Income and Racial Disparities in Markets for New Energy Technologies

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Overview

Over the past decade, policymakers offered billions of dollars in subsidies and tax credits for electric vehicles, solar PV panels, and energy efficiency retrofits to encourage clean energy investments. These policies have accelerated adoption of these emerging technologies; however, previous research shows that clean energy tax credits disproportionately benefit higher-income households (Borenstein and Davis, 2016). Moreover, Black and Hispanic families are substantially less likely to adopt rooftop solar PV systems (Sunter et al., 2019), and, therefore, less likely to benefit from federal tax credits and associated energy bill savings. Acknowledging these inequities, many lawmakers have crafted policy proposals that aim to encourage clean energy investment, while at the same time, addressing injustices affecting communities of color and low-income communities.

A distinctive feature of many markets for new energy technologies—home energy efficiency retrofits, residential battery storage installations, and rooftop solar PV installations to name a few—is that projects are customized and priced on an individualized basis. When services are quoted on a case-by-case basis, sellers possess considerable leeway in whether to serve a customer and how much to charge if they do. Inherent in these settings, is the possibility of price discrimination with respect to income or racial characteristics. Thus, disparities in technology adoption could arise from supply-side behavior, in addition to demand-driven factors. On the demand-side, different consumer groups may purchase a new technology at varying rates because of differences in willingness-to-pay or underlying preferences for the technology. On the other hand, firms can also contribute to disparities in equilibrium adoption by changing how they bid for projects across consumer demographic groups. Thus, a key component of our study will be to disentangle the relative importance of supply-side versus demand-side factors in explaining disparities in technology adoption. Understanding the mechanisms that drive disparities in adoption is critical for policymakers that aim to create policies that yield a more equitable distribution of benefits across households.

In this paper, we will investigate income and racial disparities in the residential solar PV market using new, detailed data on contractors' installation bids. While there is growing evidence of income and racial disparities in the adoption of new energy technologies, there is relatively little research documenting the key mechanisms that contribute to observed inequities in adoption. Our paper will make several contributions to the literature: (1) use new data to quantify the gap in solar PV adoption across household income and racial demographics, (2) develop and estimate an empirical model to decompose potential mechanisms that could explain a technology adoption gap, (3) use our model to evaluate the welfare implications of the adoption gap, and (4) employ our model to evaluate the efficacy of counterfactual policies such as income-based subsidies.

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To analyze distributional outcomes in the solar PV market, we have secured a data use agreement with a prominent online platform, EnergySage, Inc. The platform serves as an intermediary between solar PV buyers and installers. In particular, solar PV shoppers can solicit bids from solar installers by uploading information about their name, monthly household energy usage, and home address through the website. The platform provides installers with information about each buyer's project, and then installers decide whether or not to submit a bid. Bidding installers can customize their installation prices and the quality of their hardware components for each unique project. Consequently, sellers may bid differently based on their perceptions about a buyer's income and race. An advantage of using the platform data is that we can observe how each seller's bidding decisions—both the participation choice and quoted price—change across households. The platform has agreed to share the universe of solar installation bids uploaded through their website, which includes over 600,000 bids made to over 200,000 households between 2013 and 2020. The bid-level data will allow us to better understand the mechanisms driving any pricing disparities compared to conventional data sets that only provide transaction prices.

The rest of the proposal will proceed as follows: first, we will explicitly outline our research questions. Next, we will discuss how our paper will fit into the existing literature. Third, we will describe our data sources. Fourth, we will introduce the methods we plan to use in our analysis. Finally, we will present some preliminary results using a subset of the full data sample.

1 Research Questions

Our study has two overarching goals. Our first goal is to identify mechanisms that can explain imbalances in solar adoption across demographic groups. In particular, we want to understand and quantify factors that could lead to lower adoption rates amongst low-income and minority individuals. Our second goal is to assess the distributional impacts of alternative policies such as income-based subsidies.

Low-income or minority households may be less likely to adopt a new technology if they are either more price-elastic or face additional liquidity constraints. Purchasing a solar PV system, can often yield substantial electricity cost savings in the long-run, but typically entails a large upfront payment. Therefore, at a given price, a low-income household may be less willing to install a solar PV array relative to a higher-income household.

Sellers' behavior can also contribute to income or racial disparities in solar PV adoption. Sellers affect adoption decision through their choices of which households to submit bid to, and the prices associated with those bids. We posit several reasons for why low-income and minority households may attract fewer bids or face different prices: (1) systematic differences in installation costs across households, (2) systematic differences in price sensitivity or bidding competition across households, and (3) some sellers exhibit racially-biased preferences not to service minority households.

The first mechanism—systematic differences in installation costs—would arise if disparities exist in sellers' installation costs across locations. Suppose installers locate in predominately affluent parts of the city. In that case, it could be more time-intensive to provide installation services to low-income or racially diverse neighborhoods on the other side of town. The second potential mechanism for pricing heterogeneity stems from differing profit incentives of increasing the markup above cost for particular households. For example, if some households are less price-sensitive, installers could increase profits by quoting higher prices to these households. Finally, if sellers possess explicit racial biases, they could give higher price bids to minority households or avoid bidding on these households at all. Understanding which of these mechanisms contribute to the racial price gap is vital for policy. Namely, if policymakers or platforms aspire to reduce income and racial price disparities, an essential first step is understanding why these

disparities exist.

