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The benefits of hyper-utilisation of consumer energy resources (CERs) through a Virtual Energy Network (VEN)

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Any remaining errors or omissions are the responsibility of the authors.

Executive Summary

Consumer energy resources (CERs)—including rooftop solar, batteries and electric vehicles—represent a large and growing source of system value in Australia. However, realising this value depends on effective coordination across decentralised participants.

This study evaluates a Virtual Energy Network (VEN), a platform that enables peer-to-peer and community energy trading, using a randomised control trial. The results provide causal evidence on how such a mechanism affects energy use, prices, and consumer outcomes. Importantly, the use of a randomised controlled trial enables credible causal inference and sets a benchmark for evaluating the growing number of pilots and trials across Australia's energy sector.

We find that the VEN:

- increases the utilisation of CERs: Access to the platform shifts electricity consumption towards periods of high solar generation with suggestive, though likely not statistically significant, evidence of a stronger response on high solar days, indicating some alignment with the availability of excess solar generation.
- delivers financial benefits and sends effective price signals: Importing households pay lower prices for electricity, while exporting households receive higher prices for their generation. For importers, benefits include bill reductions from lower prices and behavioural responses that alter the pattern of electricity consumption, with heterogeneity across users; and
- improves perceptions of fairness in the energy system: Participants report increased confidence that the energy system is fair, suggesting that well-designed market mechanisms can enhance both efficiency and social licence.

The current design does not include explicit incentives or signals aimed at reducing peak demand, highlighting an important avenue for future research. Further work could explore how more granular, real-time signals and integration with network constraints might further improve system-wide outcomes. The results should also be interpreted with several qualifications, including the short-term nature of the analysis, which may not capture longer-run behavioural or investment responses, the fact that observed participants may not be representative of the broader population, and that outcomes and potential benefits could differ substantially under alternative retail market and tariff structures.

Overall, the findings provide evidence that coordination of production and consumption at scale is likely as important as technology in unlocking the value of CERs. Platforms such as VENs provide a scalable mechanism to align decentralised decisions with system needs, offering a pathway to a more efficient, flexible, and consumer-centric energy system.

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Introduction

There is widespread recognition that distributed consumer energy resources (CERs), including rooftop solar, batteries and electric vehicles, have substantial economic and system value. In the Australian context, this opportunity is particularly pronounced.

Australia has one of the highest penetrations of rooftop solar in the world, with more than one in three detached homes now hosting solar PV systems. This creates a large, decentralised generation fleet embedded within the distribution network. When combined with growing uptake of behind-the-meter batteries and electric vehicles, CERs have the potential to:

- reduce peak demand and defer network investment;
- lower wholesale prices by shifting demand to periods of high renewable generation;
- reduce curtailment of rooftop and utility-scale solar; and
- provide system services (e.g. frequency response, local network support) traditionally delivered by centralised generation.

In Australia, CERs already deliver substantial realised benefits, estimated at between $3 billion and $6 billion annually in household electricity savings (ABS, 2025; Clean Energy Council, 2024).[1] However, system-wide value is an order of magnitude larger, with tens of billions of dollars in potential benefits contingent on effective integration and orchestration (RACE for 2030, 2023).[2]

In high-renewables systems, the ability of CERs to absorb excess midday solar and shift consumption away from evening peaks is particularly valuable, as it directly addresses the growing mismatch between generation profiles and demand.

Behavioural evidence suggests that this value is at least partly realisable. Field trials show that consumers respond to price signals and incentives, for example, by shifting EV charging

[1] https://www.abs.gov.au/articles/household-solar-electricity-generation-australian-national-accounts and https://cleanenergycouncil.org.au/news-resources/rooftop-solar-and-storage-report-july-to-december-2024.
[2] https://www.racefor2030.com.au/consumer-energy-unleashed-creating-a-better-energy-system-for-all/

to midday periods when solar generation is abundant (e.g. La Nauze et al., 2024). Complementary research by Energy Consumers Australia and The Insight Centre indicates that while consumers are willing to engage with some degree of complexity in the energy transition, they place a high premium on control, transparency and fairness (ECA, 2024).

However, realising the full value of CERs is fundamentally a coordination problem. Left uncoordinated, individual optimisation can lead to suboptimal system outcomes such as:

- excessive exports of rooftop solar can exacerbate local network congestion and drive curtailment;
- unmanaged EV charging can increase peak demand rather than reduce it; and
- fragmented responses to price signals can fail to deliver the scale or timing of load shifting required for system efficiency.

Realising the system value of CERs requires coordinated shifting of generation and demand, but several structural challenges complicate effective orchestration. First, incentives are often misaligned across the supply chain. Retail tariffs are typically flat or only weakly dynamic, limiting consumers' exposure to underlying wholesale and network conditions. At the same time, network businesses, retailers and aggregators face different, and sometimes conflicting, objectives, which can dilute incentives to coordinate CERs in a system-optimal way.

Second, there are significant information and coordination frictions. Efficient orchestration depends on granular, real-time information on prices, network constraints and resource availability. In practice, however, limitations in data access, lack of interoperability, and platform fragmentation constrain the ability to coordinate distributed resources effectively.

Third, existing market design is not well suited to a highly decentralised system. Wholesale and retail arrangements were developed for a centralised generation paradigm and do not readily accommodate high-frequency, small-scale participation, nor do they fully value local network services provided by CERs.

Fourth, consumer engagement imposes additional constraints. While consumers may be willing to participate in the energy transition, effective engagement cannot rely on continuous active decision-making. Instead, successful models must balance automation with user control and trust, particularly in the presence of concerns around fairness, privacy and complexity.

Finally, there are important scale and coordination thresholds. The system benefits of CERs are highly non-linear: small, uncoordinated responses deliver limited value, whereas coordinated responses at scale can materially reshape load profiles and prices. Achieving these benefits therefore requires mechanisms capable of aggregating and synchronising distributed actions across a large number of participants.

Building on this context, this project evaluates a platform, referred to as a Virtual Energy Network (VEN), for peer-to-peer energy trading between distributed resources and loads.

The VEN concept directly addresses the coordination problem by creating a mechanism for:

- aligning individual incentives with system conditions through price-based signals;
- enabling decentralised but coordinated decision-making across participants; and
- increasing the effective scale of response by aggregating distributed resources.

The project assesses whether, at scale, a VEN can:

1. increase utilisation of CERs (e.g. rooftop solar and batteries);
2. provide system value by shifting EV charging and other flexible demand away from peak periods and towards times of high solar generation;
3. deliver financial benefits to participating consumers; and
4. increase engagement, knowledge, and social licence for the energy transition.

Virtual Energy Networks

A Virtual Energy Network (VEN) is a digital platform that enables participants to buy and sell energy through the existing electricity grid. This network enables any participating energy producer or consumer to sell their available energy or buy energy to meet their needs at prices that they determine. In this project, we study the VEN created by the Powertracer software for customers of the electricity retailer Energy Locals.

