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Reference Dependence in the Housing Market

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Introduction

- Housing—largest household asset; mortgages—largest liability.

  (Campbell, 2006; Badarinza et al., 2016; Gomes et al., 2020)

- Rich source of insights into household preferences and constraints.

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  - Mapping facts to parameters requires an explicit model of reference dependence.
  - Such a model should incorporate realistic housing market features.
  - Harnessing observables in addition to prices (e.g., Kleven, 2016; Rees-Jones, 2018).
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  - Harnessing observables in addition to prices (e.g., Kleven, 2016; Rees-Jones, 2018).
  - Empirical confounds (unobservable quality, home equity constraints).
- Subsequent literature extends our knowledge, but issues remain open.
  (e.g., Engelhardt, 2003; Anenberg, 2011; Bracke and Tenreyro, 2018; Hong et al., 2019; Clapp et al., 2020)

This paper

- Develops a structural model of house selling which flexibly embeds preferences and constraints.
  - Seller optimizes listing decision and listing price, internalizing effects on probability of sale and final sale price (i.e., demand).
  - Model predicts seller policy functions given parameters and state variables.

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- Studies Danish administrative data on housing stock, transactions, and listings, matched to mortgages and demographics.
  - Evaluates prior results using more granular data, and uncovers new facts.
  - New moments including bunching in transactions and extensive margin.
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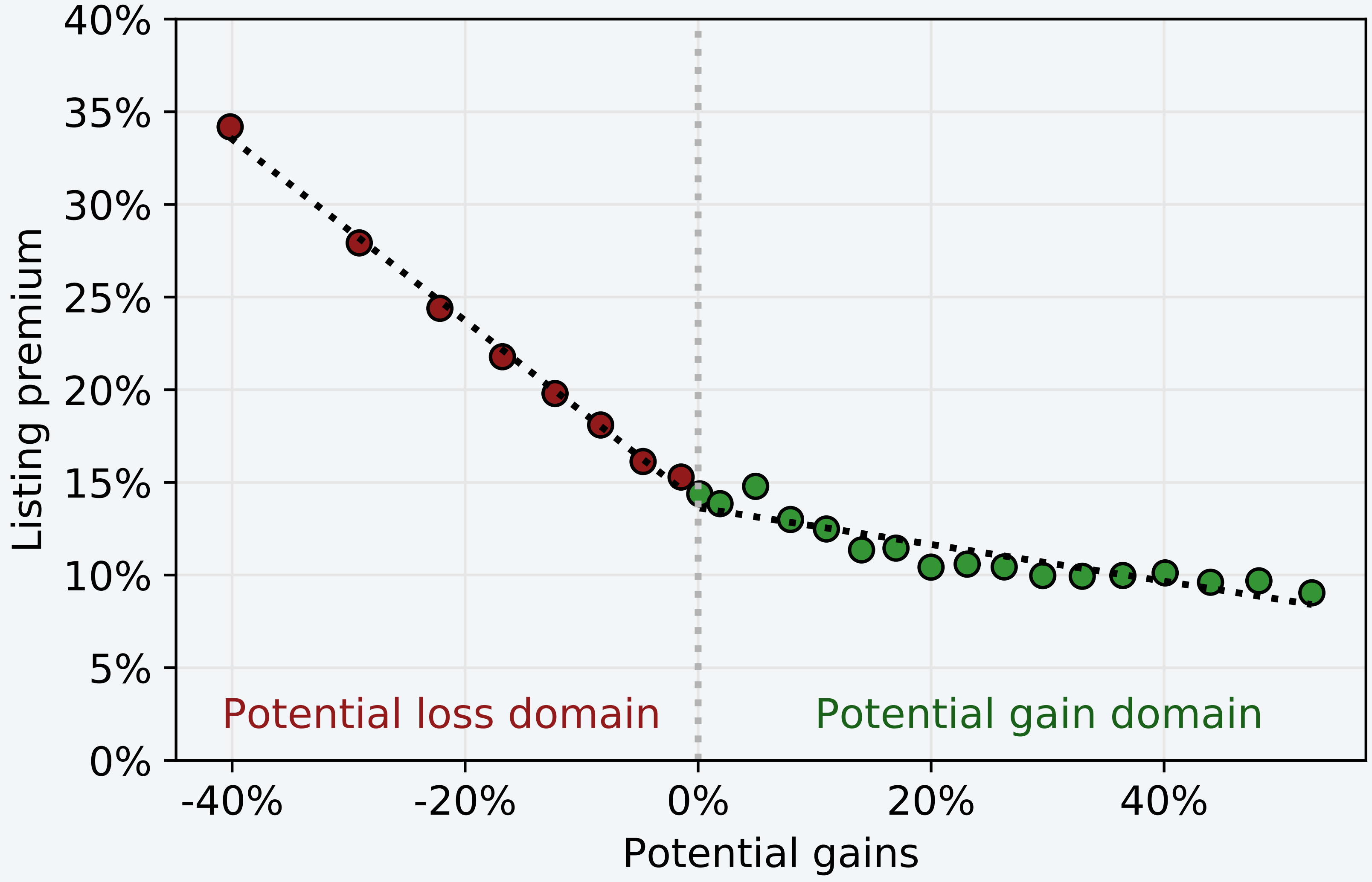
  - Confronts measurement challenges and controls for numerous confounds.
- Model rationalizes data with reference dependence and modest loss aversion; exceptions point to future theoretical work.

Listing premia in the data

- Listing premium (ℓ) = ln(Listing price) - ln(Hedonic price).



- Potential gains = ln(Hedonic price) - ln(Reference price).
  - Assumption: Reference price is nominal purchase price.

Data and Facts

Data

- Universe of Danish housing transactions from 2009 to 2016.
  - Assessed sale values from the tax registry. Original purchase values post-1992.
  - Size, location, hedonics, sale, purchase time from the property registry.
- Matched to owner's personal ID, using property ID.
  - Data on household demographics: Age, education.
  - Data on household income, outstanding mortgage debt, net financial assets.
- Property ID used to match to (external) listings data.
  - All Danish electronic listings (matched to approx. 75% of all transactions).
  - Listing price, time on the market, retracted or sold.
- Merged data: 214,508 listings (70.6% sold, 29.4% retracted) of 181,020 properties by 193,850 households between 2009 and 2016.
  - Housing stock (5,540,391 observations of 807,666 unique properties) used to understand the extensive margin, i.e., propensity to list.