We will investigate these mechanisms through a detailed analysis of seller bidding and associated consumer choice data from an online platform. We will combine the platform data with data on household-level and neighborhood demographics to empirically answer the following research questions:

1. Do seller bidding strategies vary across household demographics?
    - Do low-income and minority consumers receive fewer bids for their projects?
    - Conditional on receiving a bid, do low-income and minority consumers receive different bid prices?
    - Are low income or minority consumers less likely to be offered financing?
2. If bidding disparities exist, which channels enable discriminatory bidding?
    - How much of the disparity is explained by neighborhood characteristics versus individual buyer's characteristics (*e.g.* neighborhood racial demographics vs. individual buyer's race)?
    - Which economic factors (*i.e.* cost shifters, preferences, etc.) can explain bid disparities?
    - Are low-income and minority consumers more price-elastic?
3. If bidding disparities exist, what are the consumer welfare consequences of bid disparities for low-income or minority consumers?
    - For example, how would consumer surplus change if a typical Black household's choice set was the same as a typical White household's choice set?
4. How would income-based subsidies change the distribution of adoption and consumer welfare?
    - How would subsidies targeted to racially diverse neighborhoods and communities change the distribution of adoption and consumer welfare?

2 Link to Existing Economic Literature

There is a sizeable economics literature that studies racial discrimination. The seminal work by Becker (1957) modeled discriminatory behavior in the labor market through "taste based" preferences against hiring and working with minorities. Further theoretical research by Arrow (1971), Phelps (1972) and Aigner and Cain (1977) provided a model that allowed for "statistical" discrimination". In essence, these models allow for discriminatory behavior to pervade the market, even absent strict preferences against minorities. This research is based on suggesting that, as a result of previous discrimination, minorities are statistically less productive and, thus, would be less likely to be hired based on their lower expected productivity. Regardless of if individuals discriminate overtly against minorities (i.e. taste based discrimination) or statistically discriminate, the empirical fact remains that minorities have less access to markets.

Empirical evidence of economic discrimination is wide and varied across many sectors. Most relevant to this paper, is a suite of research documenting discrimination against minorities in both prices and access in online markets–such as Airbnb (Edelman et al., 2017), eBay (Ayres et al., 2015), ridesharing (Ge et al., 2016), and peer-to-peer lending (Pope and Sydnor, 2011). Outside of the online domain, researchers have also found that minorities, especially Black individuals, pay more for many goods and receive less generous offers in negotiations (Ayres and Siegelman, 1995; Avenancio-Leon and Howard, 2019; Hanson et al., 2016; Bayer et al., 2016, 2018).

Research suggests one mechanism for this discriminatory behavior is that firms discriminate against individuals based on their name in remote interactions. The seminal paper in this set—Bertrand and Mullainathan (2004)—experimentally demonstrates that resumes submitted with Black-sounding names receive a lower rate of job interview call-backs than identical resumes with white-sounding names (*e.g* Lakisha Washington versus Emily Walsh or Jamal Jones versus or Greg Baker). More recent research cor-

roborates this channel in the labor market (e.g. Kline and Walters (2020); Jacquemet and Yannelis (2012)) and suggests this same mechanism also impacts access to housing (Christensen and Timmins, 2018; Ewens et al., 2013) and transportation (Ge et al., 2016).

3 Data

The primary data for our analysis comes from solar auctions originating through the EnergySage platform. We will augment the solar auction data with rich census-tract-level and household-level demographic data to investigate racial and income disparities in bid pricing and solar adoption.

3.1 Solar Auction Data

The EnergySage data set includes bid prices and consumer purchase choices for solar auctions on the EnergySage platform. EnergySage Inc. runs a quote aggregation platform that facilitates connections between potential solar customers and a network of solar PV installers. More specifically, the EnergySage platform enables households to conduct multi-attribute auctions to select an installer for their installation projects. Multi-attribute auctions, also called beauty contest auctions, refer to a procurement mechanism in which each bidder submits a multi-dimensional bid that includes a price and a vector of other characteristics, such as the panel hardware brand. The buyer then selects the winning bidder based on the multi-dimensional bids. Multi-attribute auctions are related to scoring auctions but differ in that the auctioneer does not explicitly announce the choice rule ex-ante (i.e., weights on each characteristic), as they would in a scoring auction. Each EnergySage auction includes several stages. First, consumers create an account on the platform's website and provide information including: the physical address of the potential installation, a monthly electricity bill, and an indication of whether they have obtained other solar installation bids offline. Second, registered installers receive a notification of the project which includes details such as a Google Maps photo of the buyer's roof, as well as the monthly electricity usage of the buyer, and information about whether the buyer has other off-platform quotes. Installers can then submit a project quote to the buyer, which includes the system price, panel brand, inverter brand, and details about the seller, such as a star rating and a description of their solar installation experience. Finally, after installers have submitted their bids, the potential consumers can select one of the quotes and move forward with the transaction, or they can opt not to purchase any of the offers.[3]

There are several key variables that we observe in the solar auction data. First, we see characteristics of each potential buyer, including the census block where the home is located, the household's average monthly electricity bill, and an indicator for whether or not the buyer obtained other solar installation quotes from off of the platform. Second, we observe detailed information on each of the seller bids submitted to each individual buyer. The bid data includes the price, hardware to be installed, capacity of the solar array, and attributes of seller (*e.g.* star ratings). Importantly, we observe a unique installer ID associated with each bid, so we can investigate how a particular installer's bidding behavior changes across projects. Finally, we observe which of the bids, if any, are selected by each buyer.