Buyers in the study are households or small businesses without rooftop solar or who's solar is not meeting their own consumption requirements. When they have access to Powertracer, for every kWh that they buy, they pay a non-tradable price that covers the non-energy component of the cost of electricity, such as network tariffs and a retailer margin.[3] They can then buy their energy from three different types of trades:

- *peer-to-peer trades*: a private bilateral trade arranged between a buyer and another VEN participant
- *community trades*: an anonymous pool trade
- *retailer trades*: the default for the customer if it uses more than it can buy from these other types of trades.

Sellers in the study are households or small businesses with rooftop solar. They also participate in all three types of trades with the retailer trade price being the retailer's feed-in tariff. For peer-to-peer and community trades, participants establish trade rules. The Powertracer algorithm then takes realised total exports and total imports in each half-hour and matches buyers and sellers in peer-to-peer and community trades.[4]

Study Design

The study involves households and small business with a smart meter who are either:

- Electricity consumers who import and export electricity from their rooftop solar.
- Electricity consumers without rooftop solar who import all their electricity.

Participants were recruited through traditional media coverage as well as paid and organic social media posts. Recruitment materials directed interested participants to a webpage with more information, where they could complete an expression of interest. Participants were then invited to register for the study. Registration involved several steps: (1) enrol in a

[3] The plan may include other fees and charges, for example daily or monthly fixed charges that are not included in the analysis in this report.
[4] Peer-to-peer trades are matched first and according to priority orders that are also set by buyers and sellers. Community trading is cleared with a uniform price from bids and offers stating maximum buy and sell prices. For more information see the Enosi website.

residential or small business Powertracer plan with the electricity retailer Energy Locals (2) complete a baseline survey to collect demographic and home energy use information; and (3) complete an initial baseline data collection period of 2-4 weeks without trading on the VEN. Participants who completed this process received a gift card.

The study adopted a phase-in design with 6 cohorts. For each cohort, the set of eligible participants was randomly allocated to start trading (the "treatment" group) or to continue an extended baseline period of 90 days without trading (the "control" group). Participants were then placed into trading groups based on their solar/non solar status and their state. The control group received an additional gift card at the end of their extended baseline period when they started trading. Table 1 reports the cohorts, trade groups and the approximate date trading commenced for treatment and control sites within each cohort. During the study period, participants received another gift card for completing a check-in survey during the study period.

Table 1: Cohorts and Trading Dates

Cohort	Trade Groups	Treatment trading from	Control trading from
1	1-6	Aug 12 2025	Oct 13 2025
2	7-8	Aug 26 2025	Nov 6 2025
3	9-10	Sep 19 2025	Dec 11 2025
4	11-12	Oct 16 2025	Jan 12 2026
5	13-15	Nov 11 2025	Feb 11 2026
6	16-17	Dec 23 2025	Mar 25 2026

For participants who completed their baseline period, the project team established peer-to-peer trade rules within each trading group. Trade prices were set such that the cost savings were shared equally between buyers and sellers. More formally, prices were set using the following rule:

$$\text{P2P price} = \frac{(\text{Buy price} - \text{Sell price})}{2} + \text{Sell price}$$

Community trade rules were also established for trading participants, with a purchase price cap at the retailer cost (purchase anything below the retailer offer) and a seller price floor at the retailer feed-in tariff.

For peak solar producing hours, the average difference between the default retailer 'buy' and 'sell' prices across all interstate pairs was approximately 12c/kWh, which is the benefit of trading that is shared between buyers and sellers. For those hours, the average peer-to-peer price across all interstate pairs is approximately 8c/kWh.[5]

During the project, participants were also asked to complete a "check-in" survey to measure consumer sentiment, changes in appliances, and CER installation. During two windows of the study, some participants also received text alerts and additional incentives for importing electricity on days with high expected solar irradiance.[6] As data collection of these alert periods was ongoing at the time of writing this report, we do not discuss it further here.

Analysis

Sample

Registrations opened in June 2025 and finished in January 2026. In total, the project received over 1,600 expressions of interest, and 266 participants with 296 sites signed up to the study. By 1 March 2026, 42 of these sites had left the VEN.[7] Table 2 reports the characteristics of 255 participants and 279 sites.[8] Characteristics are reported for sites that were randomly assigned to a short baseline period ("Treatment"), and sites that were randomly assigned to a longer baseline period ("Control"). The table also reports the p-value for a t-test that the groups have the same mean; a value less than 0.05 or 0.1 suggests that the groups are statistically different. As the sites were randomly assigned to each group, they should be statistically indistinguishable (i.e. balanced on observable characteristics). The groups are observably the same. This provides supportive evidence for the econometric analysis below, ensuring that differences in outcomes across those with and without access

[5] Prices vary with state and time of day.
[6] For those eligible for this incentive, on days that were deemed "high-solar" days (approximately 4-5 per month), we paid 20c for each matched kWh of electricity bought.
[7] Sites in our study also traded with non-study sites either via community trades or instigated their own peer-to-peer trades with non-study participants.
[8] We exclude observations from the analysis sample due to data issues in survey collection or incomplete trade and meter data at the time of writing this report. Of the sites that left the VEN, 70% were generating sites. Ten sites left before trading. Treatment does not predict leaving the study hence we do not adjust our results for attrition.

to VEN trading can be interpreted as the causal effect of the VEN, and not an artefact of correlation between VEN adoption and site characteristics.

From Table 2, 94% of participants are residential, with an average household size of 2.65–2.85 residents. Of these participants, a high share owns their own home (90-93%). Table 3 shows characteristics separately for participants with and without solar. At baseline, solar participants import less from the grid for most periods during the day except for the evening peak period, are more likely to own an electric vehicle and more likely to own their own home. Other characteristics of the two groups are not statistically different, including average household size, household income, and share working full time.