More details

Hedonic pricing model

- Predict prices using hedonic model:

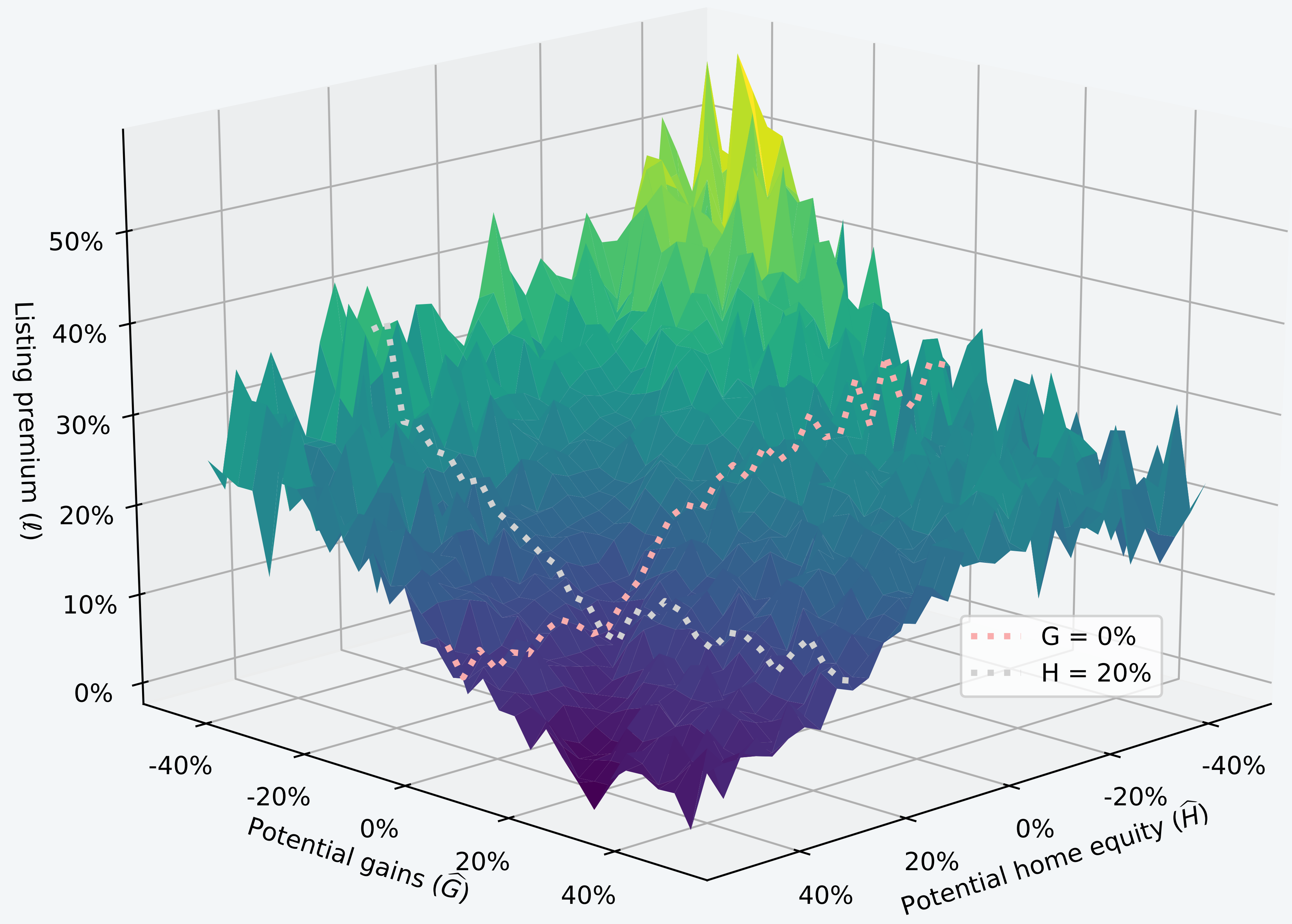
$$\begin{aligned}\ln(P_{it}) =& \delta + \delta_t + \delta_m + \delta_{tm} + \beta_f \mathbb{1}_{i=f} + \beta_{ft} \mathbb{1}_{i=f} \mathbb{1}_{t=\tau} \\ & + \beta_x \mathbf{X_{it}} + \beta_{fx} \mathbb{1}_{i=f} \mathbf{X_{it}} + \Phi(v_{it}) + \varepsilon_{it}.\end{aligned} \tag{1}$$

- R^2 from estimating this model is 0.86. Results are robust to using a range of alternative models. More details

- Use predicted prices to calculate:

Potential gains $\widehat{G} = \widehat{\ln P} - \ln R$	(note contrast with)	Realized gains $G = \ln P - \ln R$
Potential home equity $\widehat{H} = \widehat{\ln P} - \ln M$	(note contrast with)	Realized home equity $H = \ln P - \ln M$
Listing premium $\ell = \ln L - \widehat{\ln P}$	(note contrast with)	Realized premium $rp = \ln P - \widehat{\ln P}$

