Equilibrium Sorting, Moral Hazard, and Adverse Selection in Residential Energy Contracts

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Job Market Paper

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Ownership institutions

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- In rentals, the party with the decision right does not always face the cost of that decision.
- Focus: home heating because it makes up 42 % of home energy use (EIA, 2013).

Ownership institutions

- **Tenant pays utilities**: Incentive for landlord to underinvest in efficient housing attributes if efficiency is costly for the tenant to determine.
- **Landlord pays utilities**: Incentive for tenant to crank up the heat.

What do we already know?

- Renters are less likely to have energy-efficient appliances (Davis, 2012) and less likely to be insulated (Gillingham et al, 2012).
- There is convincing evidence of informational asymmetry as demonstrated by increased turnover when the tenant pays (Myers, 2018).

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- An experiment in the *PNAS* estimates a 25% (!) reduction in electricity use when Swedish tenants were made to pay for their own bills (Elinder et al, 2017).

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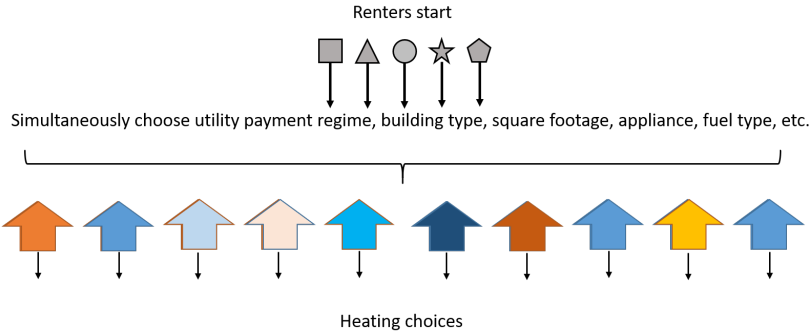
- An experiment in the *PNAS* estimates a 25% (!) reduction in electricity use when Swedish tenants were made to pay for their own bills (Elinder et al, 2017).
    - Other estimates: $<$ 1%—20% (Levinson and Niemann, 2004; Dewees and Tombe, 2011; Jessoe et al., 2018).

First question

How much money is left on the table due to utility payment regimes in housing rentals?

How to think of housing and heating



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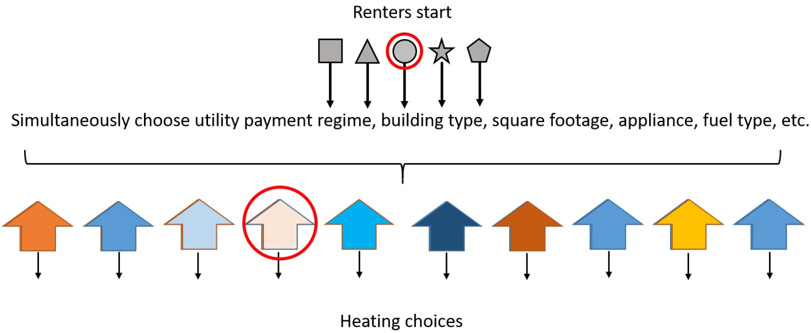

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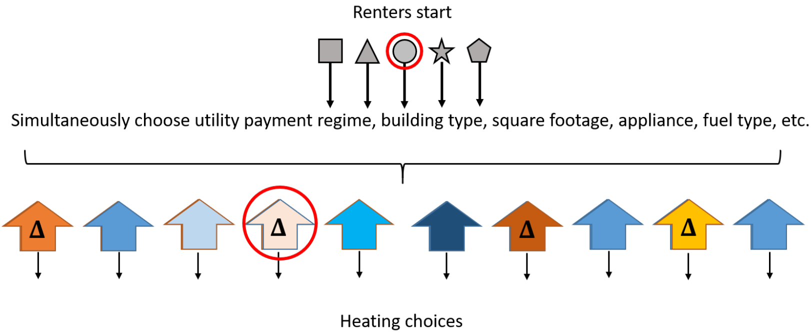

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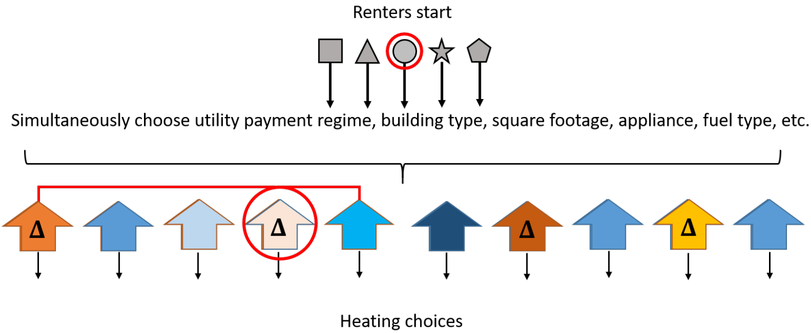

Second question

What are the relative energy-use impacts of

1. Moral hazard?
2. Adverse selection into landlord-pay utilities?
3. Selection of housing attributes?

Related to a broad literature on moral hazard and adverse selection

- **Health insurance**: Brot-Goldberg et al. (2017); Finkelstein et al. (2016); Baicker et al. (2015); Autor et al. (2014); Einav et al. (2013)
- **Crop insurance**: He et al. (2017a,b)
- **Lending markets**: Crawford et al. (2018); Veiga and Weyl (2016)
  - Vehicle leasing: Weisburd et al. (2018)
- **Online marketplaces**: Hui et al. (2016)
- **Worker contracts**: Jackson and Schneider (2011, 2015)

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Connects with the "New Economics of Equilibrium Sorting" (Kuminoff et al., 2013).

This paper

1. Build a model of housing choice and heating use.
2. Estimate key parameters in the model exploiting exogenous variation in the price of electricity and natural gas (Myers, 2018a, 2018b).
3. Use a machine-learning algorithm to characterize household type.
4. Evaluate the impact of switching *all* regimes to tenant-pay and allowing households to re-sort into different size units and choose heat settings.

Model

Following Bajari and Benkard (2002) and Bajari and Kahn (2005):

$$u_i(x_j, s_i, \xi_j, c_i) = \beta_{1,i} ln(x_j) - \frac{\beta_{2,i}}{2}(s_i - s_i^b)^2 + \beta_{3,i} ln(\xi_j) + c_i$$

Where s_i^b is household i's **bliss point temperature**.

Utility parameters vary by household.

