Received: 7 February 2023 | Revised: 26 November 2023 | Accepted: 30 November 2023

DOI: 10.1002/jid.3876

RESEARCH ARTICLE

JOURNAL OF INTERNATIONAL DEVELOPMENT WILEY

An analysis of the relationship between rental housing and adoption of self-generating energy sources in Brazil using matching methodology

Maria Laura Victória Marques[1] | Daniel de Abreu Pereira Uhr[2] | Bruno Benevit[3] | Júlia Gallego Ziero Uhr[2]

[1]Universidade do Estado do Rio de Janeiro (UERJ), Rio de Janeiro, Brazil

[2]Organization and Markets Graduate Program (PPGOM), Universidade Federal de Pelotas (UFPel), Pelotas, Brazil

[3]The Graduate Program of the Department of Economics, Universidade de Brasília (UnB), Brasília, Brazil

Correspondence
Daniel de Abreu Pereira Uhr, Organization and Markets Graduate Program (PPGOM), Universidade Federal de Pelotas (UFPel), Pelotas, Brazil.
Email: daniel.uhr@gmail.com

Funding information
FAPERGS, Grant/Award Number: 21/2551-0002189-6; CAPES, Grant/Award Number: n.001; CNPq, Grant/Award Number: 309836/2021-2

Abstract

We examine the effect of household tenure choice on adopting self-generation energy technologies in Brazil. We employ microdata from the Household Budget Survey (*POF*) dataset for 2017 and 2018 from the Brazilian Institute of Geography and Statistics (IBGE) and matching methodology to evaluate various hypotheses regarding occupancy status, credit availability, purchasing power and life cycle theory. We also use placebo treatments, propensity score weighting, entropy balancing and Rosenbaum's sensitivity analysis to evaluate the robustness of our findings. Results show that leasing a residence negatively and significantly affects families' adoption of self-generating technologies with an estimated probability reduction of around 62%, with greater effects when considering credit, wages and life cycle.

KEYWORDS

Brazil, energy transition, residential rental market, self-generation energy technologies

1 | INTRODUCTION

Recent research in energy economics highlights barriers to the adoption of micro-generation technologies and to energy-saving measures associated with the occupancy status of residential units. Mainly, empirical evidence indicates that there is low adoption rates of sustainable energy technologies among the residential rental market, resulting in households with low energy efficiency and, therefore, high rates of energy consumption and expenditure (Bird & Hernández, 2012; Green et al., 2018; McCabe et al., 2018; Poruschi & Ambrey, 2019; Vega et al., 2022).

Potential contributing factors include split incentives between landlords and tenants which can be explained by the difference in costs and benefits of adopting sustainable energy technologies, that is, the flow of investments and benefits are not adequately rationed amongst both parties, impairing investment decisions.

Best et al. (2021) found a negative effect on leased households when investigating the adoption of photovoltaic panels in Australia using data from the Survey of Income and Housing. Sommerfeld et al. (2017), employing data also for Australia at the postal code level between 2001 and 2014, found that areas with a higher concentration of tenants and apartment buildings had a lower adoption rate of photovoltaic panels. Vega et al. (2022) analysed the determinants for adopting sustainable energy technologies such as photovoltaic panels, thermal insulation and boilers and found negative effects for their adoption among tenants. Evidence also points to homeowners' under-investment in energy efficiency measures when they do not pay their energy bills. Melvin (2018) shows that when tenants pay the energy bill, landlords invest less in energy efficiency measures when compared to residences occupied by the owners.

Even though there is a consensus that occupancy status influences investment decisions, economists find this topic difficult to explain (Charlier, 2015). Socioeconomic and demographic factors that impact the choice to lease or own a home also impact the adoption of self-generation technologies (such as generators, solar and wind power). Variables include the individuals' income, level of education and capital availability (Barbose et al., 2018; Best et al., 2021; Schaffer & Brun, 2015; Sommerfeld et al., 2017). Other factors, such as the stage of the life cycle, that is, the age of the head of the household, constitute one important determinant for the adoption of photovoltaic panels and other energy efficiency measures (Best et al., 2021; Vega et al., 2022). Bondio et al. (2018), when investigating the adoption of photovoltaic panels for a sample from Queensland, Australia, showed significant differences between households in which the head of the family was over 50 years old and those in which the age was below 50.

The tenant's projected short stay at the property may be a disincentive to fixed capital expenditures, which typically have long-term returns. For middle-class and low-income families, the upfront costs of implementing alternative energy-generating technologies is often cited as a barrier to their adoption (Barbose et al., 2018; Best et al., 2021; Carley et al., 2018; Ebrahimigharehbaghi et al., 2019; Lukanov & Krieger, 2019; Zander, 2020). Finally, the absence of reliable and accessible information to support decision-making is also important (Scarpa & Willis, 2010; van Middelkoop et al., 2017; Zander, 2020). Social contexts, such as engagement in pro-environment organizations and their respective collaboration networks can influence decisions by disseminating information, opinions and credible examples from third parties (Simpson & Clifton, 2016; van Middelkoop et al., 2017; Vega et al., 2022).

Given the split incentives problem, we suggest their impact extends beyond the landlord-tenant relationship. According to the most recent Intergovernmental Panel on Climate Change (IPCC) reports, a significant decrease in carbon dioxide emissions is necessary to keep global warming at pre-industrial levels (IPCC, 2023). Intersectoral efforts should be employed in this stage of the process. Regarding the residential market, the effort needed relates to a shift in the energy consumption pattern, where the adoption of self-generation technologies plays a significant role.

Considering this context, we investigate the split incentives in the residential rental market in Brazil. Particularly if occupancy status (if tenant or owner) impacts the investment in alternative (self-generation) energy sources. We investigate three other related hypotheses to further contribute to the energy economics literature. Firstly, whether credit and financing availability influences the adoption of self-generation technologies in residences occupied by tenants. Secondly, we capture the impact of purchasing power on the choice to invest in microgeneration technologies. Thirdly, we investigate the life cycle theory and the relationship between the age of the head of the household and the adoption of alternative energy sources.

To our knowledge, we are the first to determine how occupancy status in the residential market affects Brazil's adoption of self-generation energy technologies. Additionally, we conduct subsample analyses to clarify important concerns in the literature about this phenomenon, such as credit availability, purchasing power and life cycle. We innovate by applying matching methods and survey microdata not yet employed in the literature. Therefore, we produce more accurate and ground-breaking estimations (Dugoff et al., 2014). The findings are essential to general energy policies and to direct public policies towards self-generating systems, allowing equitable distribution of the costs and benefits of the energy transition among social groups.

We employed microdata from the Household Budget Survey (*Pesquisa de Orçamento Familiar—POF)* conducted by the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*—IBGE) for the years 2017 and 2018. We combined the POF with data from the National Electric Energy Agency (*Agência Nacional de Energia Elétrica*—ANEEL) to construct the electricity tariff variables. The result variable is binary, indicating whether the residence possesses self-generating energy technologies (generator, solar or wind power). The treatment variable is also binary, indicating a leased or owned residence. The covariates originate from POF dataset. We applied the matching methodology with different metrics, and the Kernel Tricube estimator proved to be the most adequate. Our main finding indicates that occupancy status impacts the investment in self-generation energy technologies. We find significant negative effects among tenants for adopting alternative energy sources.

In addition to this introduction, the following section presents the POF and ANEEL databases, variable selection and descriptive statistics. Section three approaches the identification strategy for the employed methodology. We present the results in section four. Section five contains final remarks and policy implications.

2 | DATA

We employ the Household Budget Survey (POF) from the Brazilian Institute of Geography and Statistics (IBGE). The POF is carried out by sampling and collecting data on family budgets, their consumption structures, expenses, income and other relevant characteristics to evaluate the composition of family expenses according to income classes and the size of the consumer market for groups of products and services. Sample selection employs a conglomerate sampling plan with two stages of selection, using geographic and statistical stratification of first-stage units. The sectors correspond to the units of the first selection stage, and the households to the second stage units. Each household belonging to the POF represents a certain number of permanent private households in the general population (universe). Therefore, each household in the research is associated with a sampling weight or expansion factor that allows estimates of quantities of interest to be obtained for the general population of the research. According to IBGE, the Institute conducted POF 2017–2018 between 11 July 2017 and 9 July 2018, and the data, after compilation and analysis, was presented on 15 January 2018.

