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Reference Dependence in the Housing Market

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Introduction

- Housing is typically the largest household asset, and mortgages, the largest liability. (Campbell, 2006, Badarinza et al., 2016, Gomes et al., 2020).
- Rich sources of micro (beliefs, constraints, preferences) insights, with macro (e.g., housing liquidity and "lock") implications.
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- We revisit this question over two decades later. Key open issues:
  - *Accurate measurement* of seller's "potential gains".
  - Seller operates in the housing market—faces *housing demand*.
  - Seller also decides *whether* to list (extensive margin).
  - Confounding role of *financial constraints* (mortgage).

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  - Confounding role of *financial constraints* (mortgage).
- Large literature since the original GM papers does not fully resolve these issues (e.g., Ferreira et al. 2010, Anenberg, 2011, Schulhofer-Wohl, 2012, Hong et al. 2016, and Bracke and Tenreyro 2018).

This Paper

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- Sets up a structural framework to better understand the facts.
  - Reference-dependent loss-averse seller facing down-payment constraints.
  - Listing price choice and listing decision maximize utility, internalizing effects on final sale price and probability (i.e., demand).
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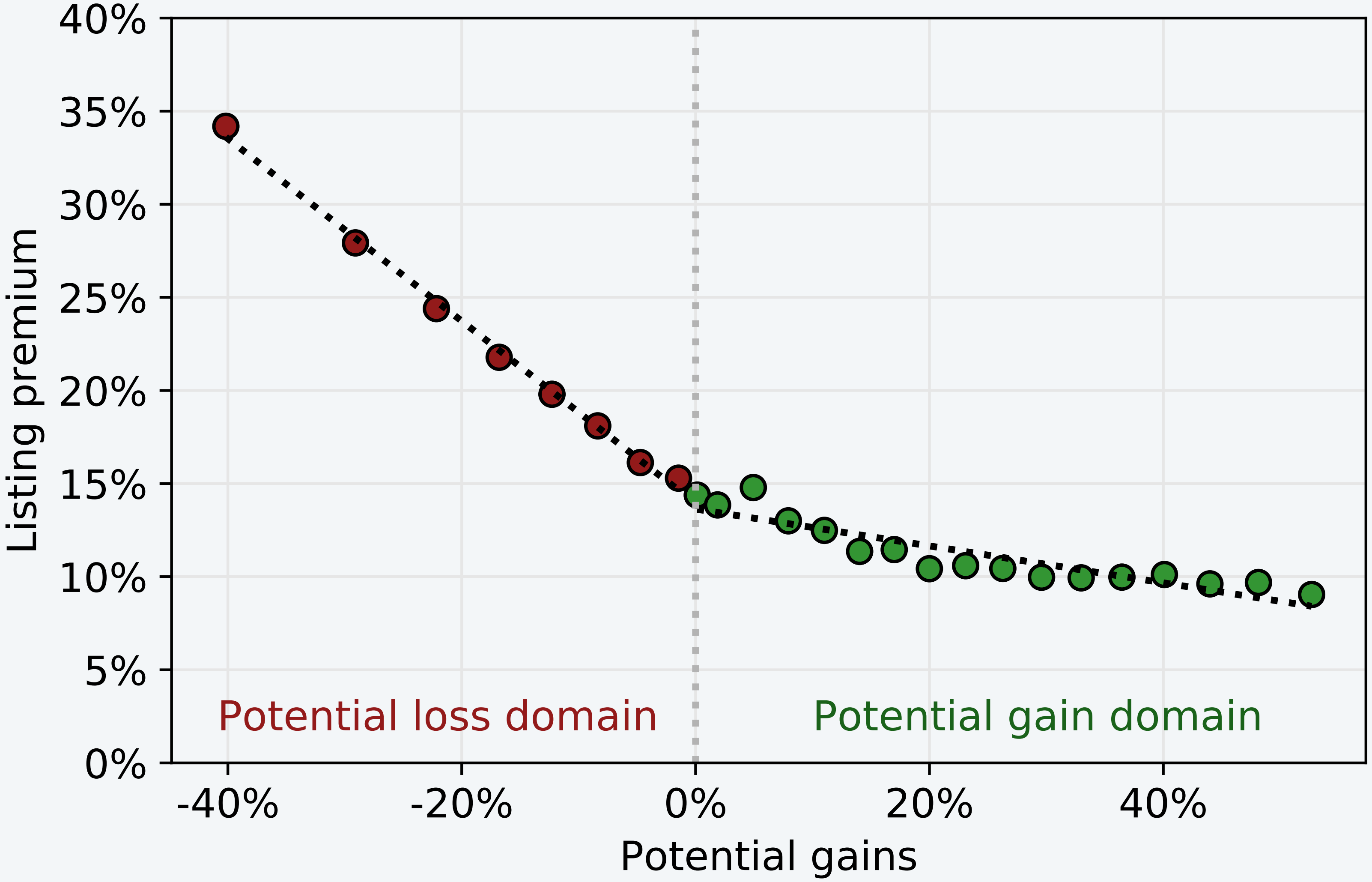
- Model can rationalize many patterns in the data; exceptions point to future theoretical work.