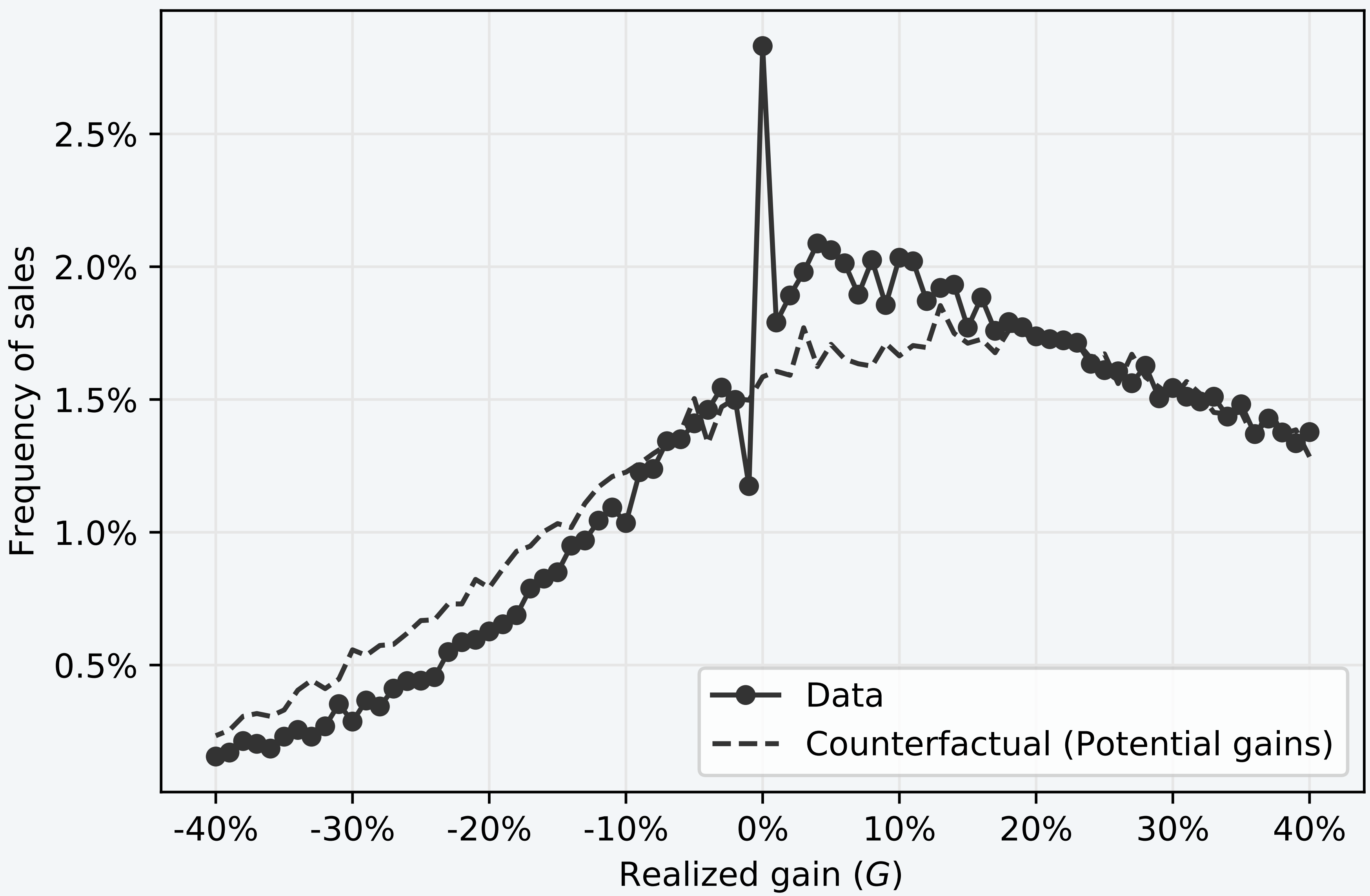
Listing premia, potential gains, and potential home equity



Summary statistics | Moments: Listing premia

Bunching

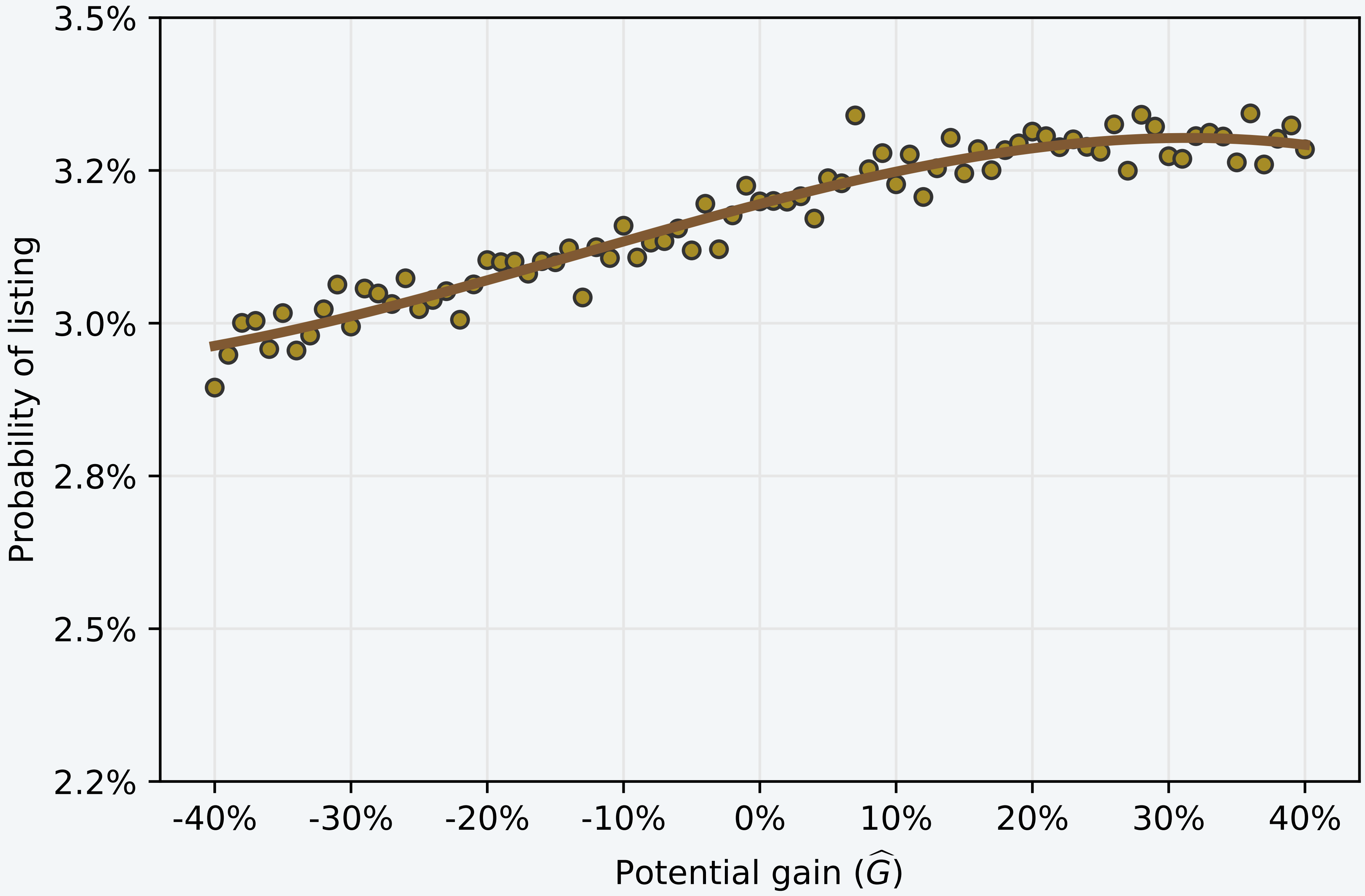
- Loss aversion predicts "bunching" of transactions at prices just above reference point R. (As sellers aim for realized gain $G = 0\%$.)