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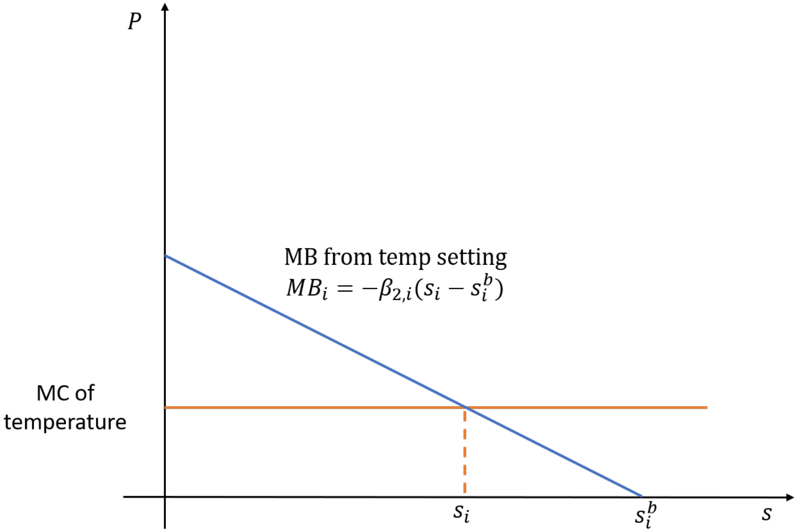
Unlimited wants, but limited resources:

$$y_i \geq p(x_j, R_j, \xi_j) + R_j \cdot H(s_i, x_j, \xi_j, T_j, P_e) + c_i$$

Structural Identification

Visualizing moral hazard



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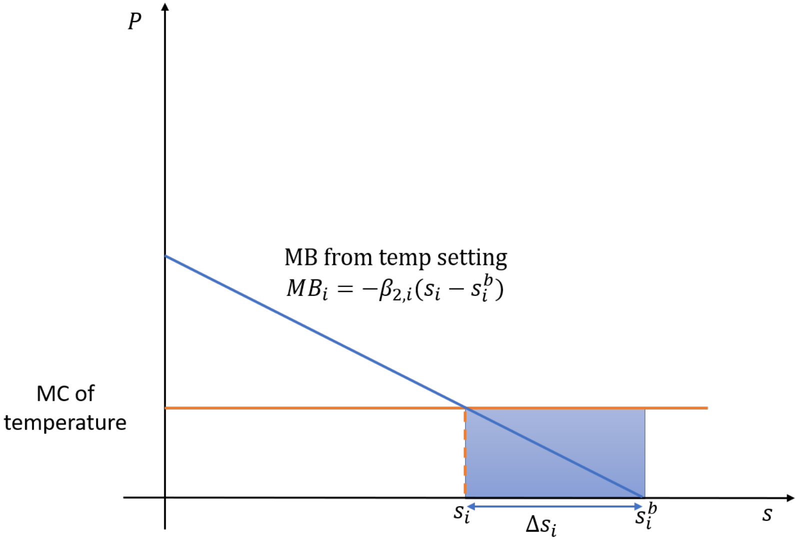

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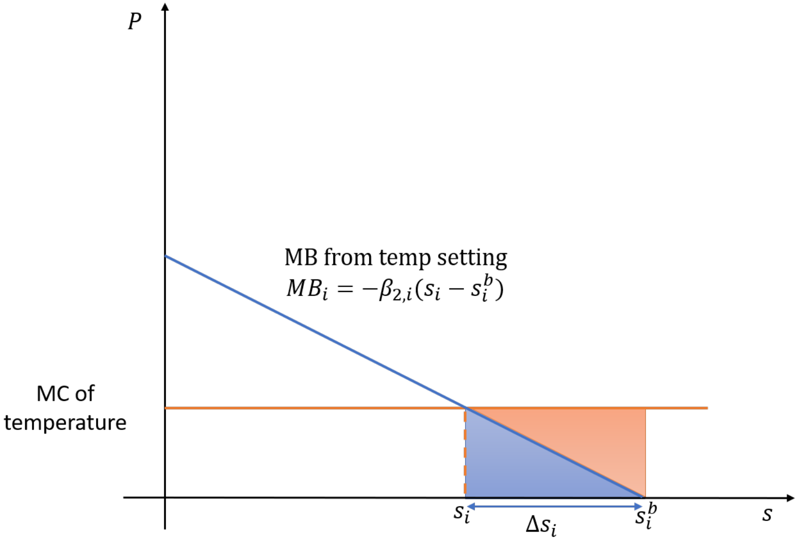
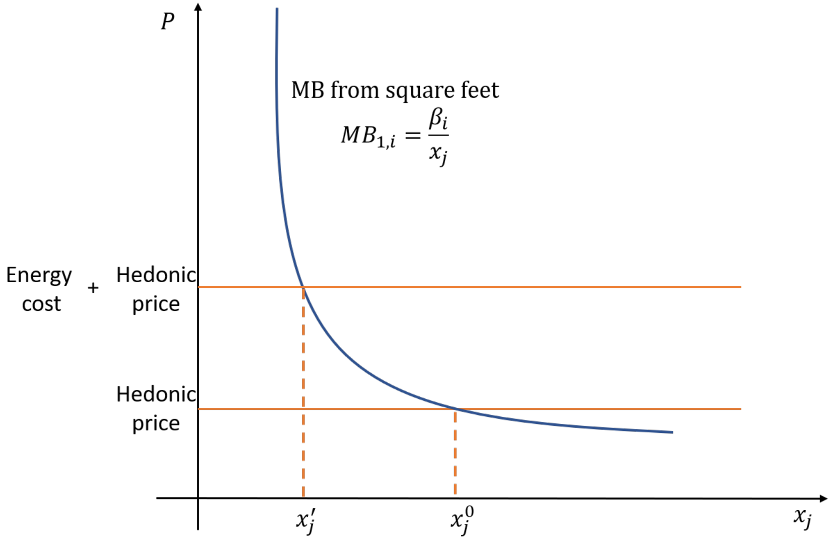


Visualizing sorting



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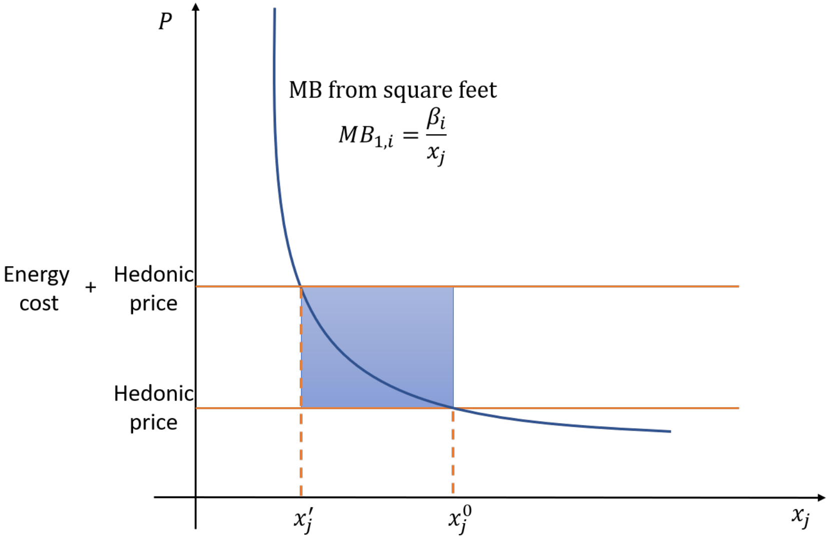