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 a First Look at the Facts

Data

- All Danish housing transactions from 2009 to 2016.
  - Assessed sale values from the tax registry.
  - 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, and 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.
- Final dataset: 217,028 listings (70.6% sold, 29.4% retracted) of 181,020 properties by 193,850 households between 2009 and 2016. Mainly focus on 175,646 listings with a mortgage.
  - Also use housing stock (6,478,391 observations of 953,868 unique properties) to understand the extensive margin, i.e., *propensity* to list.

More details

Hedonic pricing model

- Predict prices using hedonic model, to compute listing premium, potential gains, and potential home equity:

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

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

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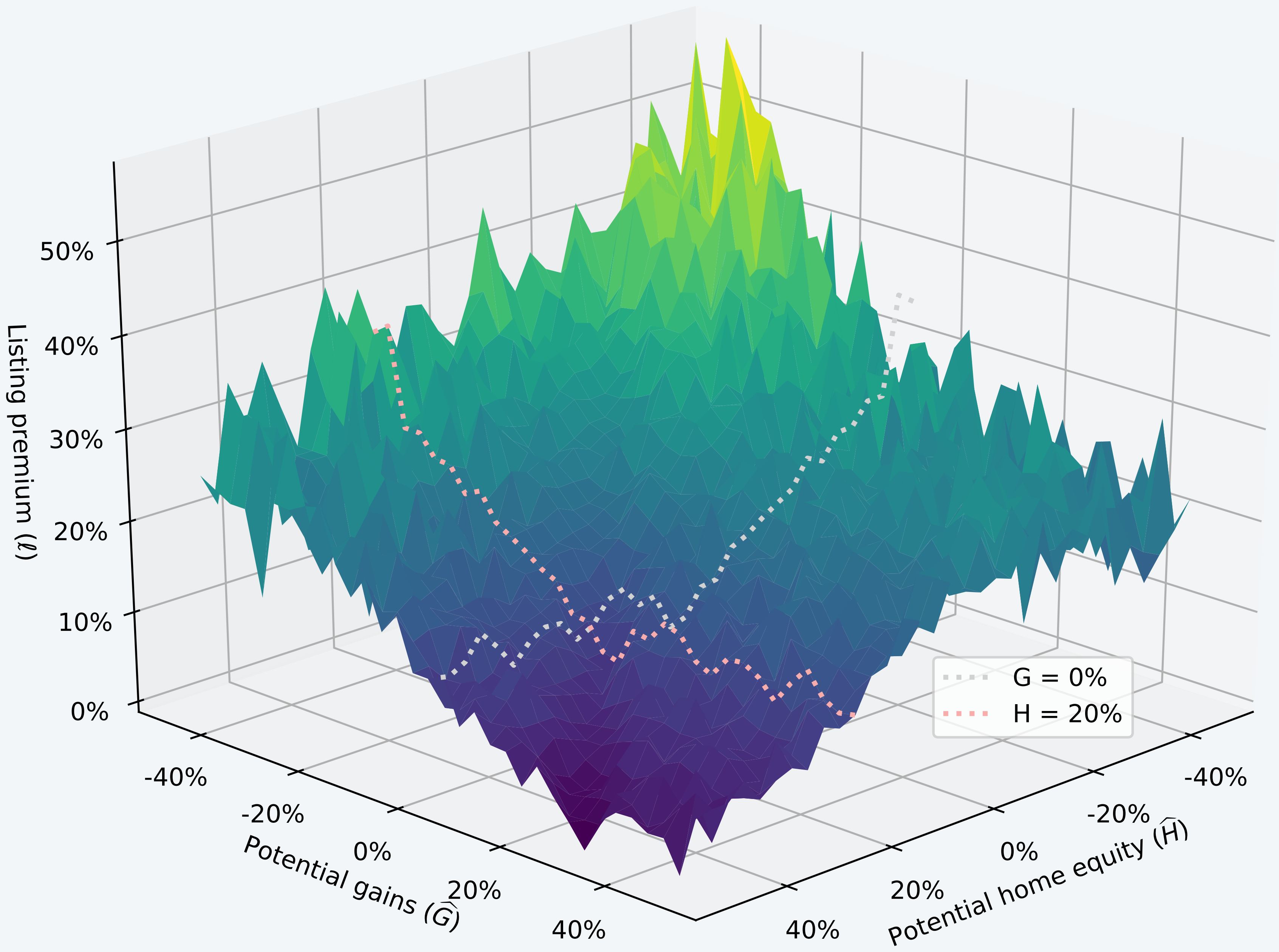
- Use predicted prices to calculate:

