1000)	0.034***	0.034***	0.034***	0.029***	0.029***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Firm-County	-	-	-	x	x	x
County	x	x	x	-	-	-
Observations	290,949	290,949	290,949	290,949	290,949	290,949
R^2	0.469	0.469	0.470	0.647	0.647	0.648
R^2 Within	0.456	0.456	0.457	0.489	0.490	0.490

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01.
Here I measure the impact of months to completion (MTC) on the log of the total cost in 2022 dollars. The first three columns are at the county or market level, and the last three columns are at the firm-county level. Compare with table 2.

Table C2: FIFO Score on Price – SCE and PG&E only

	Log Installation Price	
	(1)	(2)
Treatment	0.104	-0.005
	(0.067)	(0.020)
Anticipation	0.075	0.009
	(0.056)	(0.014)
FIFO Score	0.012	0.011
	(0.034)	(0.010)
FIFO Score × Treatment	-0.127*	-0.022
	(0.073)	(0.019)
Anticipation × FIFO Score	-0.086	-0.031**
	(0.060)	(0.014)
Size (kW)	0.137***	0.134***
	(0.004)	(0.002)
Battery Size (kWh/1000)	0.034***	0.029***
	(0.005)	(0.005)
Has Battery	0.210***	0.329***
	(0.021)	(0.021)
Output Monitoring	0.010	0.051***
	(0.012)	(0.012)
Firm-County	-	x
County	x	-
Observations	291,000	291,000
R^2	0.469	0.647
R^2 Within	0.456	0.490

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01.
Using a score for the degree to which a project follows a "First in first out" I regress the log price on the treatment period interacted with the FIFO score along with other project attributes. Compare with table 3

Table C3: Firm Age with a market on prices – SCE and PG&E only

	Log Installation Price	
	(1)	(2)
Treatment	-0.017*	-0.026***
	(0.009)	(0.005)
Age $\leq$1 mo.	-0.021*	0.018
	(0.011)	(0.015)
Age 1-3 mo.	-0.002	0.021
	(0.034)	(0.015)
Age 3-6 mo.	0.026	0.006
	(0.033)	(0.014)
Age 6-12 mo.	0.081***	0.020*
	(0.018)	(0.010)
Age 12-24 mo.	0.100***	0.004
	(0.016)	(0.009)
Anticipation	-0.008	-0.019***
	(0.005)	(0.004)
Treatment × Age $\leq$1 mo.	0.032*	0.028
	(0.018)	(0.051)
Treatment × Age 1-3 mo.	0.159***	0.050
	(0.052)	(0.045)
Treatment × Age 3-6 mo.	0.110*	0.055*
	(0.058)	(0.029)
Treatment × Age 6-12 mo.	-0.007	0.031
	(0.024)	(0.019)
Treatment × Age 12-24 mo.	0.046**	0.039**
	(0.023)	(0.015)
Anticipation × Age $\leq$1 mo.	-0.002	-0.013
	(0.021)	(0.027)
Anticipation × Age 1-3 mo.	0.103**	0.015
	(0.042)	(0.023)
Anticipation × Age 3-6 mo.	0.075*	0.037**
	(0.038)	(0.018)
Anticipation × Age 6-12 mo.	0.074***	0.019
	(0.021)	(0.014)
Anticipation × Age 12-24 mo.	-0.016	0.017
	(0.026)	(0.011)
Size (kW)	0.136***	0.134***
	(0.004)	(0.002)
Battery Size (kWh/1000)	0.033***	0.029***
	(0.005)	(0.005)
Has Battery	0.220***	0.329***
	(0.021)	(0.021)
Output Monitoring	0.013	0.051***
	(0.012)	(0.012)
County	x	-
Firm-County	-	x
Observations	291000	291000
R^2	0.474	0.647
R^2 Within	0.461	0.490

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Here we regress the log installation cost of the project on firm log firm age by bins with firms greater than 2 years old as the control, the treatment period, and months to completion. column (1) uses county fixed effects, column (2) uses firm-county fixed effects. Compare with table A4

Table C4: Relationship between cumulative installations and price – SCE and PG&E only

	Log Installation Price			
	County Level		State Level	
	(1)	(2)	(3)	(4)
Treatment	-0.020*	-0.027***	-0.015	-0.029***
	(0.011)	(0.010)	(0.010)	(0.006)
Installations $\leq$10	0.027**	0.005	-0.126***	-0.035*
	(0.011)	(0.016)	(0.017)	(0.018)
Installations 11-20	0.036***	0.011	-0.106***	-0.022
	(0.009)	(0.015)	(0.019)	(0.017)
Installations 21-50	0.056***	0.023	-0.067***	0.001
	(0.012)	(0.014)	(0.011)	(0.014)
Installations 51-100	0.047***	0.016	-0.051***	-0.002
	(0.016)	(0.013)	(0.014)	(0.012)
Installations 101-1000	0.045***	0.015	-0.009	-0.003
	(0.013)	(0.011)	(0.012)	(0.008)
Anticipation	-0.018*	-0.013*	-0.002	-0.018***
	(0.009)	(0.007)	(0.006)	(0.004)
Treatment $\times$ Installations $\leq$10	-0.026*	0.033**	-0.034*	0.039
	(0.014)	(0.014)	(0.018)	(0.026)
Treatment $\times$ Installations 11-20	0.007	0.019	-0.022	0.035
	(0.016)	(0.014)	(0.026)	(0.023)
Treatment $\times$ Installations 21-50	-0.008	0.006	-0.036*	0.020
	(0.010)	(0.013)	(0.020)	(0.016)
Treatment $\times$ Installations 51-100	0.017	0.009	-0.039	0.028**
	(0.023)	(0.013)	(0.026)	(0.014)
Treatment $\times$ Installations 101-1000	0.026	0.002	0.000	0.005
	(0.018)	(0.012)	(0.019)	(0.010)
Anticipation $\times$ Installations $\leq$10	0.013	-0.003	-0.046*	0.009
	(0.012)	(0.011)	(0.023)	(0.021)
Anticipation $\times$ Installations 11-20	0.036**	0.000	0.025	0.030
	(0.014)	(0.011)	(0.022)	(0.021)
Anticipation $\times$ Installations 21-50	0.005	-0.023**	-0.007	-0.009
	(0.012)	(0.010)	(0.016)	(0.013)
Anticipation $\times$ Installations 51-100	0.032**	-0.013	0.017	0.001
	(0.016)	(0.010)	(0.023)	(0.011)
Anticipation $\times$ Installations 101-1000	0.023	-0.004	-0.025	-0.007
	(0.016)	(0.009)	(0.017)	(0.008)
Size (kW)	0.136***	0.134***	0.138***	0.134***
	(0.004)	(0.002)	(0.004)	(0.002)
Battery Size (kWh/1000)	0.030***	0.029***	0.034***	0.028***
	(0.005)	(0.005)	(0.005)	(0.005)
Has Battery	0.225***	0.329***	0.204***	0.329***
	(0.019)	(0.021)	(0.020)	(0.021)
Output Monitoring	0.020*	0.051***	0.001	0.051***
	(0.012)	(0.012)	(0.012)	(0.012)
Firm-County	-	x	-	x
County	x	-	x	-
Observations	290,949	290,949	290,949	290,949
R^2	0.472	0.647	0.472	0.647
R^2 Within	0.459	0.490	0.459	0.490

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01. Here we show the relationship between the nth project completed by a firm and the price faced to the consumer. Columns 1-2 look at the nth completed installation within a county, columns 3-4 look at the nth completed installation in the entire state. Compare to table 4.