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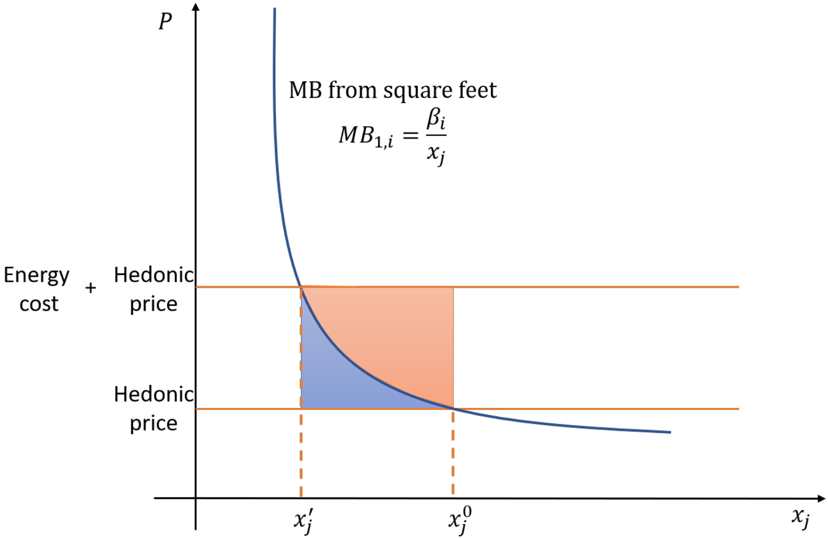
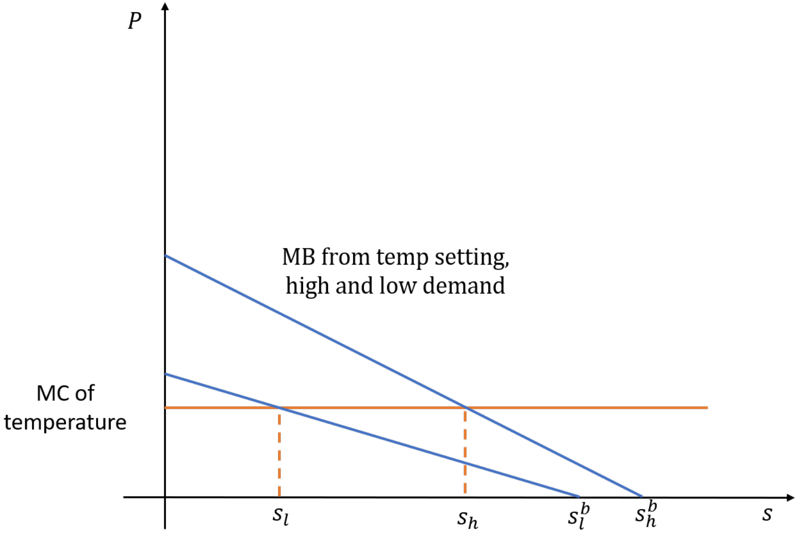


Visualizing adverse selection



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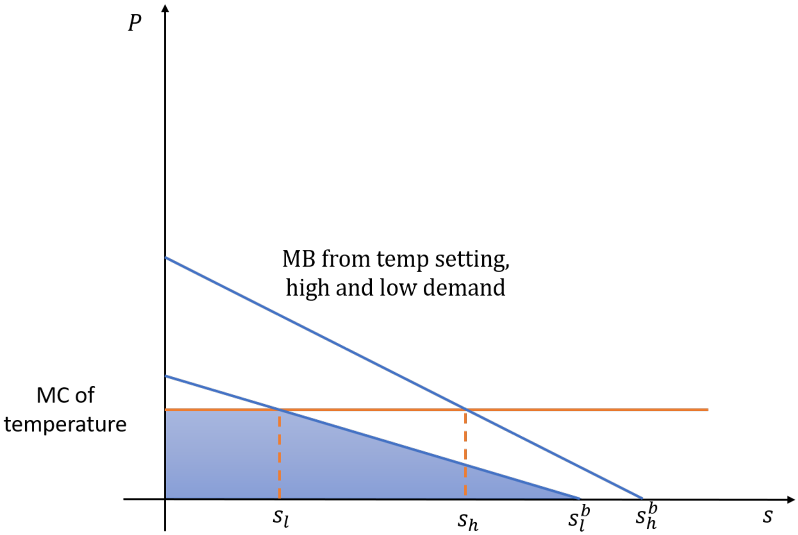

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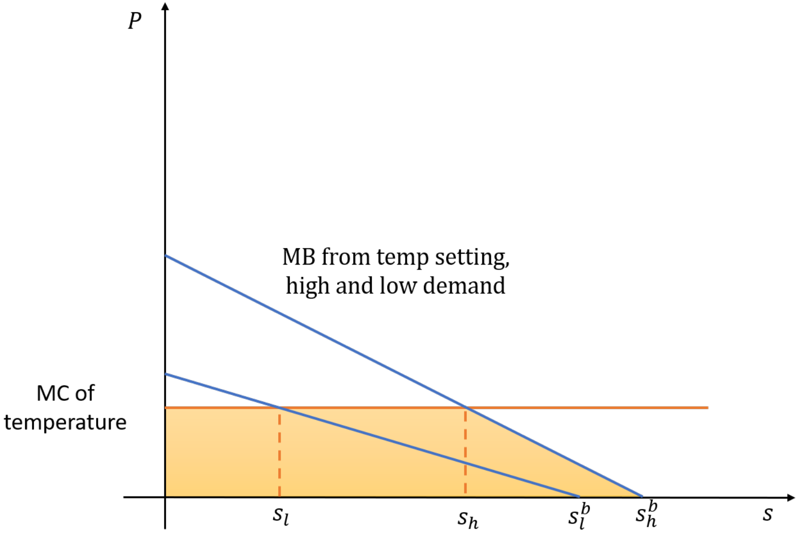