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



- Estimate model parameters off moments of selected cross-sections; subsequently evaluate model against entire surface.

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 $G = 0\%$.)
  - Can identify excess bunching using counterfactual polynomial fit (Chetty et al. 2011, Kleven 2016, Rees-Jones 2018).
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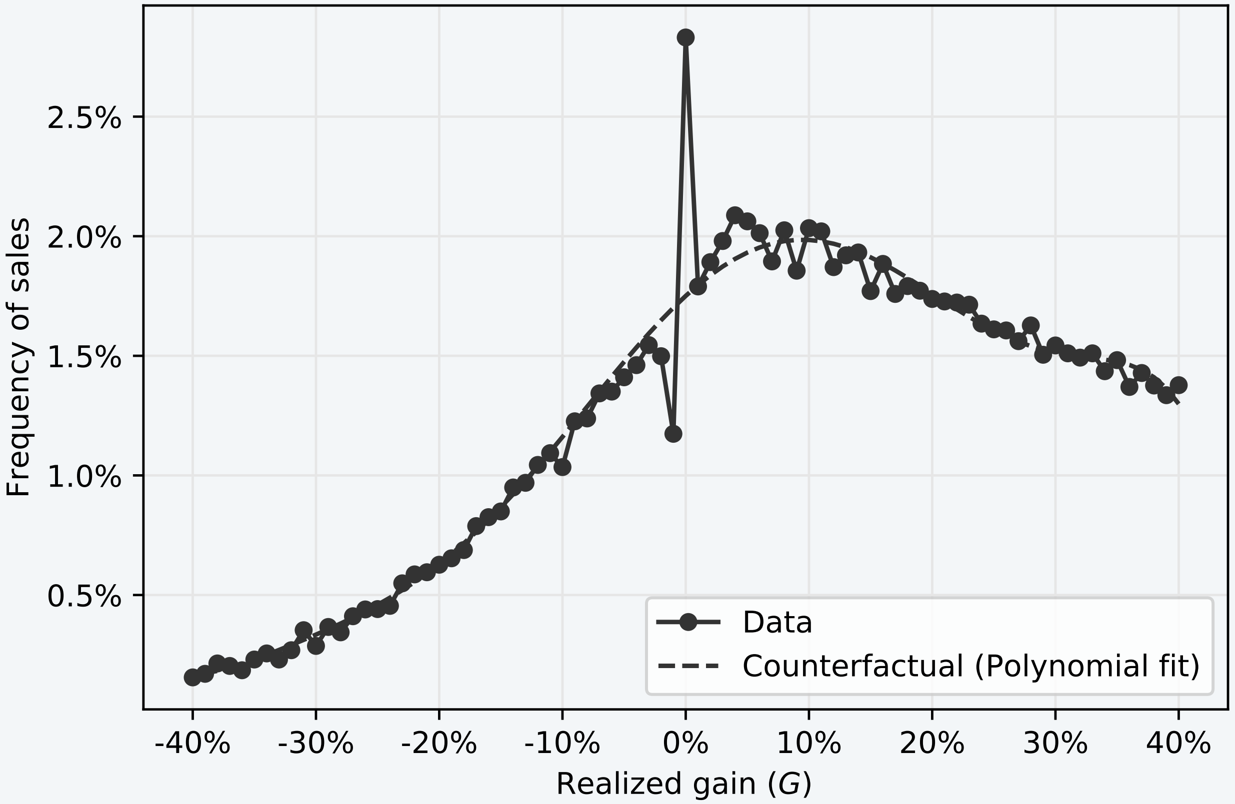
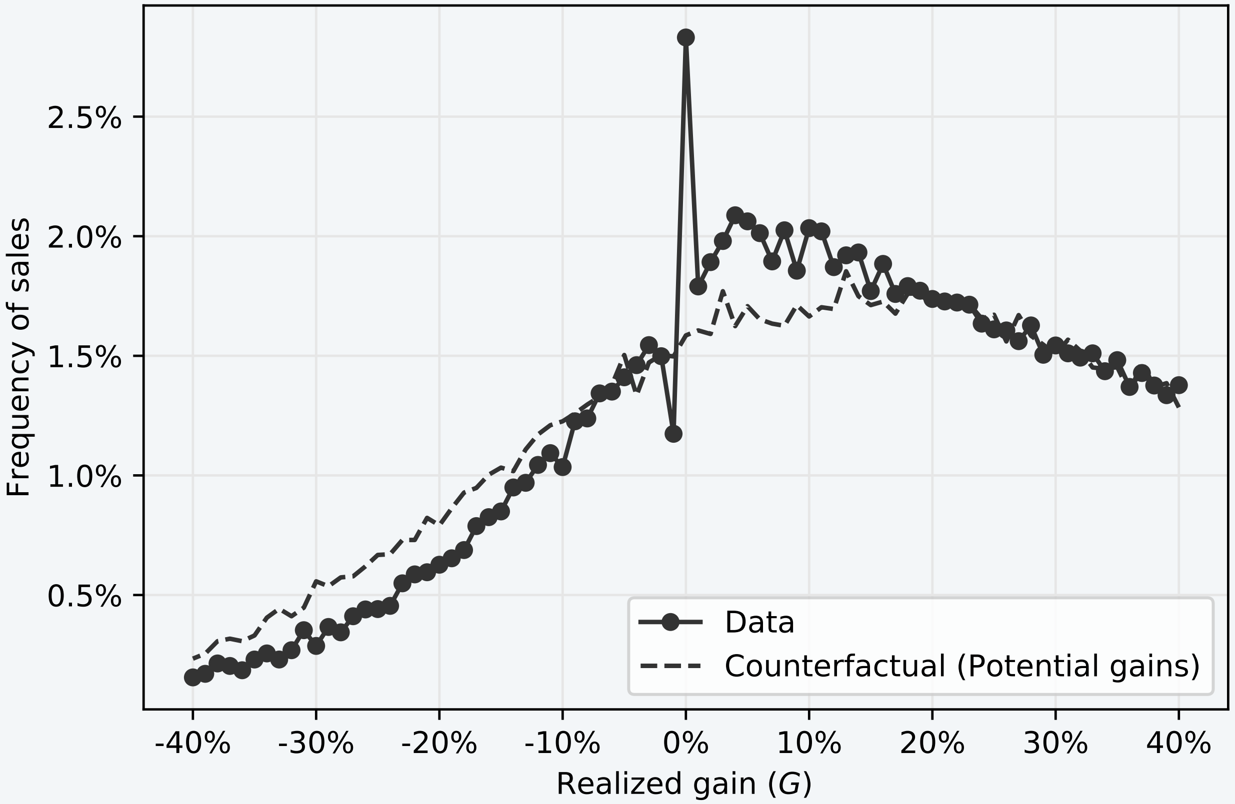
Polynomial counterfactual