Table 2 Characteristics and Balance Across Treatment and Control Groups

	Treatment			Control			Difference
Variable	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**Obs**	**p-value (t-test)**
Mean daily import^ (kWh)	16.90	20.47	131	19.19	31.85	124	0.493
Mean daily export^ (kWh)	16.27	11.36	87	15.09	10.56	82	0.484
Share import 10am-4pm^ (%)	0.18	0.13	131	0.18	0.14	124	0.969
Share import 4pm-9pm^ (%)	0.28	0.10	131	0.27	0.11	124	0.875
Share import 9pm-10am^ (%)	0.54	0.14	131	0.54	0.16	124	0.878
Rooftop solar (%)	0.66	0.48	131	0.65	0.48	124	0.957
Solar capacity (kW)	9.58	4.88	86	9.57	4.78	81	0.989
Home battery (%)	0.21	0.41	131	0.19	0.40	124	0.803
Battery capacity (kWh)	13.45	3.81	27	12.96	4.74	24	0.687
Electric vehicle (%)	0.23	0.42	131	0.21	0.41	124	0.711
Residential (%)	0.94	0.24	131	0.94	0.23	124	0.876
Home owner (%)	0.93	0.25	123	0.90	0.30	117	0.295
Work full time (%)	0.33	0.47	123	0.39	0.49	117	0.331
Household income ($)	116634.31	52439.91	103	110665.64	52458.47	103	0.415
Residents	2.65	1.21	123	2.85	1.48	117	0.249
Business employees	7.25	5.71	10	6.88	5.47	8	0.890

Notes: ^ From trade data measured during baseline period for each cohort, i.e. 14 days before column 23 of Table 1. All other variables measured using data collected at registration survey. SD is standard deviation. Obs is number of observations, which is the number of participants. Difference p-value (t-test) is the p-value of the difference in means for the treatment and control samples. For multi-site participants, trade data is averaged over sites, solar, battery, and electric vehicle are =1 if they are reported at either site.

Table 4 compares the characteristics of households in the VEN study sample to those collected in a representative sample of the Australian adult population from the online survey sample collected by Qualtrics. As previously, the final column reports the p-value for a t-test that the samples have the same mean; a value less than 0.05 or 0.1 suggests that the samples are statistically different. Households in the VEN study sample are more likely to have rooftop solar, a battery, an electric vehicle, be a homeowner, are less likely to work full time, have higher annual household income and fewer residents.

Table 3 Characteristics Across Participants for Solar and Non Solar Participants

	Solar			Non Solar			Difference
	Mean	SD	Obs	Mean	SD	Obs	p-value (t-test)
Mean daily import^ (kWh)	15.37	19.42	167	23.02	36.15	88	0.029
Share import 10am-4pm^ (%)	0.14	0.13	167	0.27	0.09	88	0.000
Share import 4pm-9pm^ (%)	0.28	0.12	167	0.26	0.07	88	0.220
Share import 9pm-10am^ (%)	0.58	0.15	167	0.47	0.11	88	0.000
Electric vehicle (%)	0.28	0.45	167	0.10	0.30	88	0.001
Residential# (%)	0.95	0.21	167	0.92	0.27	88	0.309
Home owner (%)	0.98	0.14	159	0.79	0.41	81	0.000
Work full time (%)	0.33	0.47	159	0.43	0.50	81	0.110
Household income ($)	111461.79	50098.73	136	117901.29	56756.72	70	0.405
Residents	2.77	1.18	159	2.71	1.64	81	0.742
Business employees	8.50	5.92	10	5.31	4.52	8	0.227

Notes: ^ From trade data measured during baseline period for each cohort, i.e. 14 days before column 23 of Table 1. All other variables measured using data collected at registration survey. # Reflects response to our survey question – small businesses may also operate from residential sites. SD is standard deviation. Obs is number of observations, which is the number of participants. Difference p-value (t-test) is the p-value of the difference in means for the solar and non solar sites. Multi-site participants are recorded as solar if they have solar at any site, trade data is averaged over sites and electric vehicle =1 if they are reported at either site.

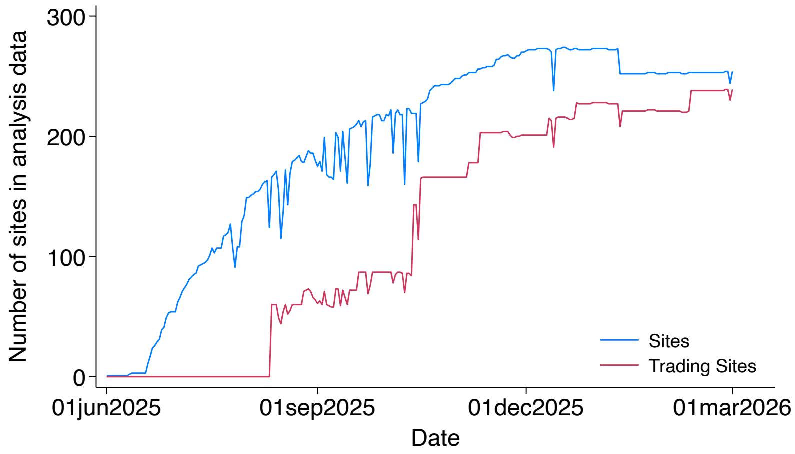
For the descriptive and econometric analysis of the VEN, we focus on trading and meter data for the period June 2025 to March 2026 downloaded from the Enosi Powertracer platform. Figure 1 shows the number of sites recorded in the analysis data over that period (blue line), and the number of sites in trading groups that had commenced trading.

Table 4 Comparison of Characteristics across Qualtrics and VEN Study Sample

	Qualtrics Sample			VEN Study Sample			Difference
Variable	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**Obs**	**p-value (t-test)**
Rooftop solar (%)	0.40	0.49	906	0.66	0.47	240	0.000
Solar capacity (kW)	8.64	4.52	364	9.23	4.55	159	0.170
Home battery (%)	0.15	0.36	906	0.21	0.41	240	0.016
Battery capacity (kWh)	11.22	5.07	134	13.22	4.24	51	0.013
Electric vehicle (%)	0.12	0.33	906	0.23	0.42	240	0.000
Homeowner (%)	0.63	0.48	906	0.92	0.28	240	0.000
Work full time (%)	0.52	0.50	906	0.36	0.48	240	0.025
Household income ($)	98,425.93	55,126.10	864	113,649.97	52,406.57	206	0.000
Residents	2.97	1.72	906	2.75	1.35	240	0.063

Notes: Variables measured at registration survey (VEN Study) or through a Qualtrics panel fielded in October 2025. Qualtrics panel questions were identical to registration survey questions. Difference p-value (t-test) is the p-value of the difference in means between the Qualtrics sample and the VEN study Sample.

Figure 1 Total Sites and Trading Sites in Analysis Data



Notes: Figure displays the daily count of sites in the analysis dataset (blue line) and the daily count of sites in the analysis dataset that were trading through the VEN (red line)**.** Reductions in the count could reflect attrition (sites leaving the study) or missing data.