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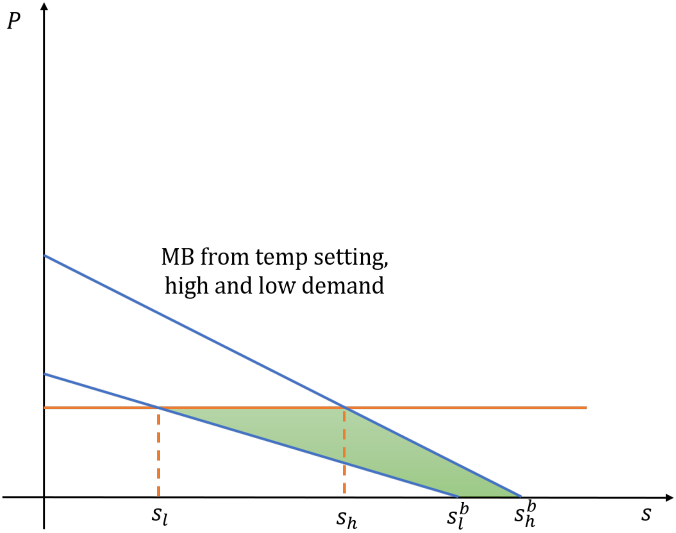
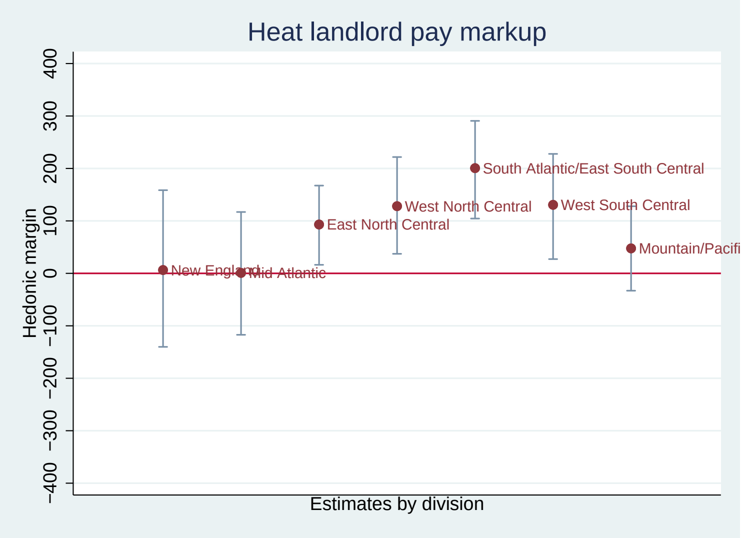


Rent hedonic

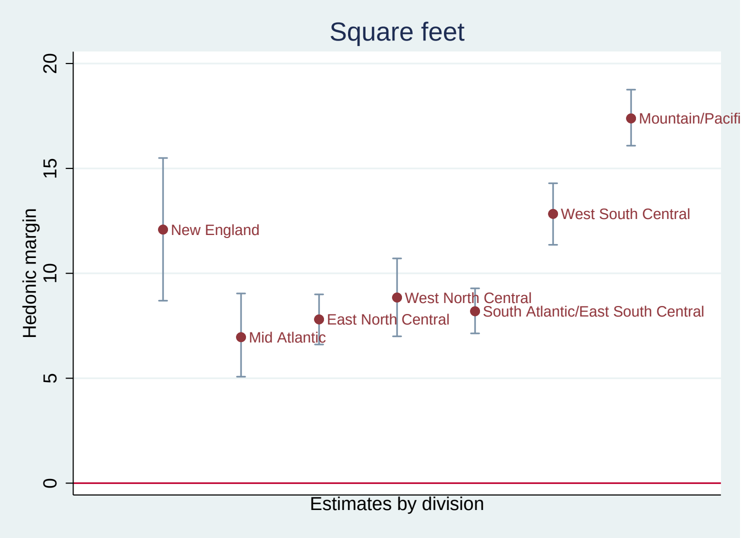
- Rent and housing characteristics come from the **American Housing Survey** (AHS).
- There are 106,071 renters in the sample that are labeled at the MSA level between 1997-2013.
- Identification strategy seen in Myers (2017a, 2017b).
  - Markup: the pass-through of exogenous energy prices to landlord-pay regimes.

▸ Specification



Heat landlord pay markup
Hedonic margin
400
300
200
100
0
−100
−200
−300
−400
South Atlantic/East South Central
West North Central
West South Central
East North Central
Mountain/Pacifi
New England
Mid Atlantic
Estimates by division

Prices for 100 square feet



Heat cost estimation

- Temperature settings, energy bills, and home characteristics from the *Residential Energy Consumption Survey* (RECS).
- Energy use in RECS is from the local servicing utility.
- Coefficients vary by fuel type.
- The final sample includes 1,653 renters with gas heat and 1,511 renters with electric heat surveyed in 2001, 2005, and 2009.

Heat cost estimation

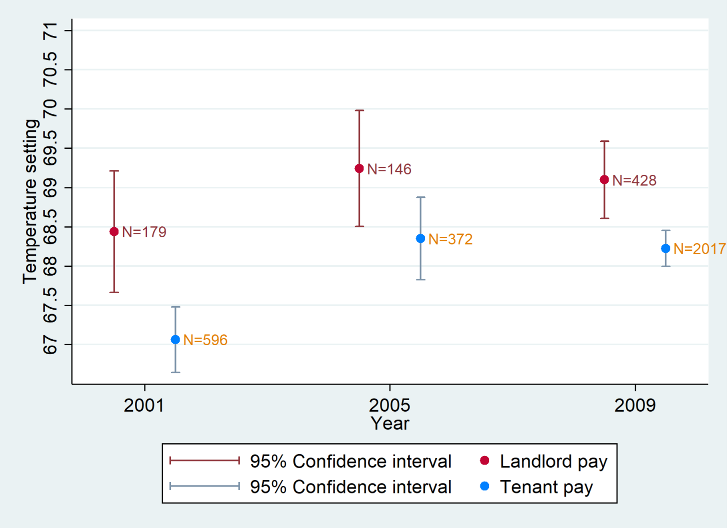
$$\begin{aligned} ln(Q_e) &= \sigma_e(s_i - T_j) + \gamma_e ln(x_j) + \epsilon_j \\ s_i - T_j &= q(price_e, HDD, ln(x_j)) + h_{ij} \end{aligned} \quad (1)$$

$$\begin{aligned} Q_e &= \text{Average quantity of fuel used} \\ s_i &= \text{Temperature setting by household } i \\ T_j &= \text{Outside temperature} \\ x_j &= \text{Housing unit characteristics} \\ \epsilon_j, h_{ij} &= \text{Error terms} \end{aligned}$$

Average $\frac{\partial H}{\partial \ell}$	Gas	Electric
Temp$_{inside}$-temp$_{outside}$	4.98	4.38
	(4.00 - 6.08)	(1.35 - 8.79)
Square feet	0.84	0.67
	(0.42 - 1.24)	(0.00 - 1.30)
Single attached unit	-3.59	-2.97
	(-7.58 - 0.72)	(-22.40 - 23.67)
Two to four unit apt	0.74	-22.66
	(-6.97 - 10.13)	(-38.71 - -6.13)
Five plus unit apt	-6.96	0.91
	(-18.56 - 7.82)	(-3.28 - 6.22)
(# units)	-5.11	0.91
	(-9.37 - -1.29)	(-3.28 - 6.22)
Division & Year	Y	Y
Appliance & Vintage	Y	Y
Household characteristics	Y	Y
Observations	1,653	1,511

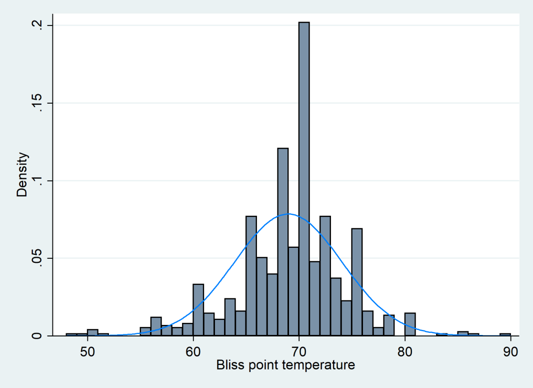
Prediction

The idea is to use revealed temperature settings to build a **predictive algorithm** for counterfactual energy use.