3.2 Household and Neighborhood Demographic Data

EnergySage did not collect consumer demographic information during the sample period of this study, so we merge the solar auction data with household demographic data we purchased from Axciom's Infobase. This consumer marketing database compiles household-level data from various sources such as public

[3]Buyers and sellers can communicate with each other via private messaging or phone calls before a selection is made. However, sellers cannot call a buyer unless they are requested to do so by the buyer.

records, (e.g., property ownership, professional licenses, or voting registries), and consumer surveys (e.g., magazine subscriber lists, catalogs, and warranty cards.) The Axciom data we purchased provides descriptive variables about the buyer's home such as the home age, home square footage, and the home market value. Additionally, Axciom reports the head of household's age, race, income, educational attainment, and political affiliation.

The solar auction data report the location of each buyer at the census block level. Census block is the smallest geographic unit used by the United States Census Bureau, and thus we can merge precise information about the demographics of each buyer's neighborhood from the American Community Survey such as median household income and racial composition.

3.3 Inferring Buyers' Ethnicity From Names

One of our primary research objectives is to identify factors that contribute to the racial gap in solar PV adoption documented by Sunter et al. (2019). The Axciom data provide information about buyer race, but both the source and accuracy of the race data is opaque. Therefore, we plan to augment our data set with additional information on buyer race based off of the buyers' names and location. In particular, we will follow the two-step approach implemented by Diamond et al. (2019). In the first step, we will feed each buyer's name through "NamePrism" API—an ethnicity/nationality classification tool intended to support academic research Ye et al. (2017). The "NamePrism" API returns baseline probabilities of race/ethnicity for each buyer based on first name and last name.[4] In the second step, we use the racial composition of the buyer's census block to update the probability that the buyer belongs to each racial group using Bayes' rule. In particular, the probability that a buyer belongs to race r conditional on having a name s and living in census block g is:

$$Prob(r|g,s) = \frac{Prob(r|s)Prob(g|r)}{\sum_{r' \in R} Prob(r'|s)Prob(g|r')} \tag{1}$$

where R denotes the set of six possible ethnic categories. As a robustness check, we will repeat this procedure using the Census Bureau's data that provide the distribution of ethnic identities associated with thousands of common surnames.

There are a few advantages of using name-based classification to identify the buyers' ethnic identity. First, the methodology is clear and transparent in contrast to the race information reported by Axciom. Second, the information that is used in the name-based classification is observable to the sellers placing bids through the platform. Because buyers and sellers connect via the online platform, sellers will not know the buyers race with certainty, but can infer race based off of the buyer's name and location. For this reason, the categorization provided via the NamePrism classifier is more consistent with the information available to seller's when making bids. Finally, we can use the name-based ethnicity classification to compare and validate the data reported by Axciom.

3.4 Descriptive Statistics from Sub-Sample of Solar Auctions

Although EnergySage Inc. has agreed to provide us the universe of data from all residential solar auctions, they are still in the process of preparing the final dataset, including querying buyer names using the NamePrism API.

[4]We do not directly observe buyer names in our data set, but EnergySage has agreed to feed the buyer names through the NamePrism API and provide us outputted probabilities.

To provide some preliminary evidence regarding our research questions, we provide some descriptive statistics on a small subset of our final data sample. The subsample we use our preliminary analysis contains the bids made to 10,522 households in seven states between 2014 and 2016. We obtained this data for previous research on the residential solar industry (Dorsey, 2020).

There are a few caveats to mention about the subsample. First, the subsample has substantially fewer observations relative to the final data sample. *In particular, the final data set will have approximately 20 times more observations relative to the subsample.* The subsample also omits several key variables. The most notable variables that our current data set omits is the census block location of each project (we currently only observe ZIP Code) and the probabilistic information about each buyer's ethnicity from NamePrism. EnergySage will include these variables in our final data set.