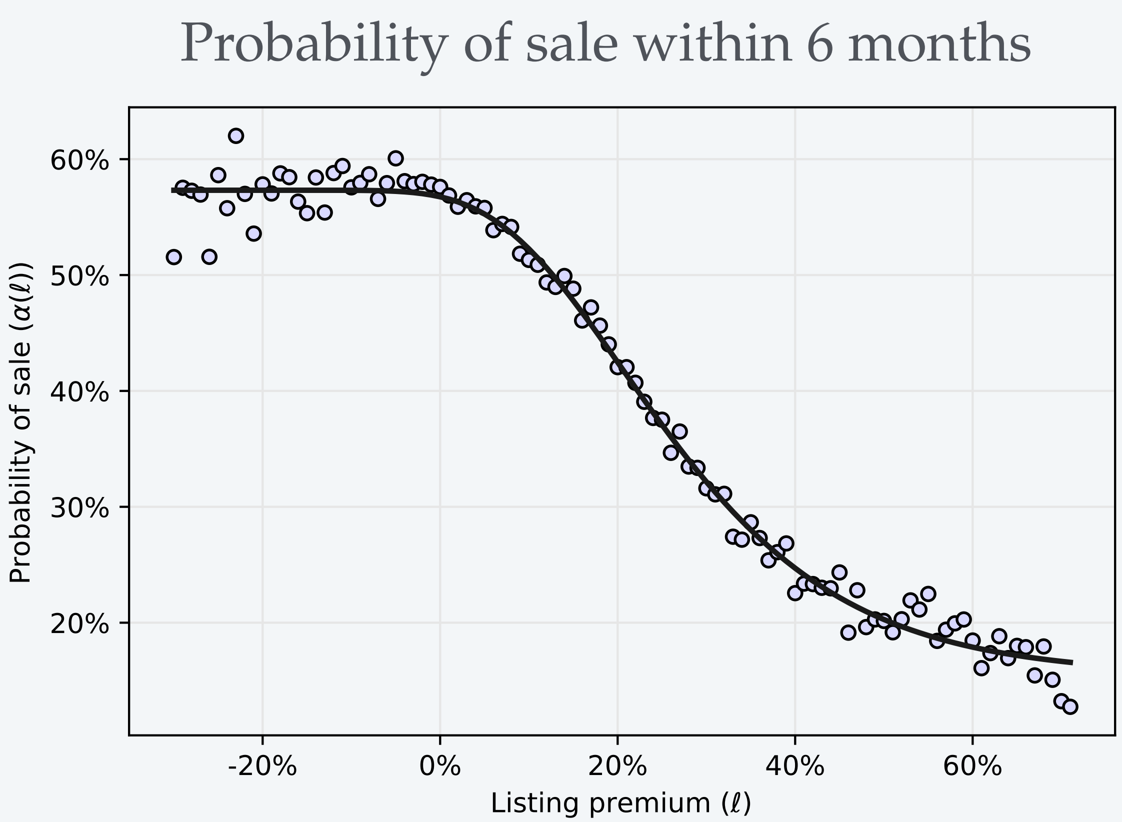
Methodology | Listing prices | Robustness

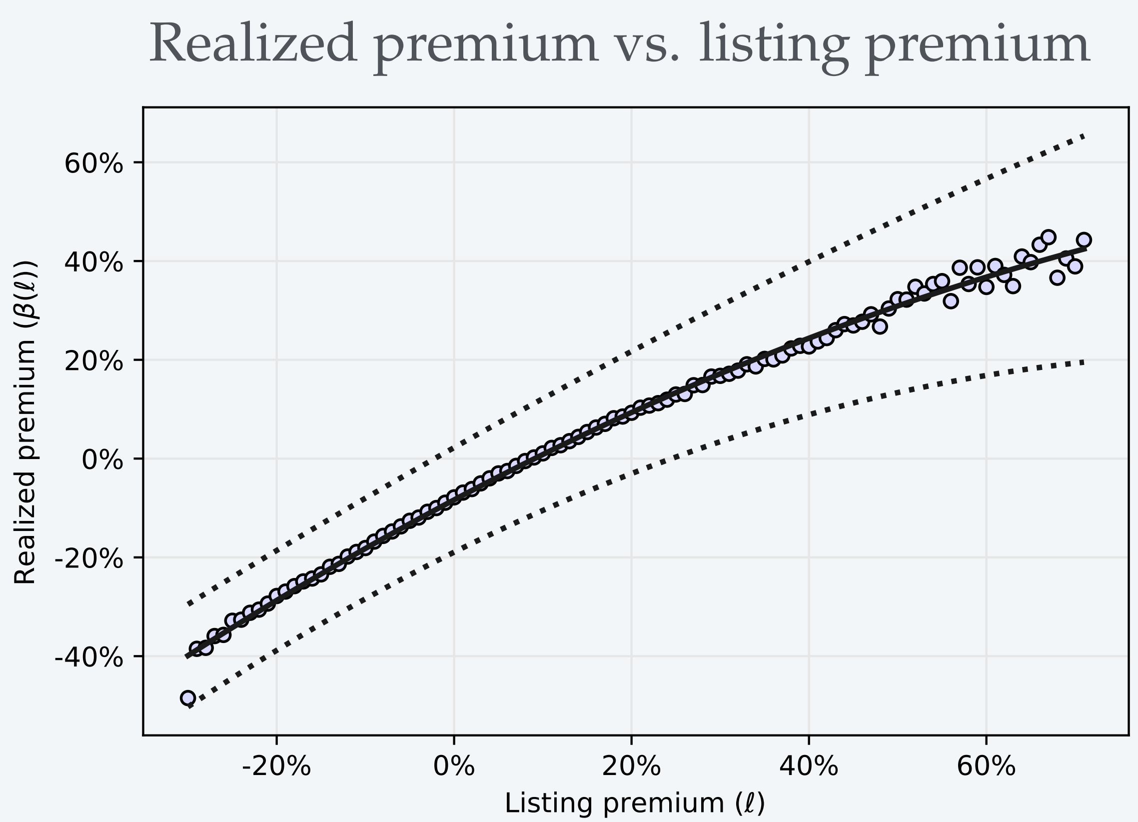
Extensive margin

- Predict prices for the entire housing stock, plot propensity to list as a function of potential gains.



Demand: Probability of sale and final prices





Unobserved quality

Estimated patterns are robust to:

- Alternative pricing models, e.g., property-specific FEs for $\widehat{P}$ ($R^2 = 0.9$).
  - OOS hedonic predictions; renovation tax exemptions (in process).

Repeat sales model | Out-of-sample simulations | Alternative spec. | Model fit

- Shire-level house prices as estimate of $\widehat{P}$.
  - 2136 shires. Smallest unit: ≈1,500 property-years and ≈45 listings.

More details

- Regressing premium on demographics, municipality, & year FE.

More details

- Genesove and Mayer (2001) bounding approach.

More details

- Regression Kink Design (RKD).
  - Significant change in slope in narrow neighbourhood around kink, while other characteristics smooth around $\widehat{G} = 0$ ($\ell = 0$ in sale probability).