Temperature setting behavior

The scientific literature argues that temperature preference is determined by **physiological factors** such as age, sex, previous exposure, etc.



Bliss point prediction

Currently:

1. Train machine learning algorithms: decision trees, support vector machines, boosted trees, and random forests.
2. Classic machine learning assumption: training and prediction samples do not differ on unobservables.
3. **Result: 70+ percent accuracy using random forests.**

Parametric selection test   Sample means are similar

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Parametric selection test | Sample means are similar

In progress (see Brewer & Carlson work in progress):

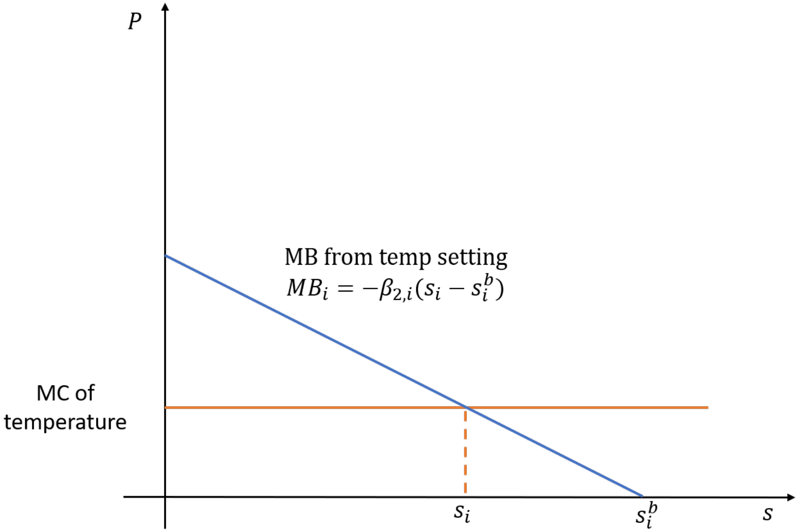
- Combines the best of machine learning with the best of econometric approaches for dealing with unobservables.

Putting it all together

We have estimated housing attribute prices, energy costs, and household types.

I use the estimates to construct the utility parameters from the model and to simulate the counterfactuals of interest.

Moral hazard is important



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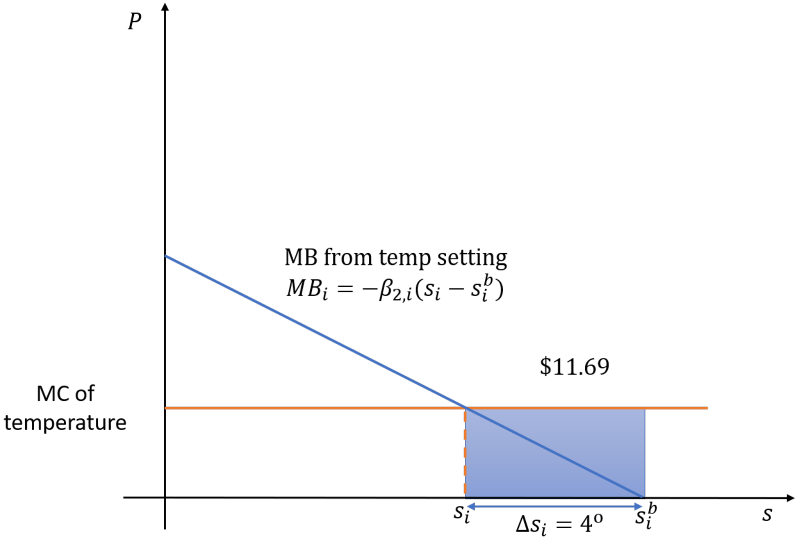

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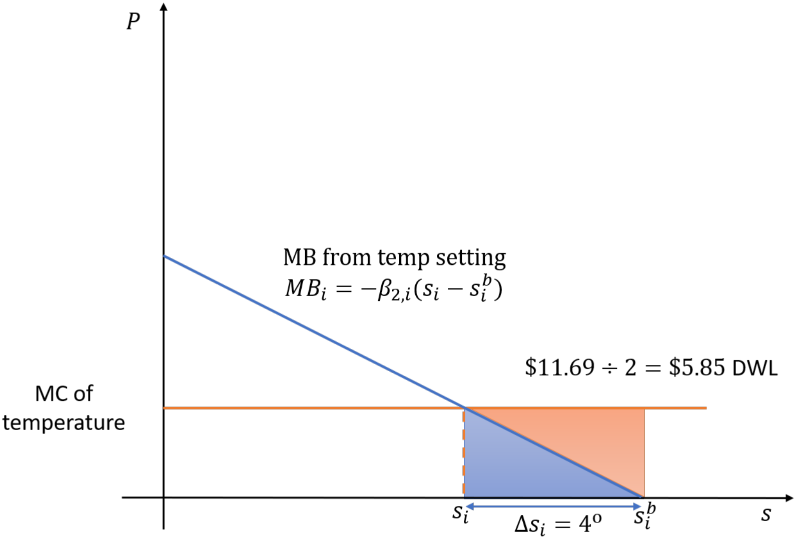
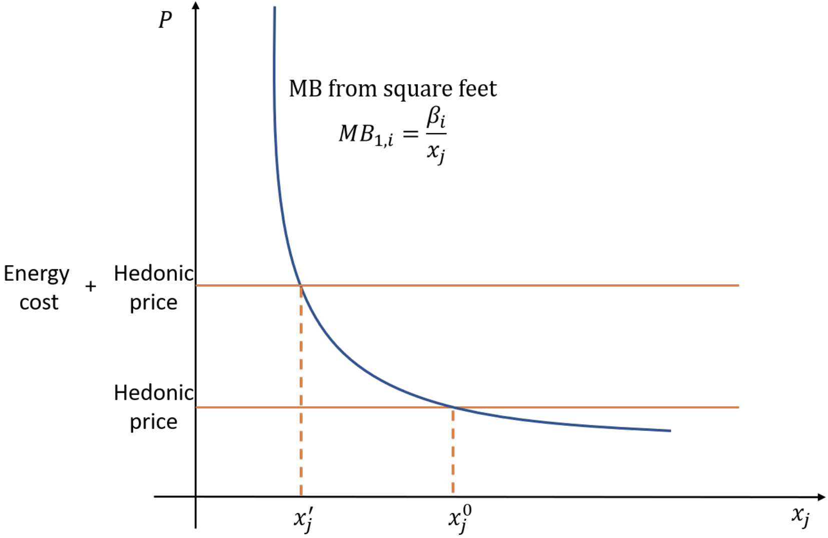