Table 1: Sub Sample - Household Demographic Summary Statistics

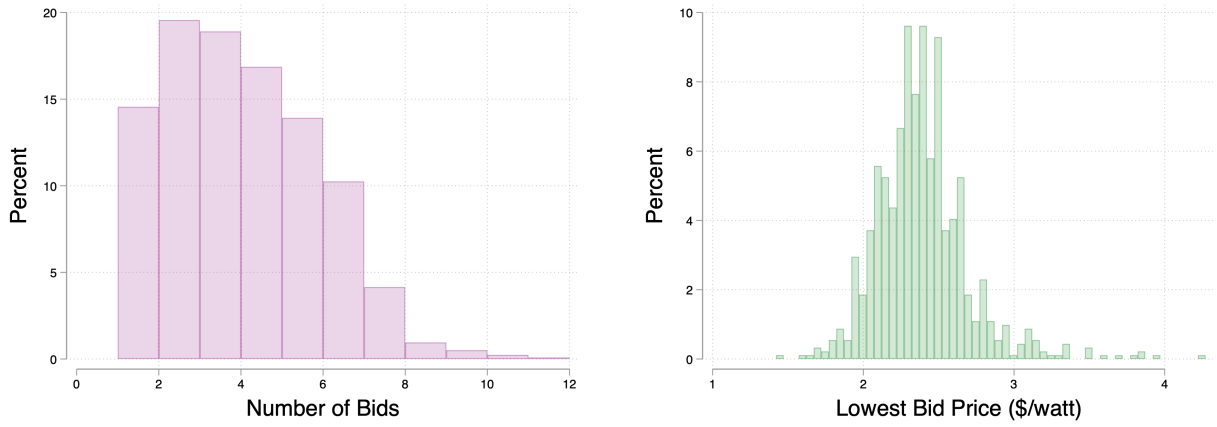
	Mean	SD	25-%tile	50-%tile	75-%tile
Home Market Value ($1,000s)	687.49	508.66	325.00	550.00	900.00
Age of Home	42.24	33.23	17.00	36.00	58.00
Home Size (sqft)	2238.57	863.92	1608.00	2100.00	2692.50
Electricity Bill ($/month)	187.03	89.38	120.00	167.28	240.00
Household Head Age	51.86	13.86	42.00	50.00	62.00
Household Head Ethnicity - Asian (0,1)	0.12	0.32	0.00	0.00	0.00
Household Head Ethnicity - Black (0,1)	0.02	0.13	0.00	0.00	0.00
Household Head Ethnicity - Hispanic (0,1)	0.10	0.30	0.00	0.00	0.00
Household Head Holds Bachelor's Degree (0,1)	0.49	0.50	0.00	0.00	1.00
Has Off-Platform Quotes (0,1)	0.17	0.38	0.00	0.00	0.00

With these caveats in mind, Table 1 provides descriptive statistics for the households in our subsample. The table demonstrates that there is substantial variation in home valuations across households, with home values ranging between $100,000 to over $2 million. The subsample consists of primarily households located in states with relatively high real estate prices including California, Connecticut, Massachusetts, and New York. Nonetheless, the high median home valuation suggests that the typical solar shopper is relatively wealthy, which is consistent with the findings presented in Borenstein and Davis (2016). Solar shoppers are also predominately White. According to the Axciom data matched to each household, 74% of potential solar buyers are White, 12% are Asian, 10% are Hispanic and 2% are Black. Thus, the subsample contains only 207 black households. As previously mentioned we will soon be able to access for another 200,000 households across 36 states. While we do not expect the racial proportions to change much in the expanded dataset – the increase in the number of observations will provide us much more statistical power than our current preliminary analysis conducted with these data.

Figure 1 demonstrates the substantial variation in auction participation and bid pricing across projects. Figure 1a illustrates that the average project received 3.54 bids, however, a quarter of projects obtained two or fewer bids, whereas 25% of projects received five or more bids.

The prices available to buyers also vary dramatically across auctions, Figure 1b shows that the lowest per-watt bid prices varies from about $2.00 to $4.00. Substantial variation in auction participation and bid prices persists even after flexibly controlling for the geographic location of the projects. In the following section, we develop a regression framework to further investigate the implications of sellers' participation and bid pricing choices on low-income and minority consumers.

Figure 1: Variation in Bids Across Auctions



(a) # of Bids per Auction

(b) Lowest Bid Price

Notes: Figure (a) plots the distribution of the total number of bids across solar auctions. Figure (b) plots the distribution of the lowest bid price in dollars per watt available in each auction.

4 Empirical Methods

Our analysis will consist of two primary parts. First, we will undertake a descriptive analysis to investigate our first research question. Namely, we will estimate a series of regression models to measure how seller bids vary across household demographics. Additionally, we will run regressions to describe which observable characteristics of buyers are associated with changes in bidding outcomes. Having established descriptive results on bidding outcomes, we will next develop and estimate a structural model of supply and demand for solar PV. The structural model will allow us to answer our remaining research questions. More specifically, the model will allow us to decompose and explain the factors that lead to differences in bidding outcomes that appear in the descriptive analysis. We will also utilize the model to evaluate several counterfactuals of interest. In one set of counterfactuals, we will measure the consumer welfare consequences of bidding disparities for low-income and minority households. In another set of policy counterfactuals, we will investigate the welfare impacts of alternative policy environments such as progressive subsidies based on household income.

4.1 Descriptive Analysis

In our descriptive analysis, we employ a series of regressions to measure the differences in the following bidding outcomes across household demographics: the number of total bids obtained, the number of bids offering financing, the average bid price, and the minimum bid price. Particularly, these regressions will measure whether low-income or minority households systematically obtain fewer bids or face different bid prices. Our initial regression model takes the following form:

$$Y_i = \alpha_1 \mathbb{1}[Black]_i + \alpha_2 \mathbb{1}[Hispanic]_i + \alpha_3 \mathbb{1}[Asian]_i + \alpha_4 \mathbb{1}[LowIncome]_i + \beta Z_i + \nu_t + \lambda_m + \epsilon_i$$

Here, the dependent variable, Y_i, is one our bidding outcomes, such as the number of bids obtained by household i. Our main explanatory variables of interest include a set dummy variables indicating the buyer's ethnicity, and a dummy indicating whether the buyer is low-income. For the preliminary analysis,

we use information from the Axciom database to determine each buyers ethnicity.[5] As a starting point, we define a buyer as low-income if their home market value is in the bottom quartile of the sample. Although, the Axciom data provides some information about household income, we focus on home market valuation as measure of the buyer's wealth because home market valuation is more likely to be observable to installers when placing bids. In the final paper, we will verify the robustness of the results alternative measures of household wealth. In all specifications, we include time (quarter-by-year) fixed effects (ν_t) and geographic fixed effects (λ_m) to remove any systematic price or bidding changes over time or specific to a given region. In our more expansive specifications, we also include additional controls (Z_i) for electricity use and college attainment of the buyer. We plan to report several specifications with different levels of fixed effects and controls to ensure that our results are robust to the inclusion of sensible control variables.