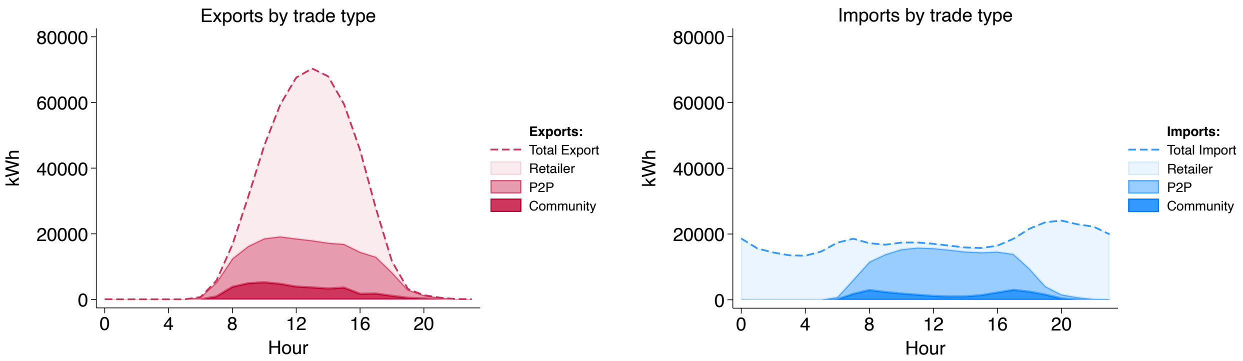
Descriptive Analysis

Figure 2 summarises total volumes of energy for participants who were trading over the period September 1, 2025 – February 28, 2026 (i.e. had completed their baseline and were set up with trades in the VEN). This includes 268 sites and 172 generators, and 32 trading groups (the control group in the final cohort did not start trading until late March and hence are excluded from this sample).

The left-hand panel shows total exports (dashed red line) for trading participants over the period by hour of the day, and volumes by trade type (shaded areas). The right-hand panel shows total imports (dashed blue line) and volumes for each trade type (shaded areas) by hour of the day over the same period. The trade types are:

- “Retailer”: exports (light pink) sold and imports (light blue) bought from the retailer
- “P2P” (peer-to-peer): exports (dark pink)/imports (medium blue) traded among nominated VEN participants
- “Community”: exports (red)/imports (dark blue) traded via anonymous pool trades in the VEN.

Figure 2 Trade and Meter Volumes (kWh) for Trading Sites September 2025 – February 2026



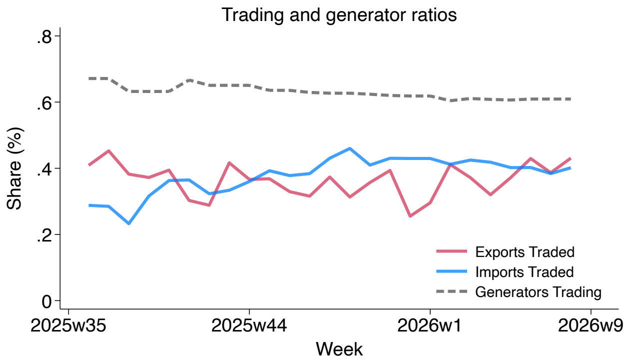
Notes: Left panel shows total exports and exports by trade type in kWh for trading sites over the period September 2025 – February 2026. Right panel shows total imports and imports by trade type over the same period. Trade types are default trades to the retailer, bilateral peer-to-peer (P2P) trades, and anonymous pool community trades.

From 8am to 4pm, peer-to-peer trades served almost all the imports of trading participants. Over all hours, 39% of imports were served by peer-to-peer or community trades (85% of which was peer-to-peer trades). At midday, approximately 23% of solar output was matched in peer-to-peer and community trades while across all hours, 36% of solar output was matched in peer-to-peer and community trades (78% of which was peer-to-peer trades).[9]

Figure 3 shows the evolution of these trading ratios and the share of trading sites that are exporting (Generators) over the study period. The proportion of exports traded through the VEN (red line) is relatively constant across the sample period, while the proportion of imports traded through the VEN (blue line) rises steadily. This could be a result of behavioural changes, changes in the composition of exporters and importers, and/or it could reflect underlying seasonality in consumption and production (e.g. due to temperature and solar irradiance). The proportion of sites with generation (black dashed line) is mostly flat over the study period, with a slight downward trend. On average, around 60% of sites have generation, equivalent to roughly 1.5 generating sites for every non-generating site.

[9] Peer-to-peer and community trades do not perfectly match for generators and importers as participants were trading with non-study participants via anonymous community trades, or self-instigated peer-to-peer trades with non-study sites.

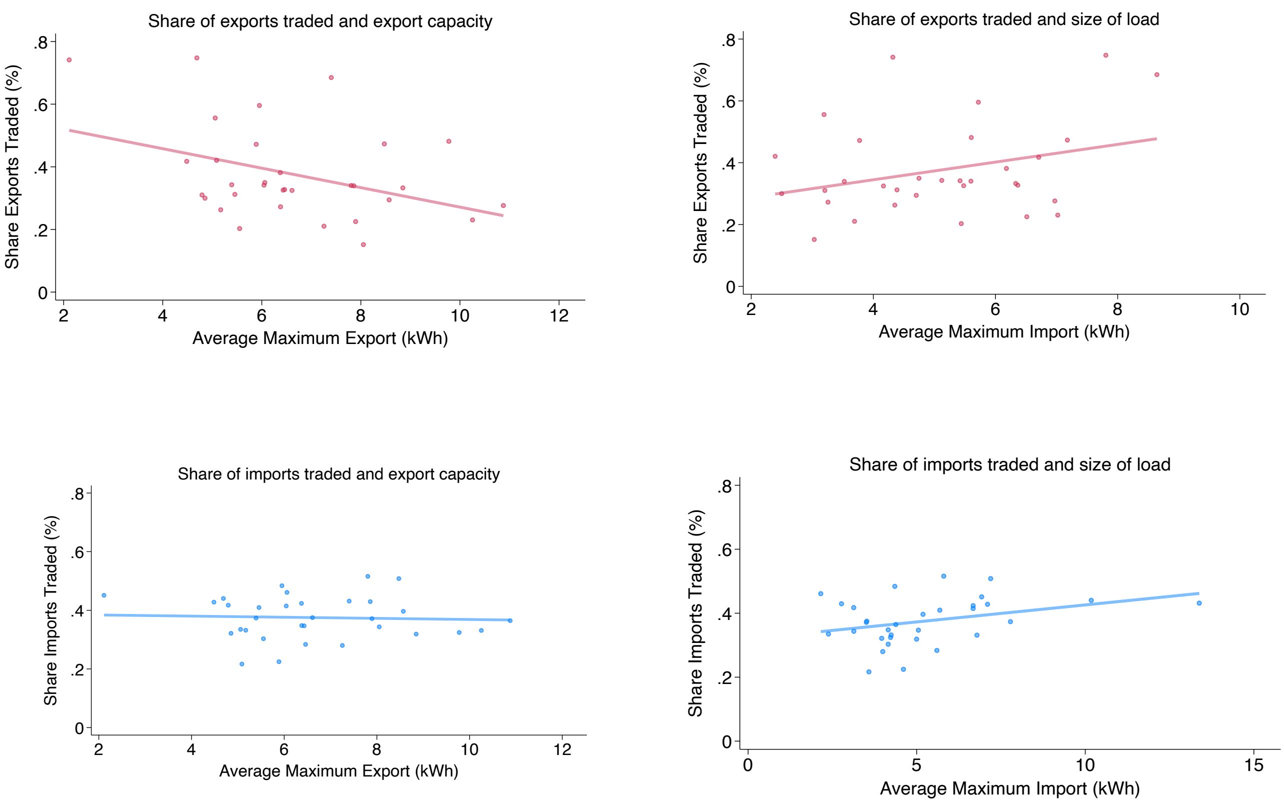
Figure 3 Trade Shares and Generator Ratios for Trade Groups September – February



Notes: Figure shows the proportion of exports and imports for trading sites that were matched in peer-to-peer or community trades and the share of sites that were generators. Data excludes incomplete weeks at the start and end of the sample period.