Sorting occurs, but matters less



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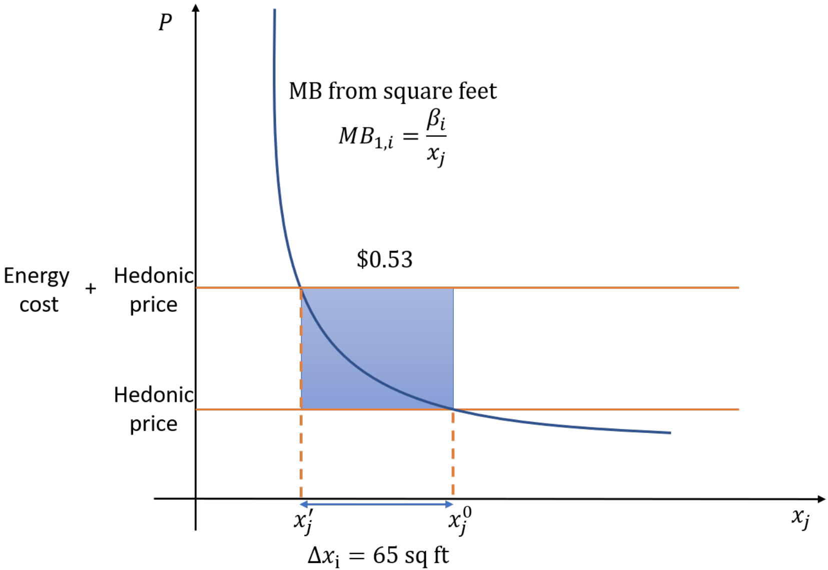

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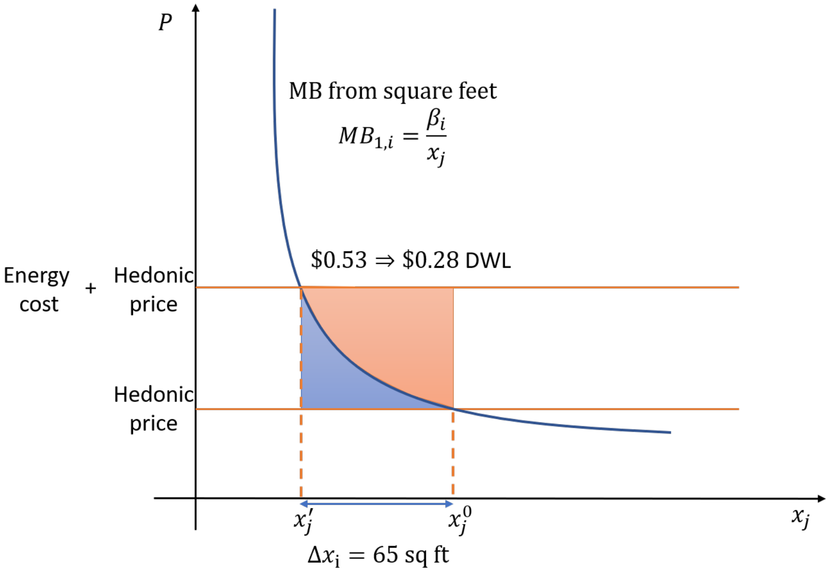
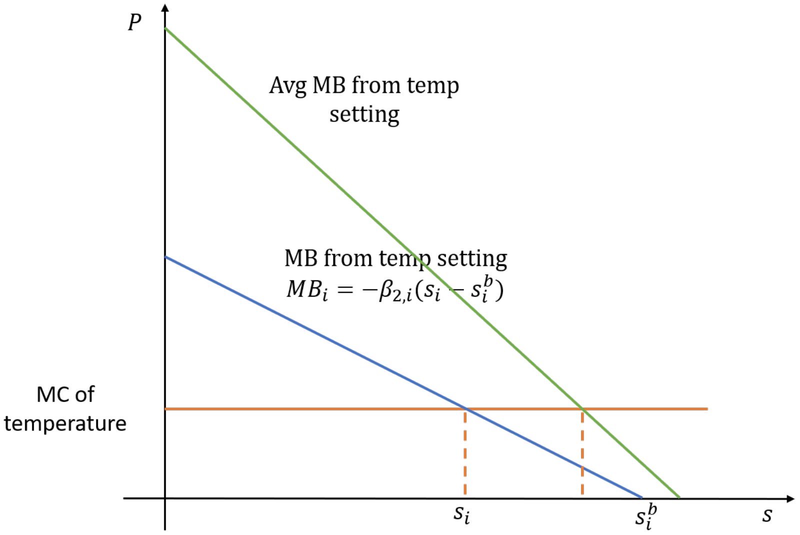


Selection is on moral hazard



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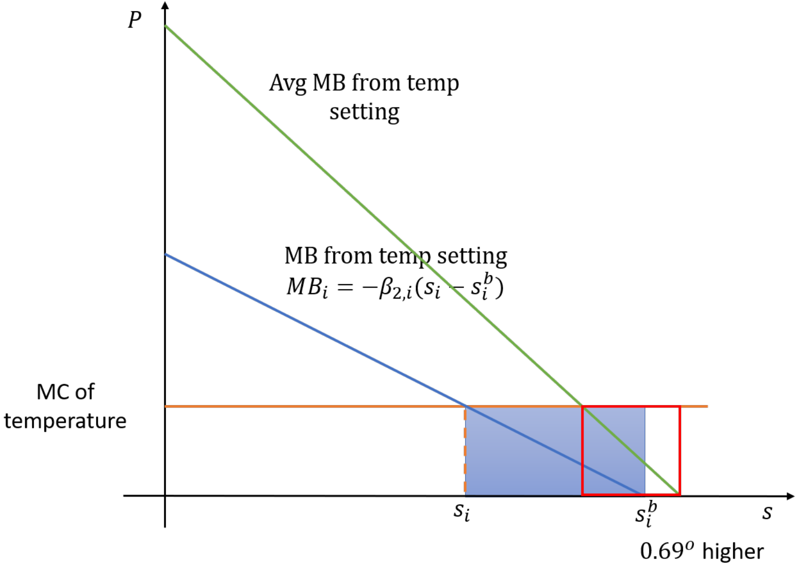

Conclusion

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In addition:

- 43% of landlord-pay households are not price-responsive.
- Economies of scale in number of units? Complementary finding to (Borck & Brueckner, 2018).