An added component of our descriptive analysis will be to identify variables that are associated with changes in seller bidding behavior. Given that the bids are being placed virtually through the online platform, installers do not directly observe a buyer's income or ethnicity. Thus, we want to understand what information sellers use to make targeted participation and pricing choices. Sellers observe two main pieces of information that could be used to infer ethnicity and income of the buyer: the buyer's geographic location and the buyers name.

We measure how the buyer's neighborhood characteristics associate with changes in bidding outcomes by running additional regressions including ZIP/ZCTA-level demographics, as independent variables. Once we obtain census block designations for each household, we can do this same analysis using census-block level demographics. Regardless of the geography used, these regressions allow us to investigate if installers are offering differential prices to neighborhoods that are predominately non-white. In particular, we will examine the impact of ZIP-code racial makeup alone and the interaction of ZIP code racial makeup with each household's demographics. The flexibility of this interacted specification allows us to characterize the nature of bidding discrimination based on both neighborhood characteristics and individual household characteristics simultaneously. These regressions take the form:

$$\begin{aligned} Y_{ij} =& \alpha_1 ZIP_PercentWhite_i + \beta_1 \mathbb{1}[Black]_i + \beta_2 \mathbb{1}[Hispanic]_i + \beta_3 \mathbb{1}[Asian]_i \\ & \gamma_1 \mathbb{1}[Black]_i \times ZIP_PercentWhite_i + \gamma_2 \mathbb{1}[Hispanic]_i \times ZIP_PercentWhite_i + \\ & \gamma_3 \mathbb{1}[Asian]_i \times ZIP_PercentWhite_i + \beta Z_{ij} + \nu_t + \lambda_m + \epsilon_{ij} \end{aligned}$$

In these regressions, the α coefficient will measure the price differential associated with going from a 0% white neighborhood to a 100% white neighborhood. We use this white percentage variable as a proxy for neighborhood diversity. The β coefficients still measure the price differentials for Black, Hispanic, and Asian customers, respectively. Moreover, we allow the ethnicity effects to change based on the type of neighborhood they live in via the γ coefficients. This specification's flexibility through the γ coefficients allows this racial effect to change based on the underlying demographics of their ZIP code. The identifying variation for γ_1, for example, is through the comparison of the bids for a Black individual living in a predominately white neighborhood to a Black individual in a predominately non-white neighborhood.

We plan to extend this analysis by investigating whether this heterogeneity in bids can be explained by the racial perceptions of buyers' names. Importantly, these regressions will allow us to comment on one potential mechanism behind any observed bidding disparities. Bertrand & Mullainathan (2004) (and the extensive suite of economics papers that find similar results) suggest that buyer names could also facilitate price discrimination on online platforms. This analysis will allow us to explicitly compare the outcomes for

[5] We plan to use the name-based measure of ethnicity described above in our baseline model once we obtain the necessary data.

Black individuals with Black-identifying names versus Black individuals without Black-identifying names. If, for example, the black price differential is driven by Black individuals who also have Black-identifying names, then EnergySage and other platforms could alleviate much of this discriminatory behavior by simply removing the name from the information provided to the installer. Once we have the data on the household's likely race by name, we can even conduct the triple difference comparing a Black person with a Black name in a white neighborhood to a black person with a non-black name in a white neighborhood to further tease out the likely mechanism behind any potentially discriminatory pricing.

In summary, the descriptive analysis is valuable for two reasons: (1) it allows us to measure income and racial disparities in the bidding data and (2) it enables us to investigate how disparities may emerge on an online platform (i.e. via buyer's neighborhood demographics or a buyer's name). Nonetheless, several important questions remain. In particular, why do sellers choose to offer different prices across buyer race? In addition, what are the welfare consequences of these bidding disparities for buyers? How would progressive subsidies change the distribution of consumer welfare and the solar PV adoption gap? To answer these remaining questions, we now turn to our structural analysis.