Figure 3 shows the correlation between the average share of exports and imports traded in the VEN and average size of sites in a trading group (used to established peer-to-peer trades). For generators, average size of a site is measured as the average maximum export (in kWh) across all sites in a trading group during the period. For non-generators, the average size of a site is measured as the average maximum import (in kWh) across all sites in a trading group during the period. The share of exports traded is more responsive to the size of exporters and importers. The share of exports is negatively correlated with average generation size and positively correlated with average importer site size. The share of imports traded is not correlated with the size of generation sites (there is more than enough generation capacity to meet average importer needs). However, there is a small positive correlation between average importer size and the share of imports traded. Larger importing sites tend to have load profiles that better match the available solar generation.

Figure 4 Trade Shares and Average Site Size for Trading Sites September - February



Notes: Figure shows the percentage of exports (top row) and imports (bottom row) traded, and correlations with the average maximum export (left column) and average maximum import (right column) of trading sites over the period September 2025 to February 2026. The solid line is the best linear fit.

Econometric Analysis

We next analyse the effect of having access to the VEN. We will estimate the impacts of the VEN by comparing outcomes of interest for those sites randomly assigned to a shorter baseline (the treatment group), with those in the same cohort, who were randomly assigned a longer baseline (the control group). To understand whether any measured impacts are statistically different from zero, we will estimate these effects using a regression. Our main regression specification is:

$$y_{it} = \alpha_{ih} + \gamma_t + \sum_h \beta_h Treatment_{it} + \epsilon_{it}$$

In this model, β_h are the estimates of interest, and measure the impact of the VEN on the outcome y_{it} for each hour of the day h. The outcome could be electricity imports, exports, or prices. The other components of the model are α_{ih} which captures differences across sites in baseline outcomes, γ_t which captures differences common to sites across hours and days (e.g. due to temperature), and ϵ_{it} which will capture any difference between the observed outcome y_{it} and the model's predicted outcome.

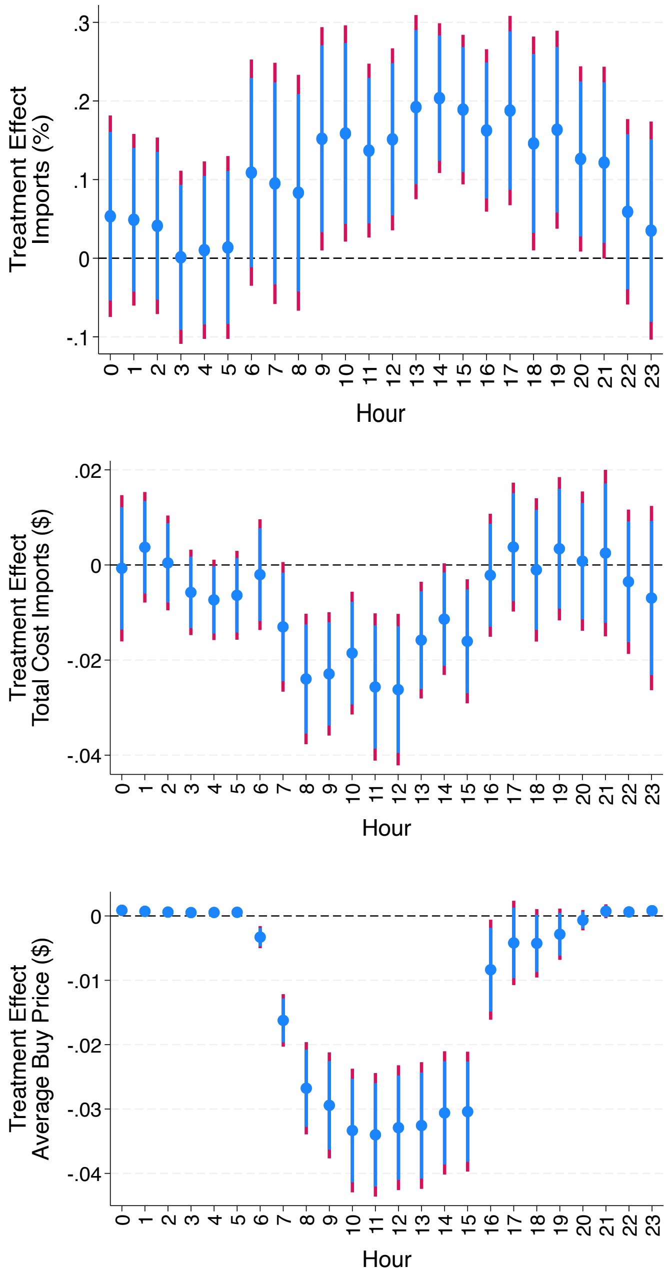
Analysis of Importing Sites

We begin with looking at the VEN impact on importing sites. Figure 5 shows the impacts of VEN trading on imports, average cost of electricity, and average prices paid for electricity. The markers show the estimated impact by hour of the day. The vertical lines show confidence intervals, which measure uncertainty in the estimate. If the confidence interval intersects the zero line, the estimated effect is not statistically significant, and we cannot rule out that there is no impact. In the top panel, we see that access to trading through the VEN increased hourly electricity imports for non-generating sites between the hours of 9am and 7pm, with the largest effects between 1pm-7pm of around 18%. The middle panel of Figure 5 shows the impacts of VEN trading on the hourly total cost of electricity used at non generating sites. This reflects the "energy-only" impacts of the VEN on the bills of non-generating sites for each hour of the day. The final panel in Figure 5 shows the impacts of the VEN on average prices paid for electricity by hour of the day. This reflects the average discount that a VEN site experiences on each unit of electricity at each hour of the day.

We next decompose the change in electricity bills into two components: a price effect and a behavioural effect. The price effect captures how much bills would have changed if participants had kept their electricity use the same but faced the new (lower) prices. The behavioural effect captures how much of the change in bills is due to households adjusting their consumption in response to those lower prices. When thinking about the benefits of the VEN, it is important to understand both effects and not just the average impact on bills. If the price and behavioural effect cancel each other out, then bills might stay the same, but participants have benefited through higher consumption of electricity.