The POF contains information about energy consumption and self-generation at the household level. Our outcome variable is binary, assuming value one if the residence possesses any self-generating energy technologies such as generator, solar and/or wind power (alt. energy source) and zero otherwise. As we want to verify the influence of occupancy status on the adoption of self-generation, we define the treatment also as a binary variable: if the family leases the residence, the household is considered treated and assumes value one (rented); zero otherwise (owned and/or financed). We only conditioned the analysis to house-type constructions since cofounding factors inherent to apartment buildings and condominiums may affect the analysis. Adopting self-generation technologies in apartment buildings, for instance, depends on the agreement between several residents and owners concerning different space uses. Furthermore, we excluded dwellings provided by other family members or those registered with a different property status or acquired through financing.

Table 1 presents the descriptive statistics.

To control the sensitivity of the household to electricity prices, we constructed a variable based on the residential electricity tariffs defined by the National Electric Energy Agency[1] (ANEEL) for each state of the federation and each year of analysis. We deflate the value of the energy tariff to 15 January 2018, and apply the natural logarithm. Other covariates originate from the POF dataset. These covariates control for internal household influences on the adoption of self-generation. Firstly, we consider variables characterizing the head of the household, such as age, race,

TABLE 1 Descriptive statistics.

	Treated		Control		Sample	
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.
Outcome Variables						
Alt. Energy Source	0.002	0.046	0.011	0.109	0.010	0.100
Groups						
Rented	1.000	0.000	0.000	0.000	0.173	0.388
Own	0.000	0.000	0.933	0.260	0.771	0.431
Financed	0.000	0.000	0.067	0.260	0.056	0.235
Own or financed	0.000	0.000	1.000	0.000	0.827	0.388
Covariates						
Ln Kwd Tax Deflated	−0.690	0.095	−0.669	0.111	−0.672	0.109
Head Age	41.744	14.045	52.799	15.799	50.885	16.079
Head Race	0.603	0.471	0.622	0.503	0.619	0.498
Head Education Years	9.432	4.006	8.050	5.071	8.290	4.918
Head Worked Last Year	0.972	0.160	0.964	0.192	0.966	0.187
Head Pub. Statutory	0.040	0.189	0.054	0.236	0.052	0.228
Head Pub. Non-Statutory	0.019	0.132	0.019	0.142	0.019	0.140
Head Military	0.005	0.068	0.006	0.079	0.006	0.077
Head Priv. Employee	0.738	0.424	0.556	0.516	0.588	0.505
Head Self-Employed	0.238	0.410	0.248	0.448	0.247	0.442
Head Employer	0.026	0.153	0.032	0.182	0.031	0.177
Residents	3.007	1.423	3.101	1.575	3.084	1.549
Children dummy	0.626	0.466	0.618	0.504	0.619	0.498
Television	1.204	0.571	1.359	0.761	1.332	0.732
Air conditioning	0.142	0.430	0.308	0.774	0.279	0.724
Refrigerator	0.999	0.206	1.026	0.278	1.021	0.266
Urban	0.968	0.170	0.833	0.388	0.856	0.360
Metropolitan	0.395	0.471	0.341	0.492	0.350	0.489
North	0.048	0.206	0.085	0.290	0.079	0.276
Northeast	0.229	0.405	0.283	0.468	0.274	0.457
Midwest	0.105	0.295	0.072	0.268	0.078	0.274
Southeast	0.486	0.481	0.397	0.508	0.413	0.505
South	0.132	0.326	0.163	0.383	0.157	0.373

Note: This table reports mean values and standard deviations for the variables of interest in the treatment and control groups and the whole sample. Reported statistics consider POF's complex sampling plan with an expansion factor adjusted for 15 January 2018 (sample weight variable), geographic and statistical stratifications (Stratum), primary sampling unit code (UPA code) and Taylor's linearized variance. State variables were omitted due to space.

level of education, formal job and children. Secondly, we consider discrete variables that reflect the household's income level and demand patterns, such as the number of televisions, air conditioners and refrigerators. Thirdly, we add indicator variables for different Brazilian regions and states (federative units) to control for geographic and cultural characteristics.

3 | METHOD

Equation (1) represents the relationship we want to study:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \varepsilon_i \tag{1}$$

where Y_i is the outcome variable (alternative energy source), T_i represents the treatment variable (occupancy status), X_i is a vector for the control covariates and ε_i represents the stochastic error term.

If families' choice between leasing or owning a residence were random, then it would be sufficient to use the difference in averages between those who received and those who did not receive the treatment to determine the average impact of adopting self-generation (alternative energy sources). However, it is reasonable to infer that observable characteristics related to economic variables cause selection bias between participants in the treated and control groups influencing the occupancy status, that is, the decision to own or rent a household. Therefore, the matching approach is the most suitable for the econometric strategy. The matching approach employs observable variables to create a control group similar to the treatment group. Additionally, if each treated unit exhibits at least one pair in the control group (common support hypothesis), then we ensure the conditional orthogonality of the treatment. Matching techniques in observational research come close to having the properties of randomized experiments under such assumptions.

King and Nielsen (2019) argue that, under certain circumstances, the Propensity Score Method (PSM) can produce fragile and non-robust estimates that vary depending on the employed model. They call this the 'propensity score paradox', which motivates using potentially more robust methodologies like the Mahalanobis Distance Method (MDM). The MDM pairs nearby units based on the Mahalanobis distance, which we can think of as a non-scaling Euclidean distance. Suppose we find control units close to the treated units at the Mahalanobis distance. In that case, each pair will have similar covariate values, and the distribution of the covariates across the treatment group in the matched sample will be similar. However, Ripollone et al. (2018) investigated the impact of the propensity score paradox on epidemiological data. They found that the paradox in fact, occurred. However, it was only problematic with extreme gauge values, far beyond what would be recommended. The PSM still produced an excellent balance in the covariates. In contrast, MDM produced a poor balance, sometimes with no matches. Since no clearly defined protocol exists, we apply MDM and PSM estimators. The performance of matching algorithms is in Table A3.

The structure of the POF dataset is a particular complication for this empirical investigation. Since the POF is a weighted/complex sample and each household represents a certain number of residences in the general population, we employ an expansion factor to render the sample representative. In this case, the literature suggests adjusting the matching methods with score weights and complex sample weights for the pairing procedures fitting matching approaches for complex data (DuGoff et al., 2014).

4 | RESULTS

4.1 | Preliminary results

The first step is to estimate the propensity score. The propensity score is computed with the occupancy status as a function of the covariates. Table 2 shows the propensity score's distribution. We present the first stage of the probit propensity score results in Table A1.

The common support is a region where the propensity score of treated and untreated units overlaps. The common support region lies between 0.000 and 0.770, meaning we should not consider residences whose propensity score is larger than the maximum (0.770) for matching purposes (Caliendo & Kopeinig, 2008). Based on that procedure, we disregard six units from the analysis (off support).

The second step is to choose the matching algorithm based on performance criteria. We test the MDM (Mahalanobis) and the different metrics of the PSM (Nearest Neighbor, One-to-one, Radius, Kernel). In Table 3, we present different selection criteria. Dehejia and Wahba (2002) suggest Pseudo-R2, resulting in a matched sample size and the balancing test. The matching algorithm that balances all explanatory variables, presenting a low pseudo-R2 value with a larger sample size, is preferable. We also add LR-Chi2 and the *p*-value as criteria. An insignificant likelihood ratio test indicates that treated and untreated units have the same distribution for the covariates after matching.

The estimators based on PSM Kernel present the best indicators for the sample size (lower Pseudo-R2 and all units on the common support region). Considering the LR test, the Kernel–Biweight and Kernel–Tricube give the best fit. Nonetheless, we propose employing all five Kernel algorithms since the performance among them was marginally different. This strategy also helps with verifying the strength of our results.