4.2 Structural Analysis

Our model follows Dorsey (2020) and incorporates solar buyer's preferences and solar installers' bidding behavior. In our model, sellers generally aim to maximize profits when making price bids, but we also allow for the possibility that sellers have a "distaste" for serving minority households. Buyers in our model make a choice between the bidding installers or the option of not installing a solar system at all. When estimating the buyers' choice rule, we allow for heterogeneity in price-sensitivity across the household's income and race. Thus, we can use our model to calculate sellers' optimal markup (price net of marginal cost), and how average markups vary across households.[6] Consequently, we can use the model to decompose a racial price gap (or income price gap) into two components: (1) the difference in implied markup across buyer race (income), and (2) the difference in implied installation cost across buyer race (income). We interpret the costs implied by our model as the sum of explicit costs (*e.g.* labor and materials) and implicit costs (*e.g.* distaste for serving minority buyers, time cost of travelling across town). We summarize the core components of the model briefly as follows:

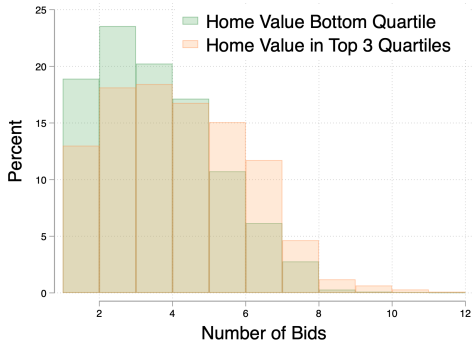
Summary of Model

1. A potential buyer i initiates a multi-attribute auction by announcing the project characterisitcs to all potential entrants
2. Each potential seller receives a private entry cost draw. Each potential entrant then compares their entry cost to the expected marginal profit conditional on entering the auction. Each potential bidder chooses to enter if and only if expected marginal profits are larger than their entry cost.
3. Each seller that enters auction i receives a private marginal cost draw, learns their non-price characteristics, and learns the exact capacity of the system. Sellers do not observe which other competitors have entered the auction. Each entrant then chooses a bid price.
4. Buyer i chooses from each of the project bids or the outside option.

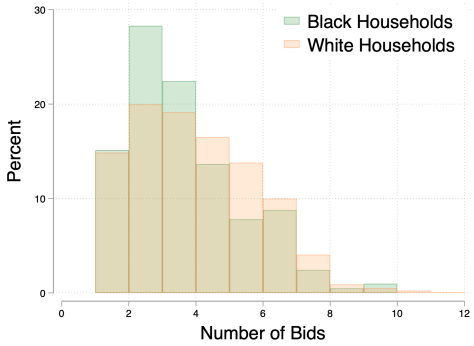
Importantly, the model will enable us to evaluate consumer welfare and counterfactuals. We will solve one set of counterfactuals to assess the consumer welfare impact of disparities in bidding outcomes. More

[6] We build on and adapt methods recently developed by Krasnokutskaya et al. (2019) and Yoganarasimhan (2015) to recover parameters in multi-attribute auction settings.

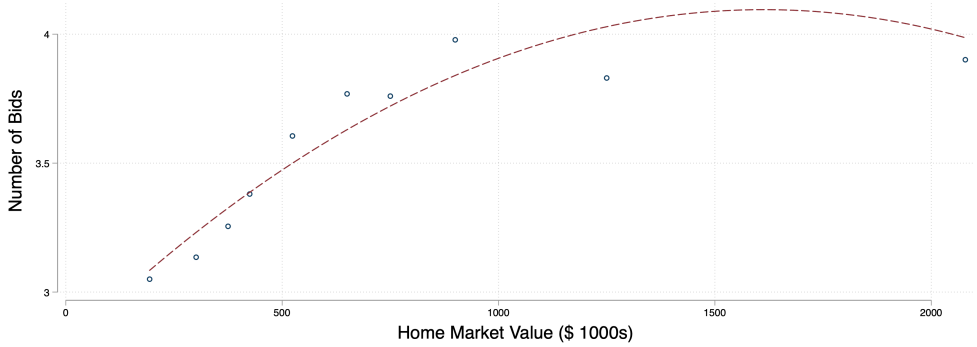
Figure 2: Auction Participation, Race, and Home Valuation



(a) Bids per Auction by Home Value



(b) Bids per Auction by Race



(c) Bids per Auction by Home Value

concretely, we can measure how consumer surplus and solar adoption rate would change if a typical low-income buyer had the same choice set as a typical high-income buyer. Analogously, we can measure the welfare impacts of giving a Black buyer an equivalent choice set to that of a White buyer. Morever, we will use the model to assess counterfactual solar adoption rates and welfare under income-based subsidies for solar PV.

5 Preliminary Findings

We now present some preliminary findings using our data subsample. We emphasize that the results are likely to change once we have access to the full dataset.

Figure 2 illustrates some key descriptive results related to seller participation decisions. The histogram in Figure 2a shows that buyers with lower home values attract fewer bids for their solar installation projects. This pattern is also demonstrated clearly in the binned scatter plot in Figure 3, the expected number of bids increases sharply between homes valued at $ 100,000 and $ 1 million. A similar pattern emerges when we compare the mean number bids across buyers of different races. Figure 2b demonstrates that Black households attract fewer bids compared to White households. These correlations largely persist after we add additional controls for the geographic location of the projects and other observable characteristics of the households.

Table 1 in the Appendix shows the results from a regression of the number of bids received on household

race and income. The different columns represent regressions with different levels of geographic fixed effects. These results indicate that black households receive between 0.41 to 0.16 fewer bids than White households located in the same market. Put in other terms, Black households receive between 4% to 12% fewer bids when compared to their White neighbors. We also find that lower income households attract between 0.5 to 0.1 fewer bids than their wealthy peers living in the same geographic market.