Conclusion

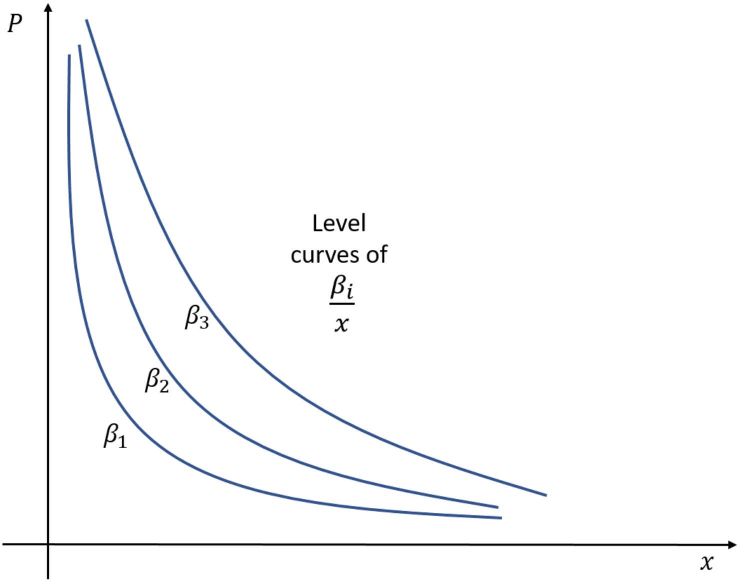
Landlord-pay households spend \$12.22 more on energy per month on average ($\sim 14\%$)

In addition:

- 43% of landlord-pay households are not price-responsive.
- Economies of scale in number of units? Complementary finding to (Borck & Brueckner, 2018).
- These results do not include pollution costs of energy use.

Are large, multi-unit (tenant-pay) buildings a key to reducing external costs?

Structural identification



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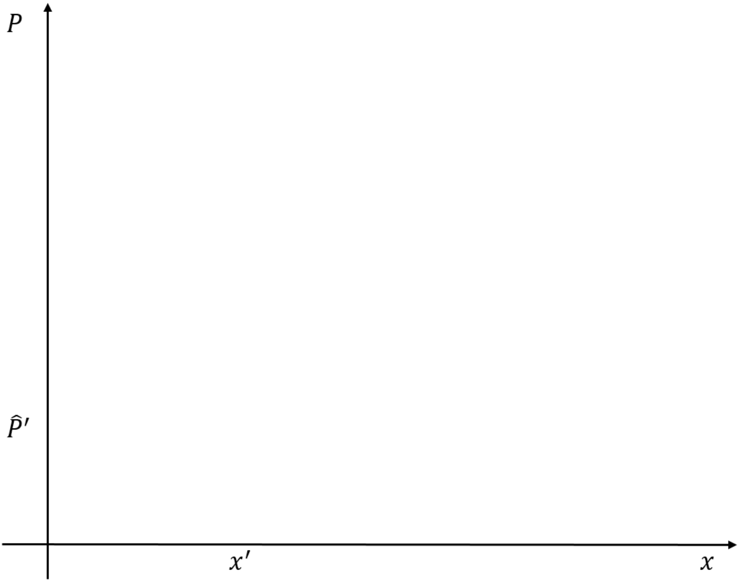

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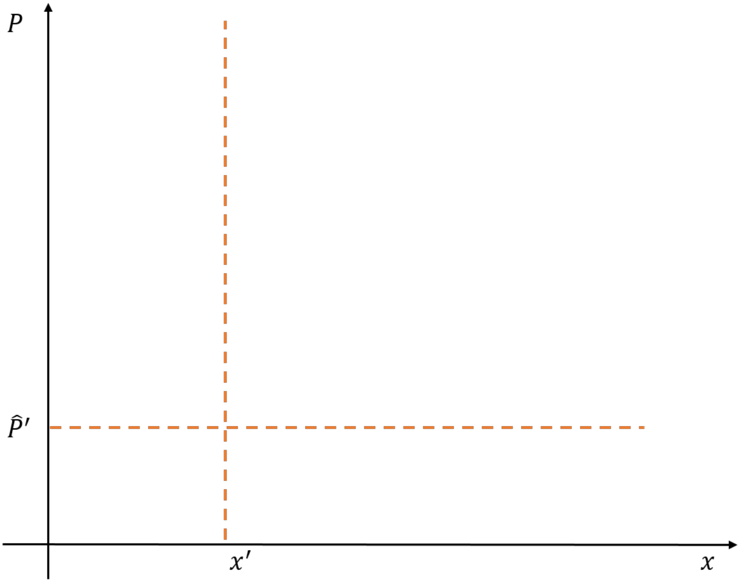

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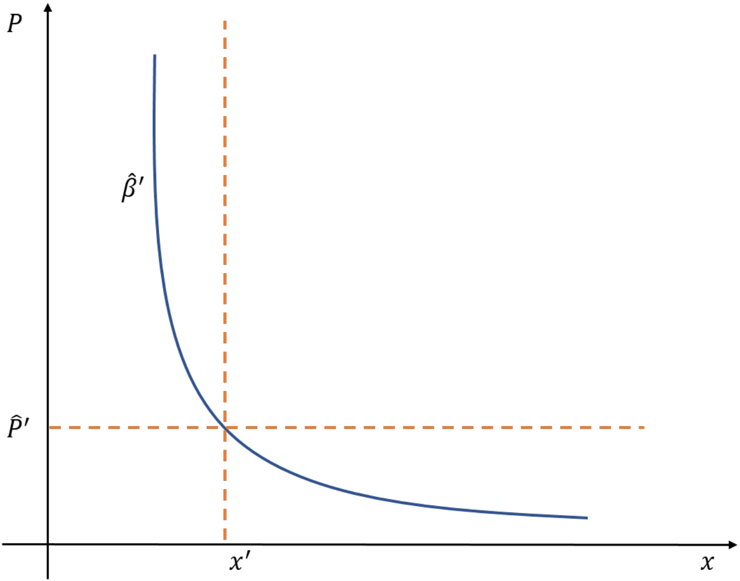

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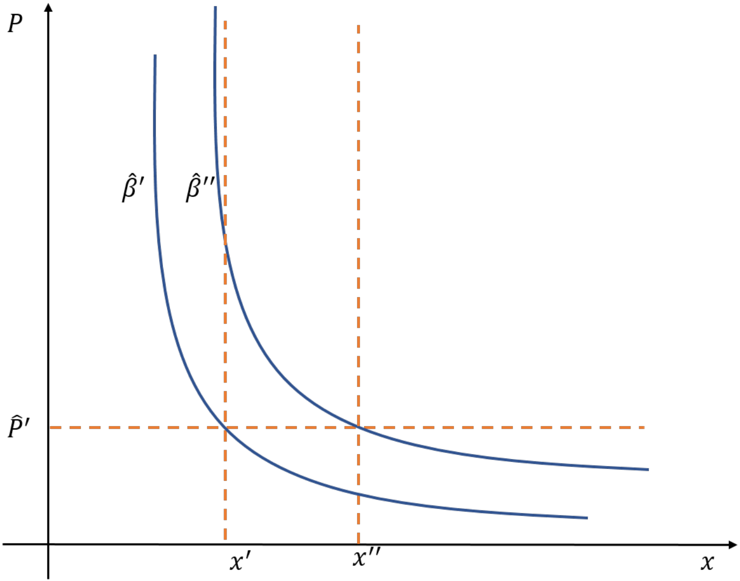