Table 4 presents the balance of covariates between the treated and control groups before and after matching. Both groups have significant differences in mean values for most covariates before the matching procedure, except for the Head Labor status (Head Pub. Non-Statutory, Head Military, Head Self-Employed) and the Children dummy variable, as indicated by p-values. After the PSM matching procedure, *p*-values indicate that both groups are comparable in their observable characteristics.

TABLE 2 Distribution of propensity score in the sample.

Sample	Mean	Min.	Max.	Observ.	Off support	On support
Treated	0.266	0.001	0.684	6814	6	6808
Untreated	0.129	0.000	0.684	38 091	0	38 091
Sample	0.150	0.000	0.770	44 905	6	44 899

Note: The first three columns report propensity score distributions' means, minimum and maximum values. The last three columns present the total number of residences, the number of residences off support region and the number of residences in the support region.

TABLE 3 Performance criteria for different matching algorithms.

Matching algorithm	Pseudo-R2	Sample size	LR-Chi2	p > Chi2
Unmatched	0.153	44 899	5867.31	0.000
Mahalanobis	0.007	44 824	137.36	0.000
Nearest Neighbor	0.004	44 899	75.93	0.002
One-to-One w/Caliper	0.004	44 899	75.93	0.002
Radius	0.002	44 899	37.51	0.744
Kernel–Gaussian	0.002	44 899	38.45	0.708
Kernel–Biweight	0.002	44 899	36.91	0.767
Kernel–Tricube	0.002	44 899	36.88	0.768
Kernel–Epanechnikov	0.002	44 899	37.05	0.762
Kernel–Uniform	0.002	44 899	37.51	0.744

Note: This table reports the performance criteria for matching algorithms. The first row considers a naive, unmatched model. All matching algorithms consider the same covariate vector. All PSM models consider the sample weight for estimation. The nearest neighbour considers only one neighbour. The caliper estimator considers a caliper of 0.01. The radius estimator considers a bandwidth of 0.01. The likelihood ratio test (LR-Chi2) and the *p*-value associated (p > Chi2) criteria consider the matched sample.

TABLE 4 Covariates balance test.

Covariates	Before Matching Mean Treated	Before Matching Mean Control	Before Matching *P*-value	After Matching Mean Treated	After Matching Mean Control	After Matching *P*-value
Ln Kwd Tax Deflated	−0.690	−0.669	0.000	−0.664	−0.661	0.211
Head Age	41.906	52.888	0.000	41.946	41.723	0.366
Head Race	0.603	0.623	0.025	0.556	0.549	0.410
Head Education Years	9.423	8.032	0.000	9.074	9.054	0.790
Head Worked Last Year	0.972	0.965	0.003	0.964	0.965	0.721
Head Pub. Statutory	0.042	0.055	0.000	0.044	0.043	0.835
Head Pub. Non-Statutory	0.019	0.019	0.959	0.021	0.021	0.803
Head Military	0.005	0.006	0.511	0.007	0.004	0.023
Head Priv. Employee	0.751	0.564	0.000	0.722	0.721	0.930
Head Self-Employed	0.241	0.253	0.145	0.254	0.257	0.611
Head Employer	0.026	0.032	0.066	0.026	0.024	0.532
Residents	2.994	3.087	0.001	3.018	3.028	0.677
Children dummy	0.623	0.615	0.315	0.625	0.616	0.295
Television	1.204	1.357	0.000	1.164	1.158	0.521
Air conditioning	0.140	0.307	0.000	0.170	0.164	0.466
Refrigerator	0.999	1.025	0.000	0.991	0.985	0.148
Urban	0.967	0.831	0.000	0.945	0.935	0.014
Metropolitan	0.396	0.338	0.000	0.380	0.384	0.655
North	0.046	0.084	0.000	0.091	0.090	0.893
Northeast	0.229	0.283	0.000	0.360	0.363	0.679
Midwest	0.103	0.072	0.000	0.147	0.143	0.566
Southeast	0.490	0.398	0.000	0.278	0.282	0.630
South	0.132	0.164	0.000	0.124	0.121	0.595

Note: This table reports the covariate's means for treatment and control groups before and after matching with Propensity Score Method (PSM) Tricube Kernel and associated *p*-values.

Next, we verify the influence of occupancy status on adopting self-generation energy technologies. Table 5 presents the results considering all five Kernel algorithms. All results are statistically significant at a 1% confidence level. As the literature suggests, we can observe that leased households (rented) negatively impact the adoption of alternative energy sources. That is, we find significantly negative effects among tenants for adopting alternative energy sources: a mean reduction between 61.91% and 62.50% when compared to the mean outcome of control units (not leased residence).

Tables A5 and A6 in the Appendix present the results considering alternative methodologies and robustness checks. Tables A2–A4 present the balance of covariates for these different methodologies. First, we consider a random treatment variable with mean and deviation like the original treatment and replicate the complete analysis considering the PSM Kernel-Biweight to verify if results from the previous section were due to chance (Type I Error). Results were not as significant as expected (Table A5, Column 1). Then, we propose adjusting the propensity score to weigh each unit in the control group by inverting the probability of not receiving treatment (PSW). Table A5 Column 2 reports the results for the PSW. As a third robustness strategy, we estimate the effect of the treatment by

TABLE 5 Estimates of the effect of occupancy status to self-generation considering PSM for Kernel matching algorithms.

	(1) Kernel Gaussian	(2) Kernel Biweight	(3) Kernel Tricube	(4) Kernel Epanech.	(5) Kernel Uniform
Rented	−3.917***	−3.833***	−3.844***	−3.848***	−3.821***
z-stat	(−4.45)	(−4.43)	(−4.43)	(−4.44)	(−4.46)
N. on support	44 899	44 899	44 899	44 899	44 899
Average outcome for control units	6.267 [−62.50%]	6.184 [−61.99%]	6.194 [−62.06%]	6.198 [−62.08%]	6.171 [−61.91%]

Note: This table reports estimates for the effect off occupancy status on the probability of adopting self-generation for different Propensity Score Method (PSM) matching estimators. Column 1 is for Gaussian Kernel, Column 2 is for Biweight Kernel, Column 3 is for Tricube Kernel, Column 4 is for Epanechnikov Kernel and Column 5 is for Uniform Kernel—coefficients for Rented variable and Average outcome for control units multiplied by 1000. All estimations consider bootstrap standard errors. The values in parentheses are *z* statistics. The values in brackets are the average percentage difference for the treated group.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

employing the entropic balancing of covariates (Hainmueller, 2012) for complex data (DuGoff et al., 2014), considering the first moment, second and third moments. Table A5 Columns 3 to 5 report the results. All estimates in Table 5 confirm the robustness of our previous results with significantly negative effects between 65.78% and 68.45%. As a last robustness strategy, we check the results from hidden bias from unobserved variables by performing the Rosenbaum bounding sensitivity analysis (Caliendo & Kopeinig, 2008; Rosenbaum, 2002). Table A6 presents the critical levels of gamma ($\gamma = 1$ to $\gamma = 4$) over which the causal inference must be questioned. Results show that estimates do not change, even when allowing treated and control groups to differ in unobserved characteristics (*p*-critical values are significant). Therefore, we can conclude that estimates do not suffer from selection bias.

Additionally, to control for the effect of household income, we included an income variable in the set of covariates. Table B1 reports results when considering income as a covariate. Results did not undergo significant changes and are still close to those found in the original specification, as expected. However, although the results remained robust, we understand that the inclusion of income may add weaknesses to the model since this covariate is usually strongly related to other variables, hence the caution in its use.

The next section will deepen the analysis to assess socioeconomic factors pointed out by the literature that might be relevant for adopting self-generation energy technologies, such as credit and financing availability, purchasing power and age of the head of the household (life cycle theory).

4.2 | Main results

In this section, we investigate three other hypotheses to further contribute to the literature on energy economics. Firstly, whether credit and financing availability influences the adoption of self-generation technologies in residences occupied by tenants. Secondly, we capture the impact of purchasing power on the choice to invest in micro-generation technologies. Thirdly, we investigate the life cycle theory and the relationship between the age of the head of the household and the adoption of alternative energy sources.