To undertake the decomposition, we first predict what each household's electricity use would have been in the absence of the pricing intervention, and what prices they would

Figure 5 Impacts of VEN Trading on Importing Sites

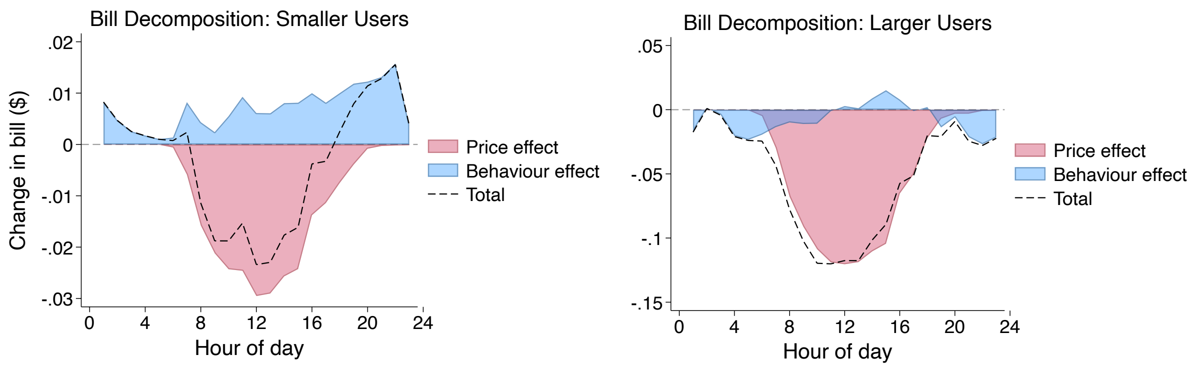


Notes: All panels display estimated treatment effects (blue markers) and confidence intervals for the treatment effects (blue and red lines). Blue lines are 90% confidence intervals; red lines are 95% confidence intervals; standard errors are clustered at the NMI. *Top* – panel shows impacts of VEN trading on imports by non-generating sites over the analysis sample period. *Middle* – panel shows impact of VEN trading on the total cost of energy for non-generating sites over the analysis period. *Bottom* – panel shows impact of VEN trading on average prices of imported electricity over sample period.

have faced without it. We then compare this counterfactual scenario to actual outcomes. The difference in bills attributable to prices holding consumption fixed is the price effect, while the remaining difference—arising from changes in consumption—is the behavioural effect. This approach allows us to separate savings from price changes from those driven by changes in household behaviour.

For this analysis, we separate importing sites into two groups by size, as sites of different size tend to respond differently to price changes. By analysing these groups separately, we can better capture how the VEN affects different types of users and avoid results being dominated by either small or large users alone. Figure 6 shows the decomposition of bill savings into price and behavioural effects for small and large users.[10] Small users are defined as those whose maximum use is in the bottom 70th percentiles, while high users are those in the remaining top percentiles.

Figure 6 Bill Decomposition for Smaller and Larger Import-only Sites



Notes: Figure displays the impact of VEN trading on the hourly bills of importing sites. Dashed line shows total bill impacts of VEN trading. Left hand panel shows price and behaviour effects for smaller users, right hand panel shows price and behaviour effects for larger users. Price effect (pink) is the effect on a bill if consumption had not changed. Behaviour effect (blue) is the effect on a bill from changes in consumption evaluated at VEN (lower) prices. Total effect (dashed black line) is the net of the two.

[10] More formally, Total Change = (P1 * Q1) - (P0 * Q0), Price Effect = (P1 - P0) * Q0, Behaviour Effect = P1 * (Q1 - Q0) where P1 is price with access to the VEN, P0 is price without access to the VEN, Q1 is consumption with access to the VEN and Q0 is counterfactual consumption. We observe P1, P0, and Q1. We estimate Q0 using treatment effects in levels by hour for each site type.

We find that smaller users show a larger behavioural response—for example, through appliance use—while larger users tend to change their electricity consumption relatively little but receive bill reductions due to lower prices. Table 5 summarises the total change in user bills at the daily level, and the decomposition into a price and behaviour effect. It also shows the relative daily use (kWh) of sites with VEN access. The mean provides an indicative estimate for each category of site. The minimum (min) and maximum (max) show the estimated range of outcomes within each category. Actual benefits are highly site-specific and depend on factors such as overall consumption, flexible appliance ownership, and the timing of electricity use.

Table 5 Summary of Daily Bill Impacts

	(1)			(2)			(3)			(4)		
	Total Change ($)			**Price Effect ($)**			**Behaviour Effect ($)**			**Daily Use (kWh)**		
	mean	min	max	mean	min	max	mean	min	max	mean	min	max
Smaller users	-0.08	-0.76	0.21	-0.24	-0.92	-0.01	0.16	0.09	0.22	11.41	2.30	37.97
Larger users	-1.14	-3.90	-0.20	-0.96	-3.70	0.00	-0.18	-0.20	-0.15	33.53	7.74	132.95

Notes: Table summarises mean, minimum and maximum bill effects and daily use (while trading on the VEN) for smaller and larger importing sites. Total Change is the overall impact (and the sum of Price and Behaviour Effects). Price Effect is the effect on a bill if consumption had not changed. Behaviour Effect is the effect on a bill of changes in consumption evaluated at VEN (lower) prices.

Figure 6 and Table 6 suggest there is considerable heterogeneity in the response of importing sites to the VEN. We next separate our analysis of importing sites by characteristics of those sites. For the heterogeneity analysis, we estimate impacts of the VEN on imports for three different periods of the day. Table 6 shows the results for all importing sites, business importing sites, importing sites of multi-site participants, and residential importing sites. For businesses and multi-site participants, the sample sizes are too small to draw strong conclusions.

Table 7 shows results for residential importing sites that have different energy-using appliances. Once again, sample sizes of some groups (electric vehicle owners and pool owners) are too small to draw strong conclusions. We do, however, see a significant consumption response for those who have electric hot water, air conditioning, and renters. Renters, in particular, have the largest consumption response.