We next investigate whether the bidding patterns outlined above can be explained by neighborhood demographics. In Figure 3, the red line indicates how the number of bids made to Black households changes as the percentage of white residents within the household's ZIP code increases. The blue line indicates the number of bids submitted to White households changes with the percentage of white residents within the household's ZIP code. The upward slope of the red line indicates Black households in non-White neighborhoods receive fewer bids than White consumers in non-White neighborhoods. However, in predominately White neighborhoods, there is virtually no difference across the two races. This pattern suggests that buyers' physical locations play a significant role in seller participation choices and can explain some of the racial disparities in auction participation that we observe on the platform. These statistical patterns are confirmed using a regression-based approach. Specifically, Table 3 shows that projects located in neighborhoods with a higher share of White residents receive more bids on average. The table also confirms that Black households receive fewer bids compared to White households, but this association is even stronger if the Black households live in neighborhood with fewer White residents.

Finally, we estimate a preliminary version of the structural model obtain several suggestive yet imprecise results. Table 4 presents discrete choice estimates of buyer demand. The model allows for heterogenity in price-sensitivity by buyer ethniticity. We find that White households are more price inelastic relative to households of other races. Having estimated buyers' price elasticities, we can derive sellers first-order condition for a profit maximizing price bid (see Dorsey (2020) for more details). Under an assumption that firms place bids to maximize profits, we can then decompose each price bid into a markup and a marginal cost component. Figure 4 plots the distribution of markups and marginal cost for all bids submitted to White households and the analogous distributions for Black households. Although White households typically obtain more bids (*i.e.*, more competition), we find that profit-maximizing markups should still be higher for White households because White households are relatively more inelastic. Yet, in the bid data, Black households obtain higher average prices than White households. Therefore, higher prices for Black households must be explained by higher average costs. Higher "costs" for Black households could be due to either direct costs (*e.g.*, installers' ease of access to White vs. Black neighborhoods) or implicit costs (*e.g.*, racial biases). Unfortunately, our estimates of the price sensitivity parameters for Black households are statistically under-powered due to the small share of Black households in the current sample. Therefore, we look forward to re-running this analysis with the expanded datasets from EnergySage.

6 Closing Remarks

In this proposal, we have presented preliminary evidence that low-income and minority households face additional barriers when shopping for new energy technologies. In particular, we are finding that low-income and minority buyers receive fewer installation bids for their solar installation projects. Initial evidence indicates that this bidding disparity can be explained by sellers choosing to bid less frequently on projects located in lower-income neighborhoods and those with more ethnically diverse populations.

To further investigate the mechanisms driving the disparities in seller participation, we use a discrete choice model to estimate buyers' price elasticities and a supply-side model to recover firms' implied costs. Our *preliminary* results show that although minority buyers are more price sensitive, buyer preferences cannot fully explain the gap in the number of bids obtained by White vs. Black buyers. Our cost estimates

Figure 3: Number of Bids, Buyer Race, and Neighborhood Characteristics

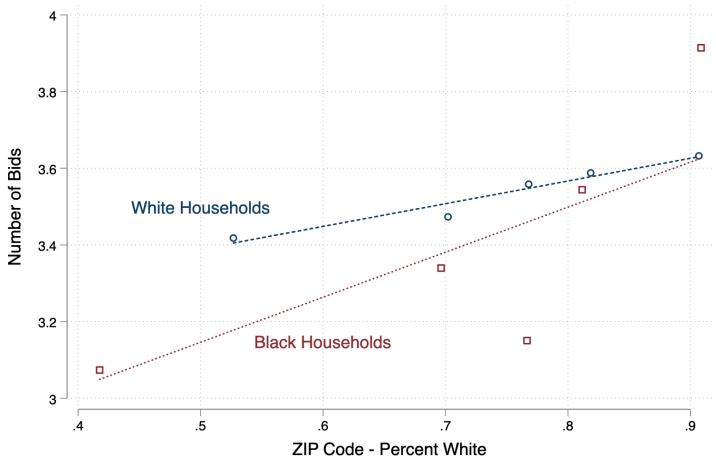
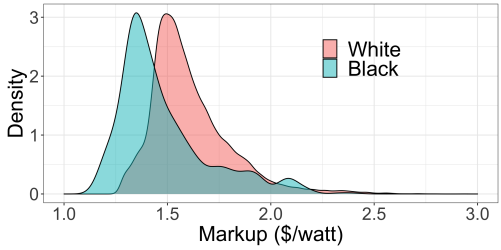
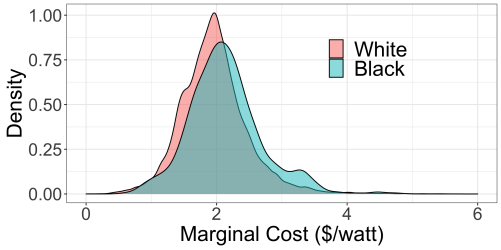


Figure 4: Price Decomposition using Structural Parameters



(a) Mark-up ($/watt)



(b) Marginal Cost ($/watt)

indicate that the bidding participation gap is partly explained by Black households projects bearing higher cost relative to White households' installations. These higher "costs" could be due to either direct costs (*e.g.*, installers' ease of access to White vs. Black neighborhoods) or implicit costs (*e.g.*, racial biases).