Stability and predictability of monthly income distinguish the Brazilian public sector from the private sector. It's well known that workers from the public sector experience easier access to credit and receive higher credit support.

Also, the private sector accounts for the smallest share of payroll loans, and its volume is highly volatile in response to changes in macroeconomic variables (de Medeiros et al., 2018). Therefore, to evaluate the effect of credit and financing availability on the adoption of self-generation among tenants, we condition the analysis by subsamples of households where the head of the family works in the public sector or the private one for diverse subcategories.

Table 6 presents the results restricting the sample to the different employment subsectors considering public servants (Panel A) and private labour (Panel B). Results are statistically significant only for Panel B. We can observe that, for the subsectors considering only private labour (domestic workers, self-employed people and employees), leasing a residence negatively impacts adopting alternative energy sources. Compared to the previous section, mean reductions in probability increase by 8 to 38 points depending on the considered estimation. We find significantly stronger negative effects among tenants employed in the private sector for adopting self-generation: a mean reduction between 100% and 70.69% compared to the mean outcome of control units (not leased residence). Less access to credit and household renting reduces the chance to invest in alternative energy sources even further. Although positive, the estimated coefficients for the treatment in Panel A (statutory, non-statutory servants and military) were not statistically significant. These results align with the literature regarding access to capital as an important factor for adopting self-generation energy technologies. Since we have found stronger impacts for treatment in the private sector, we focus on these households for the following analysis.

TABLE 6 Analysis restricted to employment sectors.

Panel A. Public Sector	**(1) Public Statutory**	**(2) Public Non Statutory**		**(3) Military**
Rented	10.946	4.338		−5.397
z-stat	(1.40)	(0.41)		(−0.48)
N. on support	2527	887		174
Average outcome var. for control units	6.061	2.805		5.397
	[180.60%]	[154.64%]		[−100.00%]
Panel B. Private Sector	**(1) Domestic Worker**	**(2) Private S. Employee**	**(3) Employer**	**(4) Self-Employed**
Rented	−2.495**	−3.853**	−11.435*	−6.489***
z-stat	(−2.31)	(−2.20)	(−1.88)	(−3.78)
N. on support	2051	10 109	1299	12 630
Average outcome var. for control units	2.495	5.450	17.352	8.230
	[−100.00%]	[−70.69%]	[−65.90%]	[−78.84%]

Note: This table reports estimates for the effect off occupancy status on the probability of adopting self-generation for different employment sectors considering Propensity Score Method (PSM) Tricube Kernel. Panel A considers public servants, Panel B private labour. Panel A Column 1: results for households where the head of the family is a public statutory worker. Panel A Column 2: results for households where the head of the family is a public worker (non-statutory). Panel A Column 3: results for households where the head of the family is a military worker. Panel B Column 1: results for households where the head of the family is a domestic worker. Panel B Column 2: results for households where the head of the family is a private-sector employee. Panel B Column 3: results for households where the head of the family is an employer. Panel B Column 4: results for households where the head of the family is a self-employed worker. Coefficients for Rented variable and Average outcome for control units multiplied by 1000. All estimations consider bootstrap standard errors. The values in parentheses are *z* statistics. The values in brackets are the average percentage difference for the treated group.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

For the second hypothesis, we want to capture the impact of purchasing power on the choice to invest in microgeneration technologies. Families living in leased households tend to be low-income. Firpo (2020) points out that 17% of Brazilians spend part of their income on rent. Concerning this group, 29% of families earn up to two minimum wages on average, while 77% make up to six minimum salaries. Additionally, 80% of working individuals are self-employed or informally employed and earn up to two minimum monthly earnings. Additionally, rents and other energy costs compromise a considerable percentage of their income. Studies show that the initial cost of adopting microgeneration technologies is a barrier for several families with lower middle income (Best et al., 2021; Simpson & Clifton, 2016; Zander, 2020). Therefore, to evaluate the effect of purchasing power on adopting self-generation among tenants, we condition the analysis by subsamples of household income measured by minimum wage strata.

Table 7 presents the results, which are also conditioned to households where the head of the family works in the private sector. Among households with lower purchasing power (0–3 and 3–6 minimum wages), leasing a residence negatively and significantly impacts adopting alternative energy sources, with an average percentage difference between 68,35% and 91,65%. We find a stronger negative effect for tenants in the 0–3 minimum wage strata, with a mean reduction in the probability of investing in alternative energy sources of almost 92% compared to the mean outcome of control units (not leased residence). Results aren't significant for households in the six or more minimum wage strata. These results also align with the literature.

Considering our last hypothesis (life cycle theory) and the referenced literature, individuals 60 or older are more likely to invest in sustainable technologies because they are more likely to make long-term investments. Therefore, concerning the relationship between the age of the head of the household and the adoption of alternative energy sources among leased residences, we expect estimation coefficient's to be statistically not significant. The average age of tenants is approximately 41, against 53 for landlords. We proceed with the analysis following the same previous strategy: we condition the estimations by subsamples of tenant's age strata. We consider five age ranges: 20–29 years, 30–39 years, 40–49 years, 50–59 years and 60 or over. Results are reported in Table 8, columns 2 to 6. As before, we restrict the analysis to households where the head of the family works in the private sector. Column 1 presents the mean results for the private sector from Table 6 (Panel B).

The treatment coefficients are significant and negative for all age groups except 60+. That is, leasing a residence negatively and significantly impacts the adoption of alternative energy sources among all age groups under 60 years,

TABLE 7 Analysis restricted by household purchasing power conditioned to private sector.

	(1) Private Sector	(2) 0–3 MW	(3) 3–6 MW	(4) 6 + MW
Rented	−4.733***	−3.811***	−4.936**	−4.869
z-stat	(−5.20)	(−4.07)	(−2.27)	(−1.53)
N. on support	24 799	12 595	7881	4318
Average outcome var. for control units	6.212	4.159	7.222	10.434
	[−76.20%]	[−91.65%]	[−68.34%]	[−46.66%]

Note: This table reports estimates for the effect off occupancy status on the probability of adopting self-generation for different household income strata conditioning to households where the head of the family works in the private sector. All estimations consider Propensity Score Method (PSM) Tricube Kernel bootstrap standard errors. Column 1 presents the mean results for private labour from Table 6, Panel B. Columns 2, 3 and 4 present the results for household strata whose income is between 0 and 3, 3–6 and 6 or more minimum wages (MW), respectively. The categories in columns 2 to 4 represent 47.55%, 29.85% and 22.60% of the subsample. Coefficients for Rented variable and Average outcome for control units multiplied by 1000. The values in parentheses are *z* statistics. The values in brackets are the average percentage difference for the treated group.

*Statistical significance at 10%.

**Statistical significance at 5%.

***Statistical significance at 1%.

TABLE 8 Analysis restricted to age range conditioned to the private sector.

	(1) Private Sector	(2) Head Age 20–29	(3) Head Age 30–39	(4) Head Age 40–49	(5) Head Age 50–59	(6) Head Age 60+
Rented	−4.733***	−6.379**	−4.693***	−4.191**	−5.722***	1.209
z-stat	(−5.20)	(−2.07)	(−2.64)	(−2.54)	(−3.18)	(0.32)
N. on support	24 799	2721	6104	6697	5687	3425
Average outcome var. for control units	6.212	7.264	5.975	6.050	7.292	2.537
	[−76.20%]	[−87.83%]	[−78.53%]	[−69.28%]	[−78.47%]	[47.64%]

Note: This table reports estimates for the effect of occupancy status on the probability of adopting self-generation for different age ranges, conditioning it to households where the head of the family works in the private sector. All estimations consider Propensity Score Method (PSM) Tricube Kernel bootstrap standard errors. Column 1 presents the mean results for private labour from Table 6, Panel B. Columns 2, 3, 4, 5 and 6 present the results for the head of the family age range between 20 and 29, 30–39, 40–49, 50–59 and 60 or more years old, respectively. Coefficients for Rented variable and Average outcome for control units multiplied by 1000. The values in parentheses are *z* statistics. The values in brackets are the average percentage difference for the treated group.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

with an average reduction in the probability of investing in alternative energy between 69.28% and 87.83%. We find a stronger negative effect among the 20–29 age strata, with an average reduction of almost 88% compared to the mean outcome of control units (not leased residence). Leased households with younger family heads are less likely to adopt or invest in self-generation technologies. These results also align with the literature.