More details

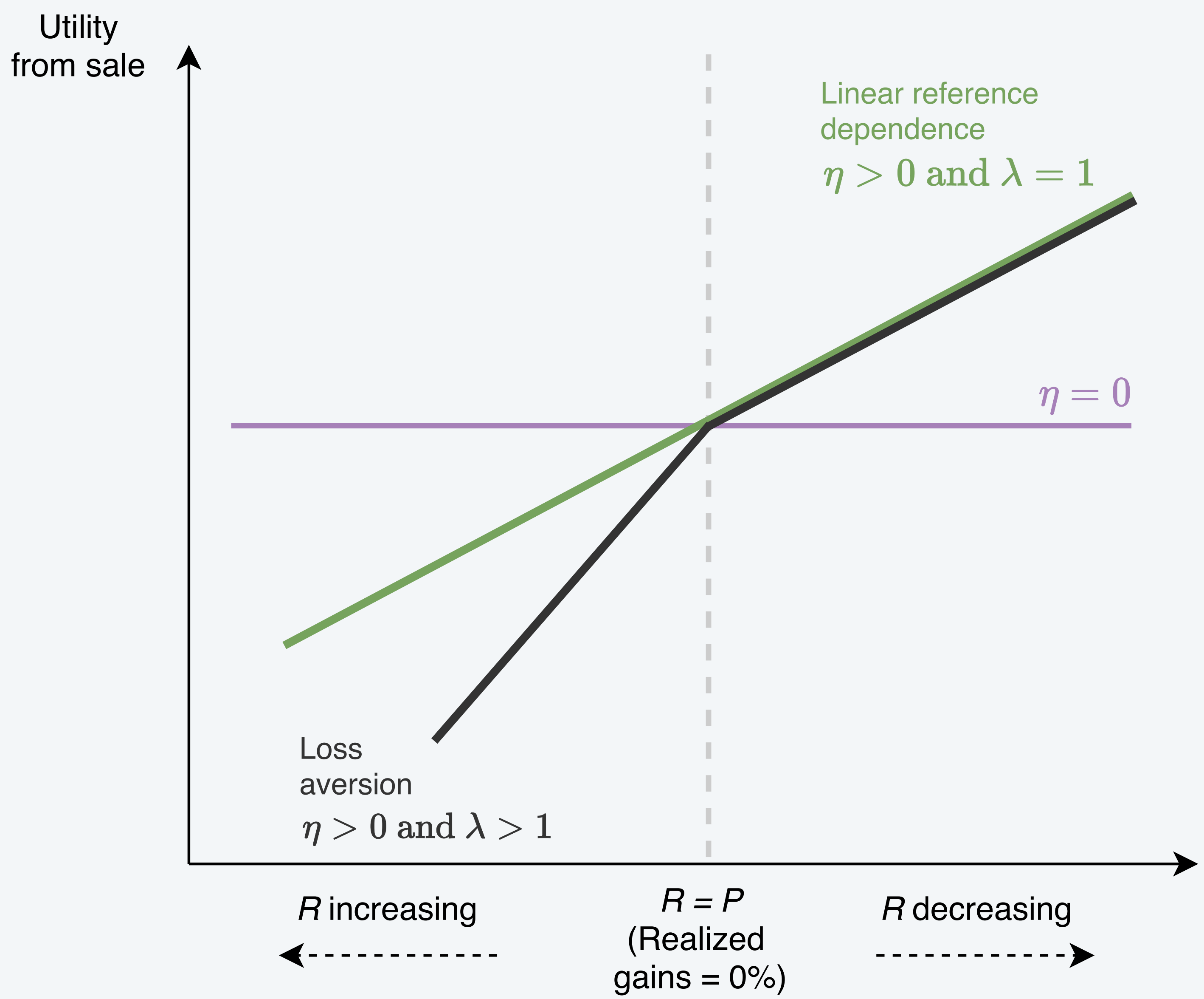
Theory

Reference dependence and loss aversion

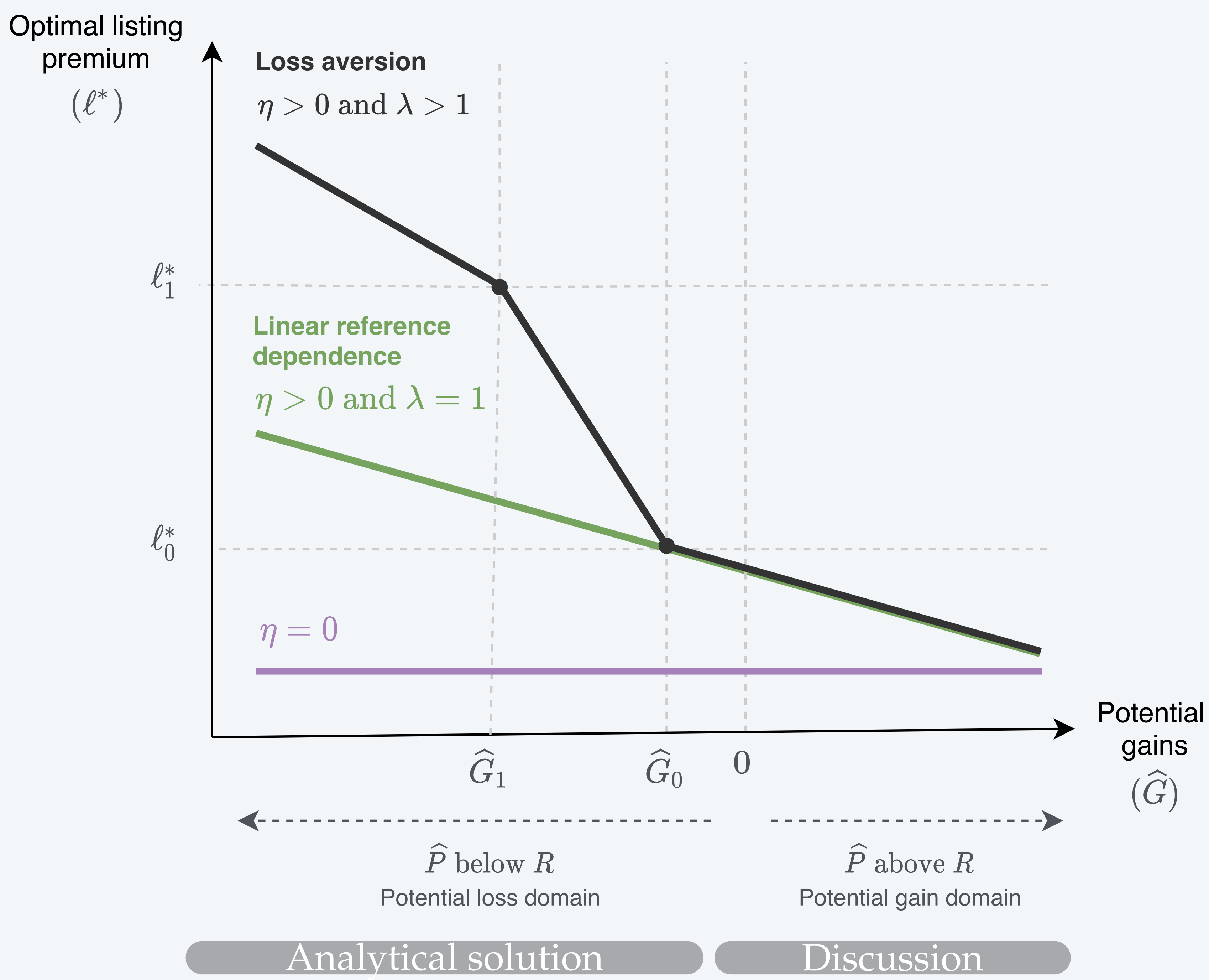
- Utility function with reference dependence and loss aversion:

$$u = P + \eta G(\lambda 1_{G<0} + 1_{G\geq 0})$$

  - Note: defined over *realized* prices P and gains G.

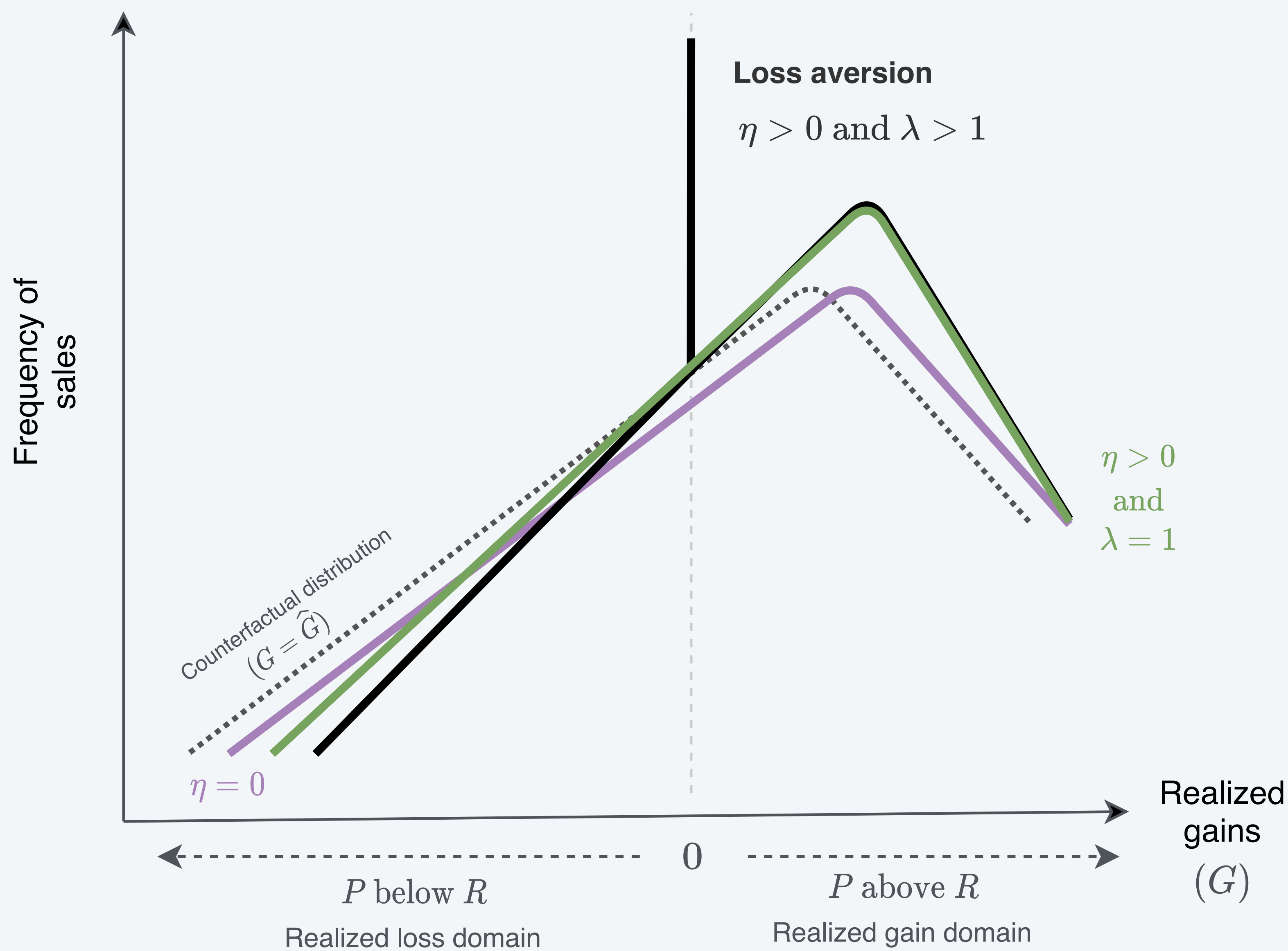


Optimal listing premia (ℓ^*)