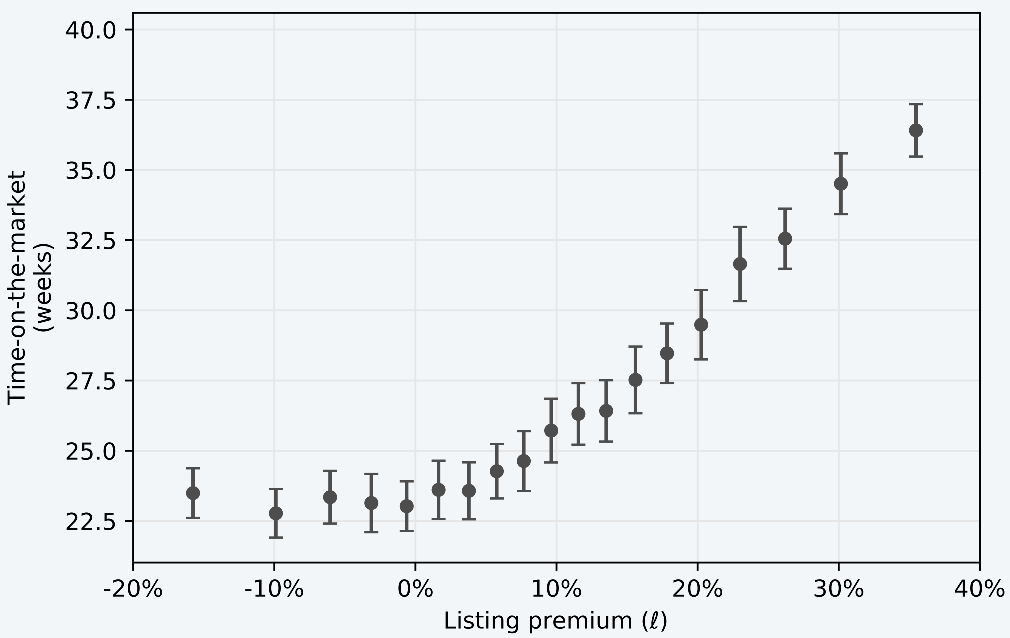
Potential gains counterfactual



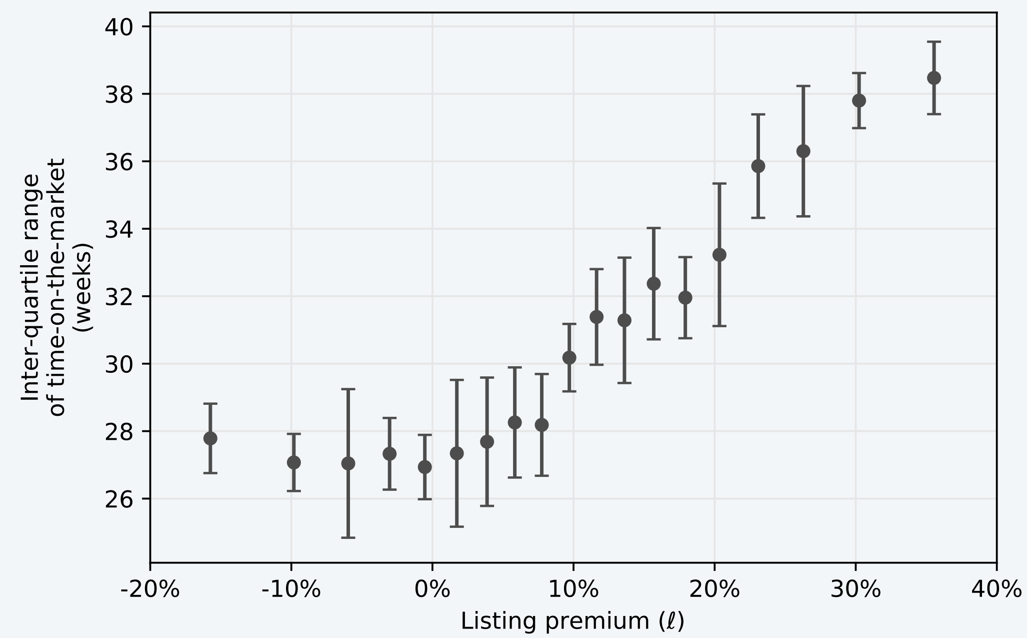
Methodology | Listing prices | Robustness