Additionally, to control for the effect of household income, we included an income variable in the set of covariates to evaluate hypotheses one and three. Table C1 reports results for the effect of credit and financing availability on the adoption of self-generation, considering income as a covariate and conditioning the analysis by subsamples of households where the head of the family works in the public sector or the private one for diverse subcategories, as in Table 6. As expected, results remain robust, and average percentage differences for the treated group in Panel B are practically equal to those in Table 6. Table C2 reports results for the relationship between the age of the head of the household and the adoption of alternative energy sources, considering income as a covariate. Results did not undergo significant changes and are still close to those found in Table 8, as expected. As informed in the preliminary results section, although results remained robust, we understand that the inclusion of income may add weaknesses to the model since this covariate is usually strongly related to other variables, hence the caution in its use.

5 | FINAL REMARKS AND POLICY IMPLICATIONS

This study was the first to evaluate the hypothesis that residential tenure choice influences the uptake of self-generation energy technologies in Brazil, inaugurating the discussion on the potential existence of split incentives between landlords and tenants in the country. We employ the Household Budget Survey (POF) dataset for 2017–2018, combined with matching approaches and diverse robustness techniques. The findings are consistent with the prediction that renting a household negatively impacts adopting self-generation energy technologies in Brazil. This impact has uneven distribution across the public and private employment sectors, employee and employer statuses and age groups. Renting a home implies a reduction of 62.5% to 71% in the probability of adoption of self-generating energy technologies. These findings are generalizable since the POF is a representative sample of the Brazilian population.

Characteristics of the residential rental market in Brazil may suggest the existence of split incentives. Firstly, the tenant is responsible for paying the power bill, which provides little motivation for the landlord to absorb the expense of investing in the residence's energy efficiency or self-generation entirely, from which only the tenant will benefit. Low investment rates by landlords result from a market feature like the one Melvin (2018) examined in German society. Furthermore, a lack of incentive to adopt self-generation technologies can be attributable to the lack of specific regulation and the uncertainties introduced by current legislation. The Tenancy Law (Law No. 8245, of 18 October 1991) states that: 'Unless expressly provided in the contract to the contrary, improvements introduced by the tenant, even if not authorized by the landlord, as well as useful improvements, provided they are authorized, will be compensated and will allow the exercise of the right of retention'. However, the same legislation states, 'Voluptuous improvements are not compensable and may be charged by the tenant at the end of the lease, as long as their removal does not affect the structure of the property'. There is no consensus in the legal sector about what voluptuous improvements are, characterizing a problem arbitrated on a case-by-case basis and resulting in legal uncertainty. Furthermore, there is no explicit reference in the law to improvements associated with energy generation, whether in terms of energy efficiency or renewable technologies. Therefore, uncertainties between property rights and the division of costs and benefits between owners and tenants related to investments of this nature can cause serious disincentives to their adoption.

These issues open space for governance models in which both landlord and tenant will benefit from adopting new technologies, thus representing an advance in the housing sector for the challenges of the energy transition. However, given our research design, we cannot control or measure such effects. It is an important subject, and an Economic Analysis of Law approach would be interesting, although challenging for the applied econometric methodology.

We recommend policies that focus on minimizing the uncertainty between owners and tenants. In Australia, the national policy Solar Victoria allows both actors to sign an agreement—'Solar Homes Landlord-Tenant Agreement'—to reduce uncertainties about the distribution of costs and benefits of installing solar panels (Zander, 2020). In the Netherlands, the 'Energy Performance Incentive Scheme for the Rental market (STEP)' and 'Energy Savings Fund for the Rental market' programmes were developed to promote subsidized financial resources for investments in the energy efficiency of buildings intended for the rental market (IEA, 2021a, 2021b; Vega et al., 2022). Brazil could apply similar programs.

Other governance models contribute to the alignment of incentives between landlords and tenants, such as solar communities or 'shared solar'. These models employ distributed solar energy, allowing those involved to buy or rent part of a larger photovoltaic system installed on apartment terraces or semi-urban open areas, creating possibilities for generating employment and income for their management. It also allows those who do not have space in their homes to participate in self-generation systems (McCabe et al., 2018; Zander, 2020). However, this kind of model may depend on specific regulations. Another model is the so-called third party-owned solar system. In this model, an outsourced agency manages the photovoltaic system in large buildings or solar complexes in exchange for a predictable agreement (between lessors, lessees and the Third Party) to buy energy for an economically satisfactory period. This third-party agent can be a private company, an association, or even a government-operated one (Green et al., 2018; Simpson & Clifton, 2016; Zander, 2020).

However, considering policies already developed in Brazil to encourage investment in energy technologies, the subsidized credit policies implemented by the National Development Bank (BNDES) can play a crucial role in overcoming barriers to the energy transition in Brazil. For example, the main line of financing for families to adopt renewable energies, 'FINAME – Baixo Carbono', is operated by private commercial banks and other regional development banks (BNDES, 2021a, 2021b, 2021c). The policy intends to stimulate purchasing energy-efficient technologies, such as solar energy generating systems, wind turbines up to 100 kW and solar heaters/collectors. An effective way to mitigate split incentives might be to create a separate credit line focused on the residential rental market with low-interest rates and extended payment periods for owners and tenants. All social classes should be able to communicate openly and easily about the need to switch to self-generating energy sources from an economic and social perspective. Municipal structures focusing on the local community and solid territorial appeals can fill this role. Economic incentives can reinforce this approach, such as gradual reductions in the Urban Property and Territorial Tax (*Imposto Predial e Territorial Urbano—IPTU*) in postal codes where renewable energy technologies are prevalent.

Finally, the database makes it impossible to extrapolate our findings to other economies and societies in other historical periods and circumstances, which is one of the work's drawbacks. Furthermore, we recognize that new investigation may deepen our study's debate, such as examining the Tenancy Law's (No. 8.245/1991) current incentives for owners and tenants or public policies listed above.

ACKNOWLEDGEMENTS

The authors are grateful to FAPERGS (grant no. 21/2551-0002189-6), CAPES (n. 001) and CNPq (grant no. 309836/2021-2) for providing partial financial support for this study.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in POF at https://www.ibge.gov.br/estatisticas/sociais/saude/24786-pesquisa-de-orcamentos-familiares-2.html?=&t=resultados, reference number 2017-2018. These data were derived from the following resources available in the public domain: - IBGE, https://www.ibge.gov.br/.

ORCID

Maria Laura Victória Marques https://orcid.org/0000-0002-9104-4054
Daniel de Abreu Pereira Uhr https://orcid.org/0000-0001-8370-0317
Bruno Benevit https://orcid.org/0000-0002-6234-6491
Júlia Gallego Ziero Uhr https://orcid.org/0000-0003-4981-848X

ENDNOTES

[1] https://www.aneel.gov.br/

REFERENCES

Barbose, G., Darghouth, N. R., Hoen, B., & Wiser, R. (2018). *Income trends of residential PV adopters: An analysis of household-level income estimates* (Technical Report LBNL-2001146; p. 36). Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States). https://emp.lbl.gov/publications/income-trends-residential-pv-adopters

Best, R., Nepal, R., & Saba, N. (2021). Wealth effects on household solar uptake: Quantifying multiple channels. *Journal of Cleaner Production*, *297*, 126618. https://doi.org/10.1016/j.jclepro.2021.126618

Bird, S., & Hernández, D. (2012). Policy options for the split incentive: Increasing energy efficiency for low-income tenants. *Energy Policy*, *48*, 506–514. https://doi.org/10.1016/j.enpol.2012.05.053

BNDES, B.N. De D. (2021a). *"BNDES Finame - Baixo Carbono"*, *BNDES*. Banco Nacional de Desenvolvimento Econômico e Social. Available at: http://www.bndes.gov.br/wps/portal/site/home/financiamento/produto/bndes-finame-baixo-carbono (accessed October 29, 2021).