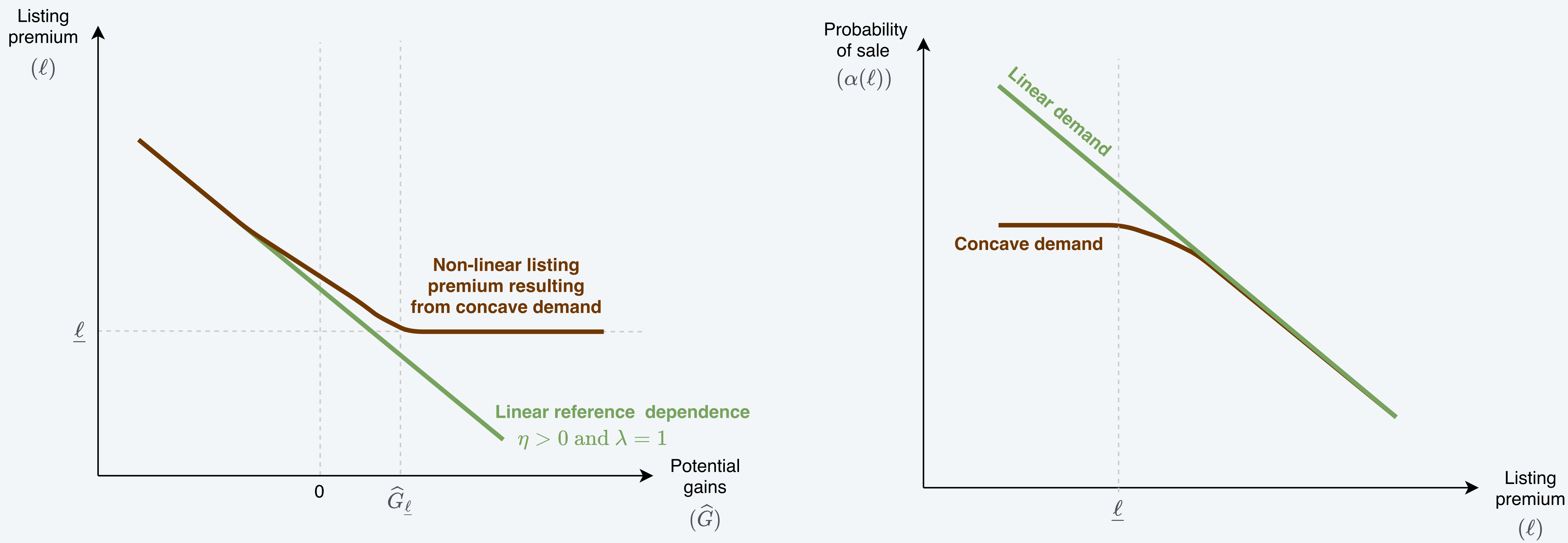
Bunching

- Distinct implications of reference dependence and loss aversion:
  - Excess mass in gain domain when $\eta > 0$; bunching at $G = 0\%$ when $\lambda > 1$, plus even less mass in loss domain.



Concave demand

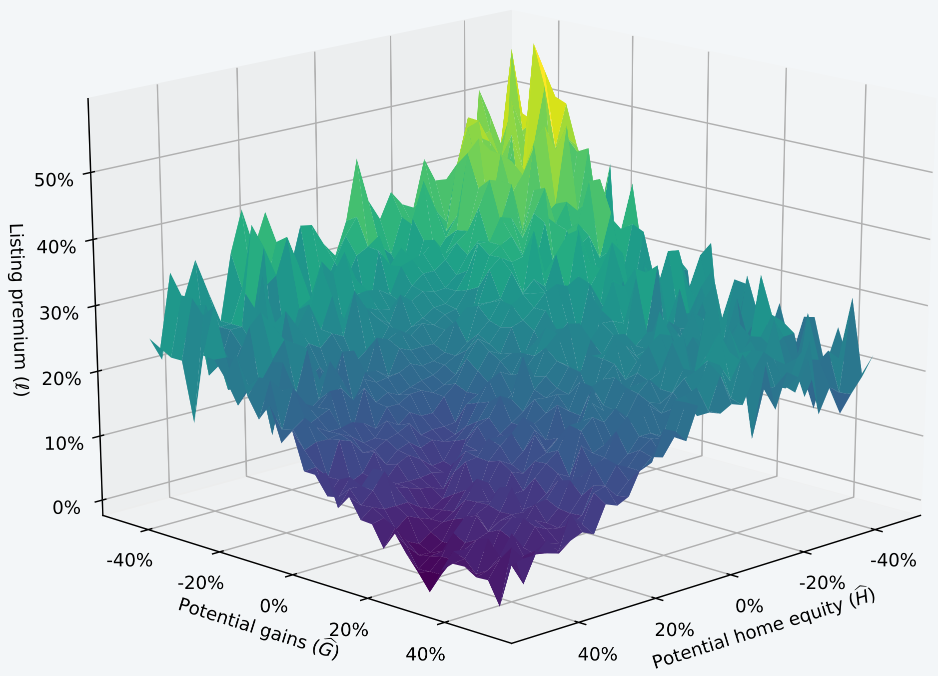
- Concave demand is a confound: Non-linear listing premia even with no loss aversion.

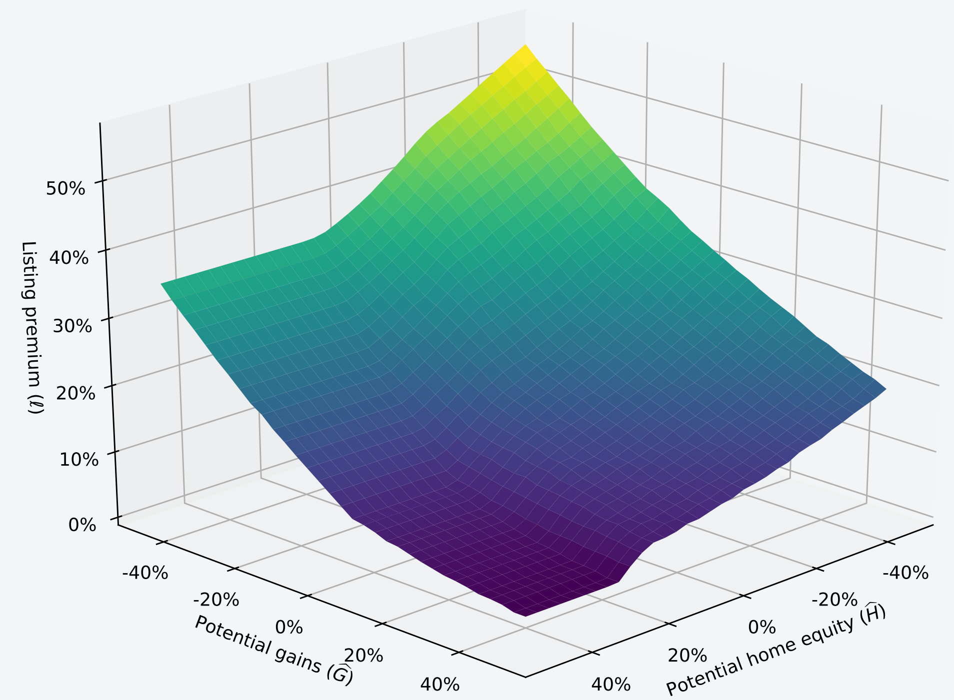


- Exploit regional variation in housing markets with differing degrees of demand concavity for identification.