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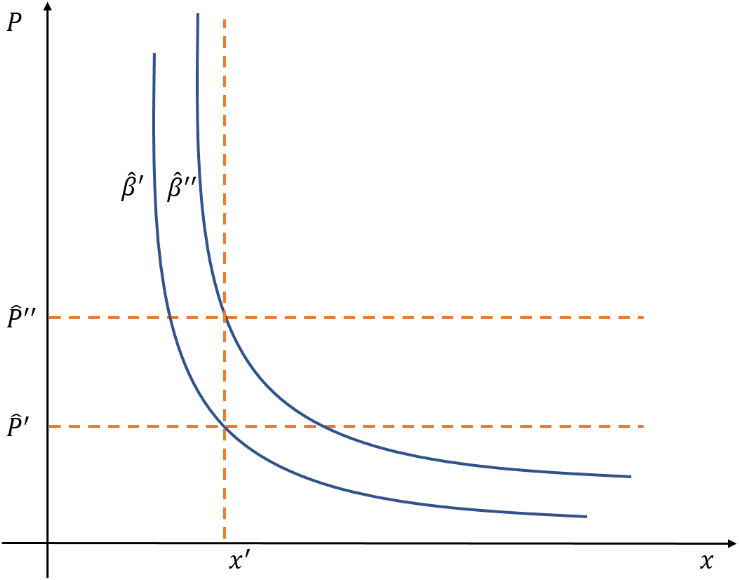

Rent hedonic

$$\begin{aligned} rent_j = &\alpha_{0,div} + \alpha_{1,div} x_j + \alpha_{5,div} gas_j + \alpha_{4,div}(1 - R_j)(gas_j) \\ &+ \alpha_{2,div} fuelprice_{div,year} + \alpha_{3,div}(1 - R_j)(fuelprice_{div,year}) + \tau + u_j \end{aligned} \tag{2}$$

$$\begin{aligned} x_j &= \text{Housing characteristics} \\ (1 - R_j) &= \text{Indicator equal to one if utility regime is landlord-pay} \\ gas_j &= \text{Indicator for gas heat} \\ fuelprice_{state,year} &= \text{Price per BTU.} \\ \tau &= \text{Dummies: vintage}\times\text{year, LL pay}\times\text{ year, and MSA} \\ u_j &= \text{Unobserved error} \end{aligned}$$

Return

Can we test for selection?

Heckman selection framework:

$$s_i^{b*} = S(D_i, x_j, T_j) + \xi_j + h_i \tag{3}$$

$$(1 - R_j) = g(w_{i,j}) + \eta_{i,j} \tag{4}$$

$$s_i^b = \begin{cases} s_i^{b*} \text{ if } (1 - R_j) = 1 \\ \text{unobserved if } (1 - R_j) = 0 \end{cases} \tag{5}$$

Can we test for selection?

Under a bivariate normality assumption:

$$\mathbb{E}\{s_i^b|(1-R_j)=1\} = S(D_i, x_j, T_j) + \rho\sigma_1 \frac{\phi(g(z_{i,j}))}{\Phi(g(z_{i,j}))}, \tag{6}$$

$$\mathbb{E}\{s_i^b|(1-R_j)=0\} = S(D_i, x_j, T_j) - \rho\sigma_1 \frac{\phi(g(z_{i,j}))}{\Phi(g(z_{i,j}))}. \tag{7}$$

An estimate of $\hat{\rho} > 0$ is evidence for adverse selection.

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An estimate of $\hat{\rho} > 0$ is evidence for adverse selection.
Result: $\hat{\rho} = -0.29$, CI $(-6.54, 2.65)$.

Return

The samples are balanced

	Landlord-pay	Tenant-pay
Average winter temp	67.16	67.28
	(66.71 - 67.60)	(67.08 - 67.48)
Household size	2.129	2.655
	(2.041 - 2.217)	(2.602 - 2.708)
Householder age	46.33	40.66
	(45.09 - 47.56)	(40.12 - 41.20)
Householder sex	0.409	0.430
	(0.378 - 0.440)	(0.413 - 0.446)
White	0.701	0.690
	(0.673 - 0.730)	(0.674 - 0.705)
Black	0.192	0.194
	(0.167 - 0.216)	(0.181 - 0.208)
Native American	0.00721	0.0173
	(0.00188 - 0.0125)	(0.0129 - 0.0217)
Asian	0.0453	0.0408
	(0.0322 - 0.0584)	(0.0341 - 0.0475)
Other race	0.00206	0.00477
	(-0.000797 - 0.00492)	(0.00244 - 0.00710)
Pacific Islander	0.0391	0.0316
	(0.0269 - 0.0514)	(0.0257 - 0.0375)
Multiracial	0.0134	0.0215
	(0.00615 - 0.0206)	(0.0166 - 0.0264)

	Landlord-pay	Tenant-pay
Householder employed full time	0.380	0.288
	(0.349 - 0.411)	(0.272 - 0.303)
Householder employed part time	0.194	0.173
	(0.169 - 0.219)	(0.161 - 0.186)
Income $0 to 4,999	0.0824	0.0504
	(0.0651 - 0.0997)	(0.0430 - 0.0578)
Income $5,000 to 10,000	0.152	0.0829
	(0.130 - 0.175)	(0.0735 - 0.0922)
Income $10,000 to $14,999	0.152	0.0906
	(0.130 - 0.175)	(0.0809 - 0.100)
Income $15,000 to $19,999	0.0989	0.0841
	(0.0801 - 0.118)	(0.0747 - 0.0934)
Income $20,000 to $29,999	0.160	0.171
	(0.137 - 0.183)	(0.159 - 0.184)
Income $30,000 to $39,999	0.118	0.148
	(0.0981 - 0.139)	(0.136 - 0.160)
Income $40,000 to $49,999	0.0844	0.118
	(0.0669 - 0.102)	(0.107 - 0.129)
Income $50,000 to $74,999	0.0968	0.146
	(0.0782 - 0.115)	(0.134 - 0.158)
Income $75,000 TO $99,999	0.0247	0.0599
	(0.0149 - 0.0345)	(0.0519 - 0.0679)
Income $100,000 or more	0.0299	0.0480
	(0.0191 - 0.0406)	(0.0408 - 0.0552)

Return