BNDES, B.N. De D. (2021b). *"BNDES Finem - Meio Ambiente - Eficiência Energética"*, *BNDES*. Banco Nacional de Desenvolvimento Econômico e Social. Available at: http://www.bndes.gov.br/wps/portal/site/home/financiamento/produto/bndes-finem-eficiencia-energetica (accessed October 29, 2021).

BNDES, B.N. De D. (2021c). *"BNDES Finem - Meio Ambiente - Produtos e processos sustentáveis"*, *BNDES*. Banco Nacional de Desenvolvimento Econômico e Social. Available at: http://www.bndes.gov.br/wps/portal/site/home/financiamento/produto/bndes-finem-meio-ambiente-produtos-processos-sustentaveis (accessed 29 October 2021).

Bondio, S., Shahnazari, M., & McHugh, A. (2018). The technology of the middle class: Understanding the fulfilment of adoption intentions in Queensland's rapid uptake residential solar photovoltaics market. *Renewable and Sustainable Energy Reviews*, *93*, 642–651. https://doi.org/10.1016/j.rser.2018.05.035

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, *22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Carley, S., Evans, T. P., Graff, M., & Konisky, D. M. (2018). A framework for evaluating geographic disparities in energy transition vulnerability. *Nature Energy*, *3*(8), 621–627. https://doi.org/10.1038/s41560-018-0142-z

Charlier, D. (2015). Energy efficiency investments in the context of split incentives among French households. *Energy Policy*, *87*, 465–479. https://doi.org/10.1016/j.enpol.2015.09.005

de Medeiros, A. P., de Oliveira, G. X., & Filho, R. B. (2018). Crédito consignado: segmentos e efeitos econômicos. *RACE - Revista de Administração, Contabilidade e Economia*, *17*(2), 783–810. https://doi.org/10.18593/race.v17i2.16604

Dehejia, R., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics*, *84*(1), 151–161. https://doi.org/10.1162/003465302317331982

Dugoff, E. H., Schuler, M., & Stuart, E. A. (2014). Generalizing observational study results: applying propensity score methods to complex surveys. *Health Services Research*, *49*(1), 284–303. https://doi.org/10.1111/1475-6773.12090

Ebrahimigharehbaghi, S., Qian, Q. K., Meijer, F. M., & Visscher, H. J. (2019). Unravelling Dutch homeowners' behaviour towards energy efficiency renovations: What drives and hinders their decision-making? *Energy Policy*, *129*, 546–561. https://doi.org/10.1016/j.enpol.2019.02.046

Firpo, S. (2020). Pobres concentram despesas com aluguel. Insper: Ensino Superior Em Negócios, Direito e Engenharia (pp. 1–2). Available at: https://www.insper.edu.br/conhecimento/politicas-publicas/pobres-concentram-despesas-com-aluguel/ (accessed 13 July 2022).

Green, J., Martin, D., & Cojocar, M. (2018). 3.1 - The Untouched Market: Distributed Renewable Energy in Multitenanted Buildings and Communities. In P. Droege (Ed.), *Urban Energy Transition* (Second ed.) (pp. 401–418). Elsevier. https://doi.org/10.1016/B978-0-08-102074-6.00039-5

Hainmueller, J. (2012). Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Political Analysis*, *20*(1), 25–46. https://doi.org/10.1093/pan/mpr025

IEA, I.E.A. (2021a). *The STEP subsidy (Incentive scheme for energy performance in the rental market) – Policies*. IEA. available at: https://www.iea.org/policies/7733-the-step-subsidy-incentive-scheme-for-energy-performance-in-the-rental-sector (accessed November 25, 2021).

IEA, I.E.A. (2021b). *Energy-saving fund for loans in the rented sector (FEH) – Policies*. IEA. available at: https://www.iea.org/policies/7726-energy-saving-fund-for-loans-in-the-rented-sector-feh (accessed November 25, 2021).

IPCC, I.P. on C.C. (2023). Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. In C. W. Team, H. Lee, & J. Romero (Eds.), *Summary for Policymakers*. IPCC. (in press).

King, G., & Nielsen, R. (2019). Why Propensity Scores Should Not Be Used for Matching. *Political Analysis*, Cambridge University Press, *27*(4), 435–454. https://doi.org/10.1017/pan.2019.11

Lukanov, B. R., & Krieger, E. M. (2019). Distributed solar and environmental justice: Exploring the demographic and socio-economic trends of residential PV adoption in California. *Energy Policy*, *134*, 110935. https://doi.org/10.1016/j.enpol.2019.110935

McCabe, A., Pojani, D., & Broese van Groenou, A. (2018). Social housing and renewable energy: Community energy in a supporting role. *Energy Research & Social Science*, *38*, 110–113. https://doi.org/10.1016/j.erss.2018.02.005

Melvin, J. (2018). The split incentives energy efficiency problem: Evidence of underinvestment by landlords. *Energy Policy*, *115*, 342–352. https://doi.org/10.1016/j.enpol.2017.11.069

Poruschi, L., & Ambrey, C. L. (2019). Energy justice, the built environment, and solar photovoltaic (PV) energy transitions in urban Australia: A dynamic panel data analysis. *Energy Research & Social Science*, *48*, 22–32. https://doi.org/10.1016/j.erss.2018.09.008

Ripollone, J. E., Huybrechts, K. F., Rothman, K. J., Ferguson, R. E., & Franklin, J. M. (2018). Implications of the Propensity Score Matching Paradox in Pharmacoepidemiology. *American Journal of Epidemiology*, *187*(9), 1951–1961. https://doi.org/10.1093/aje/kwy078

Rosenbaum, P. (2002). Covariance Adjustment in Randomized Experiments and Observational Studies. *Statistical Science*, *17*(3), 286–327. https://doi.org/10.1214/ss/1042727942

Scarpa, R., & Willis, K. (2010). Willingness-to-pay for renewable energy: Primary and discretionary choice of British households' for micro-generation technologies. *Energy Economics*, *32*(1), 129–136. https://doi.org/10.1016/j.eneco.2009.06.004

Schaffer, A. J., & Brun, S. (2015). Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. *Energy Research & Social Science*, *10*, 220–227. https://doi.org/10.1016/j.erss.2015.06.010

Simpson, G., & Clifton, J. (2016). Subsidies for residential solar photovoltaic energy systems in Western Australia: Distributional, procedural and outcome justice. *Renewable and Sustainable Energy Reviews*, *65*, 262–273. https://doi.org/10.1016/j.rser.2016.06.060

Sommerfeld, J., Buys, L., Mengersen, K., & Vine, D. (2017). Influence of demographic variables on uptake of domestic solar photovoltaic technology. *Renewable and Sustainable Energy Reviews*, *67*, 315–323. https://doi.org/10.1016/j.rser.2016.09.009

van Middelkoop, M., Vringer, K., & Visser, H. (2017). Are Dutch residents ready for a more stringent policy to enhance the energy performance of their homes? *Energy Policy*, *105*, 269–282. https://doi.org/10.1016/j.enpol.2017.02.050

Vega, S. M. H., Van Leeuwen, E., & Van Twillert, N. (2022). Uptake of residential energy efficiency measures and renewable energy: Do spatial factors matter. *Energy Policy*, Elsevier, *160*, 112659. https://doi.org/10.1016/j.enpol.2021.112659
Zander, K. K. (2020). Unrealised opportunities for residential solar panels in Australia. *Energy Policy*, *142*, 111508. https://doi.org/10.1016/j.enpol.2020.111508

How to cite this article: Marques, M. L. V., Uhr, D. d. A. P., Benevit, B., & Uhr, J. G. Z. (2023). An analysis of the relationship between rental housing and adoption of self-generating energy sources in Brazil using matching methodology. *Journal of International Development*, 1–23. https://doi.org/10.1002/jid.3876

APPENDIX A: PRELIMINARY RESULTS AND ROBUSTNESS TESTS

TABLE A1 First stage Propensity Score results (Probit).