Structural estimation: Work in progress

Model fit and estimated parameters



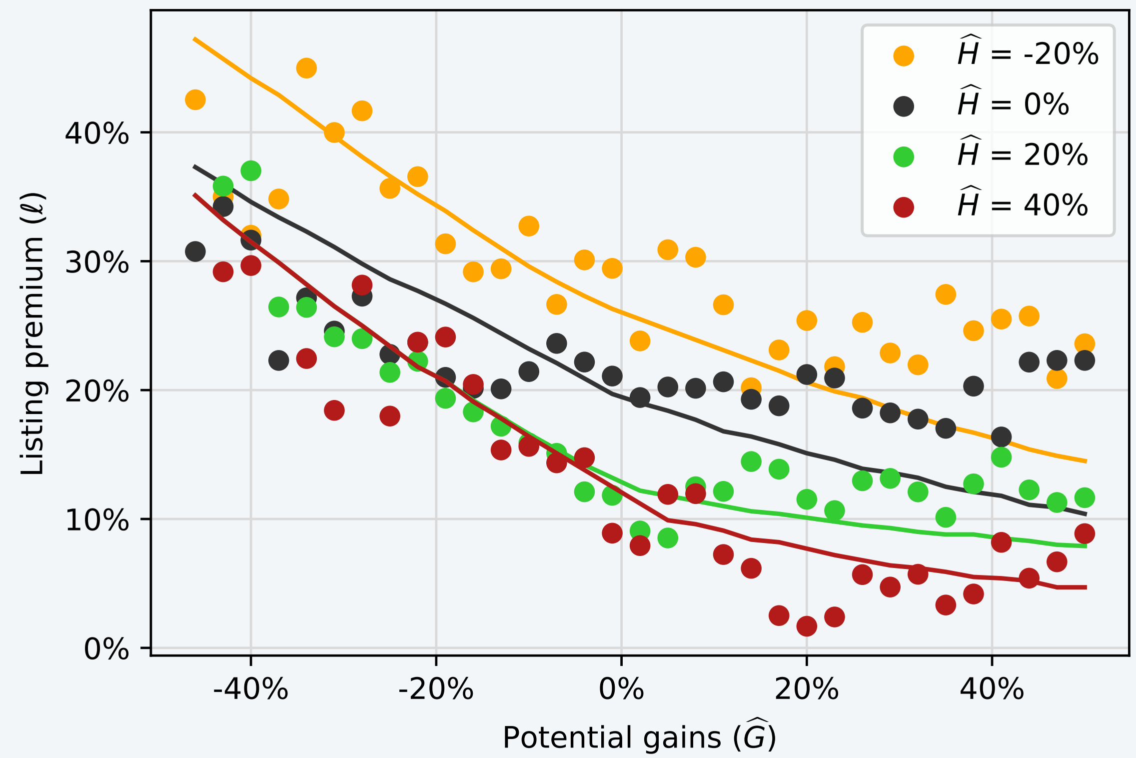


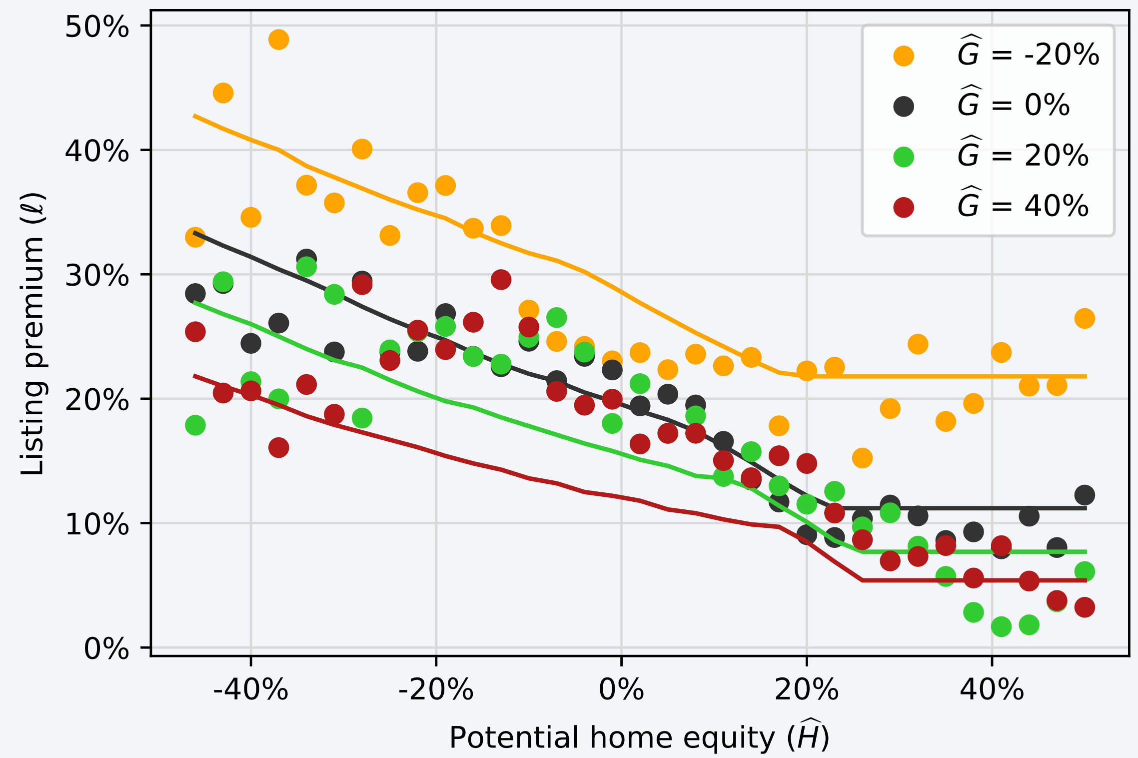
Reference dependence	η	=	0.948^{***}	(0.344)
Loss aversion	λ	=	1.576^{***}	(0.570)
Down-payment constraint	μ	=	1.060^{***}	(0.107)
Distrib. of moving shocks	θ_{min}	=	0.217	(0.165)
	θ_{max}	=	1.005^{***}	(0.197)
Cost of listing/search	φ	=	0.037	(0.011)
Adjustment to concavity	δ	=	-0.097^{***}	(0.009)

- λ in the literature: 2 to 2.5 (Kahneman et al. 1990, Tversky and Kahneman, 1991). When we shut down concave demand channel: $\lambda = 3.29$. Linear demand Identification Sensitivity analysis

Discussion and Conclusions

Interactions





- Model fails to explain lower response to losses when home equity constraint is tighter.
- Similarly, it appears as if downsizing aversion kicks in at higher potential home equity levels when potential gains are high.

Discussion

Conclusions

- We set up a structural model of house listing behavior, and document the importance of the following ingredients:
  - Reference dependence plus loss aversion.
  - Seller optimization in the presence of "demand concavity."
  - Penalty for realized home equity less than down-payment constraint thresholds.
  - Gains from trade for a successful sale and costs of listing.
- Acquire new estimates of key behavioral parameters from an important high-stakes household decision in a search and matching market.
- However, the model cannot completely match some new facts which we identify in the data.
  - Potential new target for behavioral economics theory.

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