Table 6 VEN Impacts on Imports by Site Type

	(1)	(2)	(3)	(4)
	All sites	**Business**	**Multi-site participants**	**Residential**
10am-4pm # VEN Trading	0.173***	-0.022	0.147	0.208***
	(0.050)	(0.083)	(0.096)	(0.057)
4pm-9pm # VEN Trading	0.157***	-0.075	0.108	0.197***
	(0.057)	(0.083)	(0.118)	(0.066)
9pm-10am # VEN Trading	0.064	-0.140	-0.029	0.104
	(0.055)	(0.097)	(0.094)	(0.063)
Observations	419095	72620	95069	346475
Sites	104	19	25	85

Notes: Table reports results of a regression of import (kWh) by hour of the day on an indicator for a site was trading the in VEN, and whether that hour was in a specified time period. Standard errors clustered at NMI in parentheses. Samples differ across columns: (1) all importing sites (2) business sites only (3) multi-site participants only (4) residential sites only. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7 VEN Impacts on Imports by Appliance Type

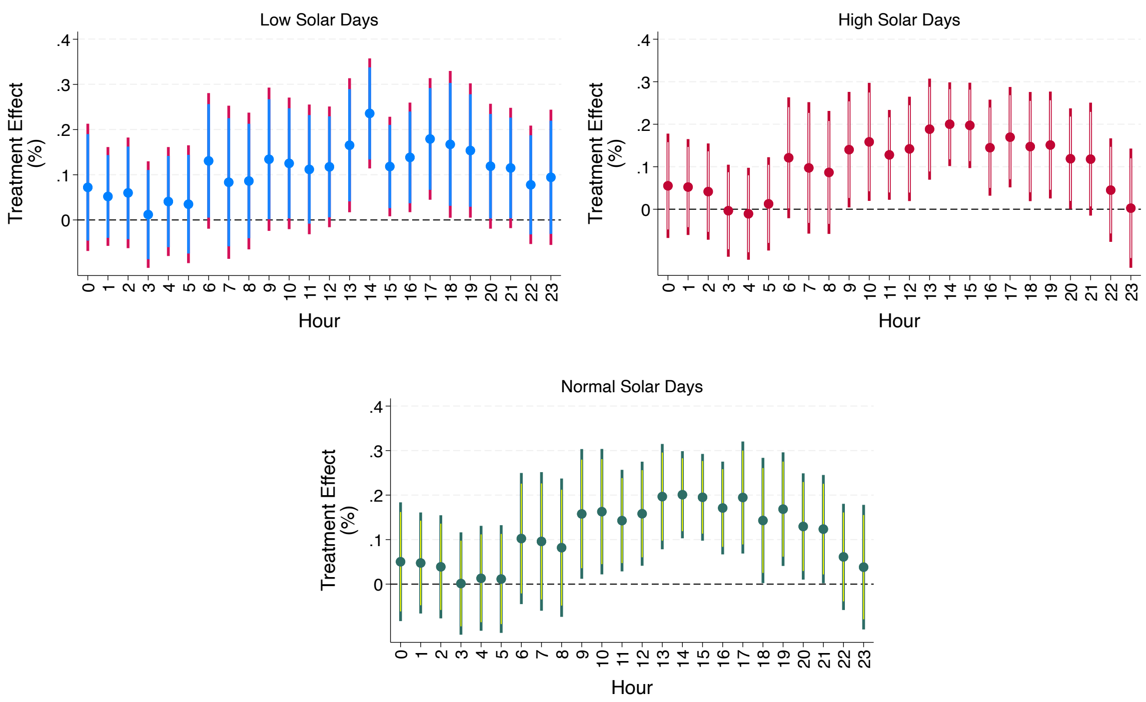
	(1)	(2)	(3)	(4)	(5)	(6)
	Electric Vehicle	**Pool**	**Hot Water**	**Air-conditioning**	**Income< $110,000**	**Renter**
10am-4pm # VEN Trading	0.276	0.013	0.242**	0.161**	0.251**	0.389***
	(0.201)	(0.102)	(0.090)	(0.065)	(0.096)	(0.112)
4pm-9pm # VEN Trading	0.210	-0.068	0.180*	0.165**	0.311***	0.541***
	(0.212)	(0.063)	(0.091)	(0.077)	(0.107)	(0.119)
9pm-10am # VEN Trading	0.077	-0.014	0.104	0.102	0.202*	0.161
	(0.144)	(0.084)	(0.108)	(0.069)	(0.113)	(0.128)
Observations	47392	30724	166089	283578	150346	75395
Sites	11	7	39	70	38	21

Notes: Table reports results of a regression of import (kWh) by hour of the day on an indicator for a site was trading in the VEN, and whether that hour was in a specified time period. All sites are residential sites. Samples differ across columns: (1) participant has an electric vehicle (2) participant has a pool pump (3) participant has electric hot water (4) participant has air conditioning (5) participant has household income below $110,000 (median income in the sample) and (6) participant is a renter. Standard errors clustered at NMI in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, we consider how consumption responds to the availability of excess solar on the VEN. To do so, we define each day as a “Low” solar day, a “High” solar day, or a “Normal” solar day. A “Low” solar day is a day in the bottom 20% of daily solar exports in a trading group. A “High” solar day is a day in the top 20% of daily solar exports in a trading group. A “Normal” solar day is the middle 20-80th percentiles of solar exports in a trading group.

Figure 7 shows that importers on the VEN increase their consumption during daylight hours across all types of days. Contrasting high and low solar days, it seems that there is a larger response on high solar days, potentially indicating awareness of days that have more excess solar energy available, though this difference in responses is unlikely to be statistically significant.[11]

Figure 7 Consumption Responses on Low, High, and Normal Solar Days



Notes: Figure shows point estimates (markers), 90%, and 95% confidence intervals (lines) for hourly impacts of VEN trading on imports for low solar days (top left), high solar days (top right), and normal solar days among importers. Low solar days are in the bottom 20% of exports for a trading group, high solar days are in the top 20% of exports for a trading group. Normal solar days are in the 20-80th percentiles of exports for a trading group.

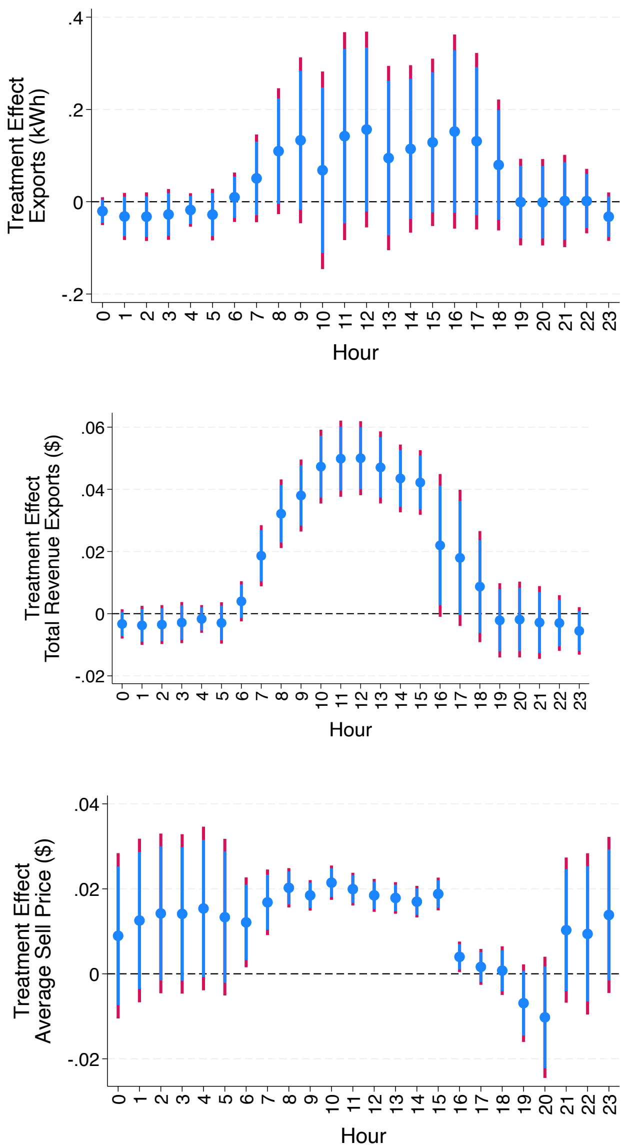
Analysis of Exporting Sites

Figure 8 shows the impacts of VEN trading on exports, average revenue from selling electricity, and average prices received for electricity for generating sites. The top panel shows no impact on exports of energy. The middle and bottom panels show the positive impacts of VEN trading on the total revenue received for selling electricity, and the average