Covariates	Coefficient	Stand. error	*T*-stat	*P* > *T*-stat
Ln Kwd Tax Deflated	−0.012	0.266	−0.04	0.964
Head Age	−0.029	0.001	−27.60	0.000
Head Race	−0.034	0.023	−1.47	0.143
Head Education	−0.001	0.003	−0.20	0.840
Head Labor status	0.113	0.058	1.96	0.050
Head Pub. Statutory	−0.159	0.058	−2.75	0.006
Head Pub. Non-Statutory	−0.067	0.077	−0.87	0.387
Head Military	−0.252	0.201	−1.26	0.208
Head Priv. Employee	0.086	0.034	2.57	0.010
Head Self-Employed	−0.087	0.028	−3.08	0.002
Head Employer	−0.102	0.072	−1.42	0.155
Residents	−0.051	0.010	−5.08	0.000
Children dummy	−0.025	0.029	−0.87	0.383
Television	−0.143	0.020	−7.11	0.000
Air conditioning	−0.209	0.023	−9.28	0.000
Refrigerator	−0.153	0.046	−3.29	0.001
Urban	0.930	0.044	21.19	0.000
Metropolitan	−0.008	0.031	−0.27	0.787
North	−0.039	0.119	−0.33	0.740
Northeast	0.026	0.084	0.31	0.756
Midwest	0.539	0.087	6.17	0.000
Southeast	0.390	0.080	4.90	0.000
South	0	(omitted)	-	-

Note: This table reports coefficient, standard errors, *T*-stat and significance test (*P* > *T*-stat) for the covariates of the propensity score model. The propensity score considers a probit algorithm. State variables omitted due to space.

TABLE A2 Covariates balance test—Placebo PSM Kernel.

	Before matching			After matching		
	Mean			Mean		
Covariates	Treated	Control	*P*-value	Treated	Control	*P*-value
Ln Kwd Tax Deflated	−0.646	−0.645	0.761	−0.646	−0.646	0.742
Head Age	50.933	51.010	0.709	50.933	50.911	0.935
Head Race	0.571	0.573	0.848	0.571	0.577	0.504
Head Education Years	7.775	7.796	0.749	7.774	7.779	0.955
Head Worked Last Year	0.963	0.960	0.217	0.963	0.960	0.311
Head Pub. Statutory	0.054	0.057	0.316	0.054	0.056	0.535
Head Pub. Non-Statutory	0.019	0.020	0.588	0.019	0.019	0.921
Head Military	0.005	0.005	0.761	0.005	0.005	0.999
Head Priv. Employee	0.588	0.581	0.309	0.588	0.581	0.438
Head Self-Employed	0.279	0.282	0.634	0.279	0.275	0.623
Head Employer	0.031	0.029	0.553	0.031	0.030	0.730
Residents	3.091	3.135	0.036	3.092	3.091	0.979
Children dummy	0.607	0.620	0.055	0.608	0.608	1.000
Television	1.275	1.263	0.201	1.274	1.261	0.255
Air conditioning	0.316	0.304	0.214	0.316	0.295	0.090
Refrigerator	1.006	1.007	0.686	1.006	1.002	0.457
Urban	0.775	0.781	0.274	0.775	0.780	0.433
Metropolitan	0.309	0.316	0.232	0.309	0.311	0.771
North	0.143	0.149	0.174	0.143	0.143	0.982
Northeast	0.335	0.349	0.021	0.335	0.341	0.419
Midwest	0.122	0.112	0.014	0.122	0.118	0.437
Southeast	0.248	0.242	0.269	0.248	0.247	0.885
South	0.152	0.147	0.353	0.152	0.151	0.835

Note: This table reports the covariate's means for the placebo treatment and the control groups before and after the Propensity Score Matching Kernel Tricube and associated p-values for the mean differences. Panel A reports the results before the Propensity Score Method (PSM) procedure. Panel B reports the results after the PSM procedure.

TABLE A3 Covariates balance test—PSW.

Covariates	Before Matching: Mean Treated	Before Matching: Mean Control	Before Matching: *P*-value	After Matching: Mean Treated	After Matching: Mean Control	After Matching: *P*-value
	A. Before Matching			**B. After Matching**		
Ln Kwd Tax Deflated	−0.690	−0.669	0.000	−0.690	−0.689	0.730
Head Age	41.881	52.888	0.000	41.881	42.585	0.337
Head Race	0.603	0.623	0.023	0.603	0.605	0.844
Head Education Years	9.425	8.032	0.000	9.425	9.443	0.828
Head Worked Last Year	0.972	0.965	0.003	0.972	0.972	0.971
Head Pub. Statutory	0.042	0.055	0.000	0.042	0.043	0.788
Head Pub. Non-Statutory	0.019	0.019	0.966	0.019	0.019	0.835
Head Military	0.005	0.006	0.509	0.005	0.005	0.914
Head Priv. Employee	0.751	0.564	0.000	0.751	0.745	0.467
Head Self-Employed	0.241	0.253	0.138	0.241	0.238	0.740
Head Employer	0.026	0.032	0.064	0.026	0.027	0.932
Residents	2.993	3.087	0.000	2.993	3.017	0.395
Children dummy	0.623	0.615	0.329	0.623	0.623	0.979
Television	1.203	1.357	0.000	1.203	1.217	0.242
Air conditioning	0.140	0.307	0.000	0.140	0.147	0.367
Refrigerator	0.999	1.025	0.000	0.999	0.997	0.620
Urban	0.967	0.831	0.000	0.967	0.967	0.833
Metropolitan	0.397	0.338	0.000	0.397	0.403	0.608
North	0.046	0.084	0.000	0.046	0.045	0.724
Northeast	0.229	0.283	0.000	0.229	0.236	0.330
Midwest	0.104	0.072	0.000	0.104	0.099	0.410
Southeast	0.490	0.398	0.000	0.490	0.489	0.921
South	0.132	0.164	0.000	0.132	0.131	0.906

Note: This table reports the covariate's means for the treatment and the control groups before and after the Propensity Score Weighting and associated *p*-values for the mean differences. Panel A reports the results before the PSW procedure. Panel B reports the results after the PSW procedure.

TABLE A4 Covariates balance test—Entropy balancing.

Covariates	Mean Treated	Mean Control	P-value	Mean Treated	Mean Control	P-value
	A. Before Matching			B. After Entropy Matching 1		
Ln Kwd Tax Deflated	−0.690	−0.669	0.000	−0.690	−0.690	0.990
Head Age	41.881	52.888	0.000	41.881	41.885	0.990
Head Race	0.603	0.623	0.023	0.603	0.603	0.996
Head Education Years	9.425	8.032	0.000	9.425	9.423	0.980
Head Worked Last Year	0.972	0.965	0.003	0.972	0.972	0.998
Head Pub. Statutory	0.042	0.055	0.000	0.042	0.042	0.997
Head Pub. Non-Statutory	0.019	0.019	0.966	0.019	0.019	1.000
Head Military	0.005	0.006	0.509	0.005	0.005	0.999
Head Priv. Employee	0.751	0.564	0.000	0.751	0.751	0.988
Head Self-Employed	0.241	0.253	0.138	0.241	0.241	0.993
Head Employer	0.026	0.032	0.064	0.026	0.026	1.000
Residents	2.993	3.087	0.000	2.993	2.993	0.998
Children dummy	0.623	0.615	0.329	0.623	0.623	0.999
Television	1.203	1.357	0.000	1.203	1.203	0.997
Air conditioning	0.140	0.307	0.000	0.140	0.140	0.982
Refrigerator	0.999	1.025	0.000	0.999	0.999	0.995
Urban	0.967	0.831	0.000	0.967	0.967	0.825
Metropolitan	0.397	0.338	0.000	0.397	0.396	0.984
	C. After Entropy Matching 2			D. After Entropy Matching 3		
Ln Kwd Tax Deflated	−0.690	−0.690	0.987	−0.690	−0.690	0.996
Head Age	41.881	41.887	0.985	41.881	41.881	0.998
Head Race	0.603	0.603	0.995	0.603	0.603	0.998
Head Education Years	9.425	9.422	0.977	9.425	9.425	0.999
Head Worked Last Year	0.972	0.972	0.998	0.972	0.972	0.999
Head Pub. Statutory	0.042	0.042	0.998	0.042	0.042	0.999
Head Pub. Non-Statutory	0.019	0.019	1.000	0.019	0.019	0.999
Head Military	0.005	0.005	0.998	0.005	0.005	1.000
Head Priv. Employee	0.751	0.751	0.985	0.751	0.751	0.997
Head Self-Employed	0.241	0.241	0.993	0.241	0.241	0.997
Head Employer	0.026	0.026	0.998	0.026	0.026	0.999
Residents	2.993	2.993	1.000	2.993	2.993	0.999
Children dummy	0.623	0.623	0.997	0.623	0.623	0.998
Television	1.203	1.203	0.999	1.203	1.203	1.000
Air conditioning	0.140	0.141	0.966	0.140	0.140	0.992
Refrigerator	0.999	0.999	0.996	0.999	0.999	0.997
Urban	0.967	0.967	0.826	0.967	0.967	0.997
Metropolitan	0.397	0.396	0.984	0.397	0.397	0.999