Once we obtain the final data set we anticipate using the structural estimates to evaluate how bidding disparities influence consumer welfare for low-income and minority households. We will also investigate the distribution of consumer welfare and solar adoption under alternative subsidy structures based on household income. Our research will provide new insights to better understand the mechanisms that drive racial and income gaps in adoption of new technologies. Our finding will also provide guidance to online platforms or policymakers that seek to achieve more equitable distribution outcomes in markets for new energy technologies.

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Appendix Tables

Table 2: The Impact of Income & Race on Number of Rooftop Solar Bids Received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low Income	−0.545***	−0.123***	−0.221***	−0.189***	−0.110*	−0.510***	−0.072*	−0.176***	−0.124***	−0.029
	(0.036)	(0.038)	(0.041)	(0.043)	(0.059)	(0.036)	(0.039)	(0.042)	(0.044)	(0.059)
Black	−0.406***	−0.348***	−0.247**	−0.148	−0.160	−0.390***	−0.330***	−0.228**	−0.138	−0.152
	(0.120)	(0.108)	(0.107)	(0.107)	(0.132)	(0.117)	(0.106)	(0.105)	(0.105)	(0.132)
Hispanic	−0.013	−0.110**	−0.094*	−0.090*	−0.114*	−0.020	−0.102**	−0.077	−0.070	−0.094
	(0.055)	(0.051)	(0.050)	(0.051)	(0.060)	(0.055)	(0.051)	(0.050)	(0.050)	(0.059)
Asian	0.149***	0.016	0.017	0.032	0.016	0.221***	0.084*	0.076	0.089*	0.073
	(0.053)	(0.051)	(0.050)	(0.050)	(0.059)	(0.052)	(0.050)	(0.049)	(0.049)	(0.057)
Constant	3.669***	3.579***	3.602***	3.594***	3.620***	3.651***	3.556***	3.581***	3.568***	3.591***
	(0.022)	(0.021)	(0.021)	(0.021)	(0.024)	(0.022)	(0.021)	(0.021)	(0.021)	(0.024)
R-Sq	0.167	0.281	0.328	0.353	0.474	0.193	0.297	0.344	0.368	0.487
Observations	10552	10552	10552	10516	9678	10552	10552	10552	10516	9678
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FE		Y					Y			
CBSA FE			Y					Y		
County FE				Y					Y	
ZIP FE					Y					Y
College FE						Y	Y	Y	Y	Y
Bill FE						Y	Y	Y	Y	Y

Heteroskedasticity-robust standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Electricity bill fixed effects based on bill deciles. College fixed effects measure the mean shift associated with the household head having a college degree.

Table 3: Impact of Race and Neighborhood Demographics on Number of Bids

	(1)	(2)	(3)	(4)	(5)
ZCTA Percent White	0.450***		0.464***	0.378***	0.158
	(0.104)		(0.106)	(0.125)	(0.129)
Black		−0.235**	−0.172	−0.535**	−0.518**
		(0.105)	(0.106)	(0.208)	(0.205)
Hispanic		−0.082	−0.066	−0.143	−0.151
		(0.050)	(0.050)	(0.196)	(0.197)
Asian		0.080	0.117**	−0.018	−0.125
		(0.049)	(0.050)	(0.154)	(0.155)
Black × ZCTA Percent White				0.583*	0.575*
				(0.326)	(0.323)
Hispanic × ZCTA Percent White				0.103	0.118
				(0.270)	(0.272)
Asian × ZCTA Percent White				0.199	0.308
				(0.226)	(0.227)
White Mean	3.504	3.504	3.504	3.504	3.504
R^2	0.345	0.344	0.346	0.346	0.350
Observations	10516	10516	10516	10516	10514
Income FE					Y

Heteroskedasticity-robust standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. All regressions include CBSA, home value, electricity bill and college attaintment fixed effects. Race percentages based on ZIP Code Tabulation Areas (ZCTAs).

Table 4: Discrete Choice Demand Estimates with Preference Heterogeneity by Race

Nesting Parameter		**Non-Price Bid Attributes**	
λ	0.375 (0.061)	Premium Panel	0.558 (0.078)
Price Coefficients		Premium Plus Panel	1.424 (0.152)
Constant	−0.702 (0.110)	Microinverter	0.369 (0.083)
× Black	−0.061 (0.117)	**Installer Attributes**	
× Hispanic	−0.100 (0.058)	Star Rating ≤ 4	−0.258 (0.260)
× Asian	−0.022 (0.046)	Star Rating = 4.5	−0.407 (0.290)
Household Attributes (× Inside Option)		Star Rating = 5	0.279 (0.108)
Electric Bill - Quartile 2	−0.068 (0.102)	Installs Completed: 100-1000	0.693 (0.250)
Electric Bill - Quartile 3	−0.244 (0.106)	Installs Completed: >1000	0.745 (0.256)
Electric Bill - Quartile 4	−0.590 (0.118)		
Has Off-Platform Quotes	0.371 (0.097)		

Race	**Mean Own-Price Elasticity**	**Avg Number of Bids**
Asian	-1.62	3.83
Black	-1.74	3.16
Hispanic	-1.81	3.51
White	-1.57	3.5

Notes: Standard errors are in the parentheses. The utility specifications include CBSA, half-year, and seller fixed effects.