[11] We account for the correlation between high solar output and temperature (or other determinants of electricity demand) by interacting the date-hour fixed effects with an indicator for the type of day. This ensures that the treatment effects in Figure 7 are estimated from differences between treatment and control on high/low/normal solar days, rather than differences across high/low/normal days within the treatment group.

prices received for selling electricity.[12] We do not see a change in exports from sellers in the VEN. This is not surprising, as due to our abundance of generating sites in the study, sellers continue to have significant unmatched exports, preserving the incentives of the feed-in tariff at the margin.

Figure 8 Impacts of VEN trading on Generating Sites



Notes: All panels display estimated treatment effects (blue markers) and confidence intervals for the treatment effects (blue and red lines). Blue lines are 90% confidence intervals; red lines are 95% confidence intervals; standard errors are clustered at the NMI. *Top* – panel shows impacts of VEN trading on exports by generating sites over the analysis sample period. *Middle* – panel shows impacts of VEN trading on total revenue from exports for generating sites over the analysis period. *Bottom* – panel shows impact of VEN trading on average prices of exported electricity over sample period.

[12] The discontinuous jump in the treatment effect on average sell price at 4pm reflects the underlying time-of-use structure of the feed-in tariffs of the retailer.

Consumer Sentiment

In the midline survey, participants were asked the following questions about their perceptions of the energy market:

1. *How confident are you that the energy system is fair for households like you?*
2. *How confident are you that technological advances will help reduce energy costs and improve supply reliability in the next 5 years?*
3. *How confident are you that you have the tools and assistance you need to manage your energy use and costs?*

Responses were on a 1-5 scale with 5 being the most confident. The midline survey was first fielded in October 2025 and re-fielded in March 2026. To understand whether access to trading on the VEN influenced consumer sentiment about the energy market and the energy transition, we define a sentiment measure as an outcome variable and regress it on whether the respondent had longer access to the VEN at the time of responding.[13] Table 10 reports the results using 148 responses to the midline survey.

We find a statistically significant increase in perceptions that the energy system is fair. We find no change in other measures of sentiment. For context, the increase in perceptions of fairness is approximately 13% of the mean level of confidence (2.797) that the market is fair.

Table 8 Impact of VEN on Consumer Sentiment

	(1)	(2)	(3)
	Fairness	Cost and reliability	Tools to manage
Longer VEN access	0.374^{**}	0.152	-0.242
	(0.197)	(0.249)	(0.226)
Observations	148	148	148
Mean Dep Var	2.797	3.176	2.655

Notes: Table reports results of regressing the dependent variable (measures of consumer sentiment) on whether the respondent had longer (above median) access to trading energy on the VEN. All regressions also include cohort fixed effects to capture potential differences across earlier and later joining participants. Mean Dep Var is the mean of the dependent variable. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.06$, *** $p < 0.01$

[13] Responses use data collected up to April 30, 2026. Respondents who had longer access to the VEN are defined as those who had had more than 60 days trading at the time of their response. Respondents to the midline survey may not be a random subset of all participants in the study. Results are very similar if instead we use "assigned to a shorter baseline period" (i.e. treatment) as the explanatory variable.

Limitations

The results should be interpreted in light of several limitations of the trial. First, the study was conducted over a relatively short period and therefore captures behavioural responses to participation in the VEN rather than longer-term investment responses. That is, the analysis is conducted with the stock of consumer energy resources largely fixed.

As a result, the estimated impacts reflect changes in the utilisation of existing resources rather than structural changes in household energy infrastructure over time. For example, the analysis does not capture potential changes in household investment decisions, such as the adoption of batteries, electric vehicles, or other electrified appliances that may arise from continued participation in a VEN.

Second, the results are specific to the retail pricing structure and trading arrangements implemented in this trial. Alternative retail offerings, pricing mechanisms, and trading rules may influence both participant behaviour and the distribution of benefits between importing and exporting sites.

Finally, participants had limited visibility of broader system conditions. Trading decisions were not informed by real-time information on renewable generation availability, network constraints, or wholesale market conditions, and the trial did not include explicit incentives aimed at reducing peak demand. Consequently, the observed behavioural responses should be interpreted within the context of the information and incentives available to participants during the trial.

Conclusion

This study provides causal evidence that a Virtual Energy Network (VEN) can improve the utilisation and value of consumer energy resources (CERs) by addressing the core coordination problem in decentralised energy systems. Three key conclusions emerge:

First, price-mediated coordination works. Access to the VEN increases electricity imports during daylight and shoulder periods for non-generating participants, consistent with an increase in demand at times of abundant solar generation. There is suggestive, though likely not statistically significant, evidence of a stronger response on high solar days, indicating some alignment with the availability of excess solar generation. Decomposing bill impacts into price and behavioural effects shows that smaller users are more price responsive while larger users benefit primarily through lower pricing.

Second, the VEN improves allocative efficiency without imposing large behavioural burdens. Our results suggest that relatively simple, rule-based trading arrangements, alongside automated matching, can induce meaningful changes in consumption patterns.

Third, gains are shared across participants and extend beyond purely financial outcomes. Generating sites receive higher prices for exports, while importing sites face lower effective prices. At the same time, access to the VEN increases perceptions of fairness in the energy system. This suggests that appropriately designed market mechanisms can strengthen both economic efficiency and social licence—an increasingly important constraint in the energy transition.

Finally, while the VEN primarily shifts demand towards periods of high solar generation, we also observe some increase in consumption during evening hours. This response reflects the current design's focus on utilising excess solar generation rather than explicitly incentivising peak demand reduction. This observation highlights an important avenue for further investigation.

Future work could also examine whether providing participants with more granular and timely information about system conditions, introducing dynamic network pricing, or offering targeted incentives for peak-demand reduction further improves alignment between consumer behaviour and system needs. More broadly, a randomised controlled trial that incorporates network constraints or wholesale market signals would provide valuable insights into their potential to support system-wide optimisation.