Note: This table reports the covariate's means for the treatment and the control groups before and after the Entropy Matching procedure and associated *p*-values for the mean differences. Panel A reports the results before matching. Panels B, C and D report the results after the entropy balancing procedure for the first, second and third moments.

TABLE A5 Robustness test results.

	(1) Placebo	(2) PSW Svy	(3) Entropy1	(4) Entropy2	(5) Entropy3
Rented	1.066	−4.546**	−4.886**	−5.130**	−4.894**
z-stat/*t*-stat	(0.65)	(−2.37)	(−2.23)	(−2.20)	(−2.24)
N.	44 823	44 824	44 905	44 905	44 905
Average outcome var. for control units	12.132	6.911	7.251	7.495	7.259
	[8.79%]	[−65.78%]	[−67.39%]	[−68.45%]	[−67.42%]

Note: This table reports robustness estimates of the effect of occupancy status on the probability of adopting self-generation for different Propensity Score Method (PSM) matching estimators. Column 1 is for placebo treatment PSM Kernel Tricube, Column 2 is for PSW, and Columns 3 to 5 are for entropy balancing (first, second and third moments). Coefficients for Rented variable and Average outcome for control units multiplied by 1000. Column 1 considers bootstrap standard errors, and the values in parentheses are z statistics. The values in parentheses in Columns 2 to 5 are *t*-student statistics. The values in brackets are the average percentage difference for the treated group.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

TABLE A6 Rosenbound sensibility test.

Outcome variable	Bound	$\gamma = 1$	$\gamma = 1.7$	$\gamma = 2.4$	$\gamma = 3.1$	$\gamma = 3.8$
Alt. Energy Source	Upper	0.000	0.000	0.000	0.000	0.000
Alt. Energy Source	Lower	0.000	0.000	0.000	0.004	0.034

Note: This table reports the p-values of the Rosenbound test for hidden bias due to unobservable confounding variables. The test employs the Mantel–Haenszel statistic to evaluate the overestimation (upper bound) and underestimation (lower bound) assumptions. All results consider Propensity Score Method (PSM) estimates with Tricube Kernel.

APPENDIX B: PRELIMINARY RESULTS WITH INCOME AS COVARIATE

TABLE B1 PSM Kernel matching algorithms with income covariate.

	(1) Kernel Gaussian	(2) Kernel Biweight	(3) Kernel Tricube	(4) Kernel Epanech.	(5) Kernel Uniform
Rented	−3.606***	−3.498***	−3.495***	−3.501***	−3.524***
z-stat	(−5.16)	(−4.97)	(−4.98)	(−4.99)	(−4.98)
N. on support	44 893	44 885	44 885	44 885	44 885
Average outcome var. for control units	5.957 [−60.53%]	5.852 [−59.77%]	5.850 [−59.75%]	5.856 [−59.79%]	5.878 [−59.95%]

Note: This table reports estimates of the effect of occupancy status on the probability of adopting self-generation for different Propensity Score Method (PSM) matching estimators, including income as a covariate. Column 1 is for Gaussian Kernel, Column 2 is for Biweight Kernel, Column 3 is for Tricube Kernel, Column 4 is for Epanechnikov Kernel and Column 5 is for Uniform Kernel. Coefficients for Rented variable and Average outcome for control units multiplied by 1000. All estimations consider bootstrap standard errors. The values in parentheses are *z* statistics. The values in brackets are the average percentage difference for the treated group.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

APPENDIX C: MAIN RESULTS WITH INCOME COVARIATE

TABLE C1 Analysis restricted by working sector with income covariate.

Panel A. Public Sector	(1) Public Statutory	(2) Public Non-statutory	(3) Military	
Rented	10.692	3.836	−4.082	
z-stat	(1.40)	(0.37)	(−0.63)	
N. on support	2530	883	176	
Average outcome var. for control units	6.143	3.517	4.082	
	[174.06%]	[109.07%]	[−100.00%]	
Panel B. Private Sector	**(1) Domestic Worker**	**(2) Private S. Employee**	**(3) Employer**	**(4) Self-Employed**
Rented	−2.589**	−3.076**	−11.202	−6.440***
z-stat	(−2.23)	(−2.56)	(−1.36)	(−3.75)
N. on support	2050	10 100	1300	12 625
Average outcome var. for control units	2.589	4.679	17.084	8.186
	[−100.00%]	[−65.74%]	[−65.57%]	[−78.67%]

Note: This table reports estimates for the effect off occupancy status on the probability of adopting self-generation for different employment sectors, including the income logarithm as a covariate and considering Propensity Score Method (PSM) Tricube Kernel. Panel A considers public servants and Panel B considers private labour. Panel A Column 1: results for households where the head of the family is a public statutory worker. Panel A Column 2: results for households where the head of the family is a public worker (non-statutory). Panel A Column 3: results for households where the head of the family is a military worker. Panel B Column 1: results for households where the head of the family is a domestic worker. Panel B Column 2: results for households where the head of the family is a private-sector employee. Panel B Column 3: results for households where the head of the family is an employer. Panel B Column 4: results for households where the head of the family is a self-employed worker. Coefficients for Rented variable and Average outcome for control units multiplied by 1000. All estimations consider bootstrap standard errors. The values in parentheses are *z* statistics. The values in brackets are the average percentage difference for the treated group.

*Statistical significance at 10%.

**Statistical significance at 5%.

***Statistical significance at 1%.

TABLE C2 Analysis restricted by age in affected private sector with income covariate.

	(1) Private Sector	(2) Head Age 20–29	(3) Head Age 30–39	(4) Head Age 40–49	(5) Head Age 50–59	(6) Head Age 60+
Rented	−4.756***	−6.031*	−4.977***	−4.290**	−5.240***	1.194
z-stat	(−4.74)	(−1.77)	(−2.87)	(−2.48)	(−2.78)	(0.31)
N. on support	24 796	2711	6094	6691	5681	3423
Average outcome var. for control units	6.236	6.923	6.268	6.159	6.824	2.579
	[−76.27%]	[−87.11%]	[−79.40%]	[−69.65%]	[−76.78%]	[46.31%]

Note: This table reports estimates for the effect of occupancy status on the probability of adopting self-generation for different age ranges, conditioning it to households where the head of the family works in the private sector and including the income logarithm as a covariate. All estimations consider Propensity Score Method (PSM) Tricube Kernel bootstrap standard errors. Column 1 presents the mean results for private labour from Table 6, Panel B. Columns 2, 3, 4, 5 and 6 present the results for the head of the family age range between 20 and 29, 30–39, 40–49, 50–59 and 60 or more years old, respectively. Coefficients for Rented variable and Average outcome for control units multiplied by 1000. The values in parentheses are *z* statistics. The values in brackets are the average percentage difference for the treated group.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.