Time-on-the-market and final prices

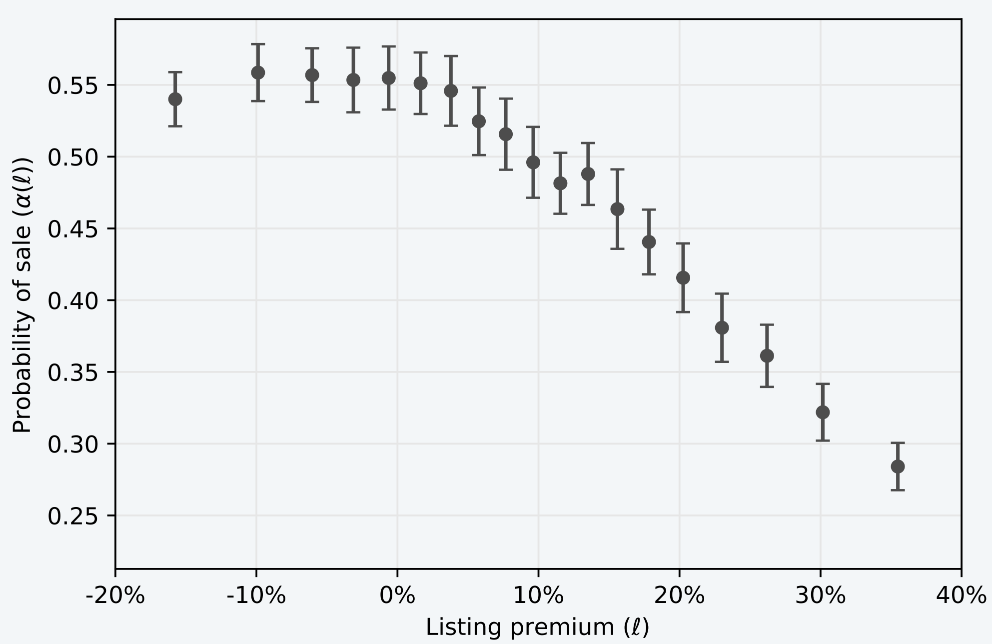
Average time-on-the-market



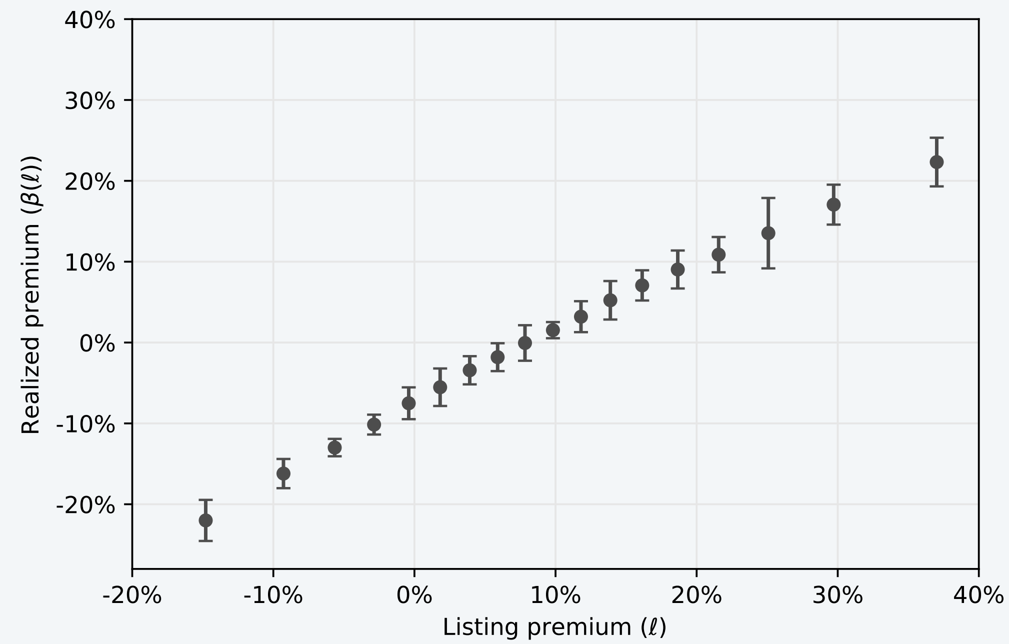
IQR of time-on-the-market



Probability of sale within 6 months



Realized premium vs. listing premium



Note: Error bars indicate 99% confidence intervals based on bootstrap standard errors.

Unobserved quality

Estimated shapes we've seen are robust to:

- Alt. pricing models, e.g., repeat sales (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 TOM). More details

Theory

Model

$$\max_{s\in\{0,1\}} \left\{ (s) \max_{\ell} \left[\alpha(\ell) \left(U(P(\ell), \cdot) + \theta \right) + (1-\alpha(\ell))\underline{u} - \varphi \right] + (1-s)\underline{u} \right\}$$

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Preferences and constraints

- $U\left(P(\ell), \cdot\right) = u(P(\ell), \cdot) - \kappa(P(\ell), \cdot)$ nests reference-dependent loss-aversion à la Kahneman and Tversky (1979) and down-payment constraints à la Stein (1995).

More details | Institutional framework

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Concave demand

- $\alpha(\ell)$ and $\beta(\ell)$ estimated from the data.

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More details

Additional "fitting" parameters

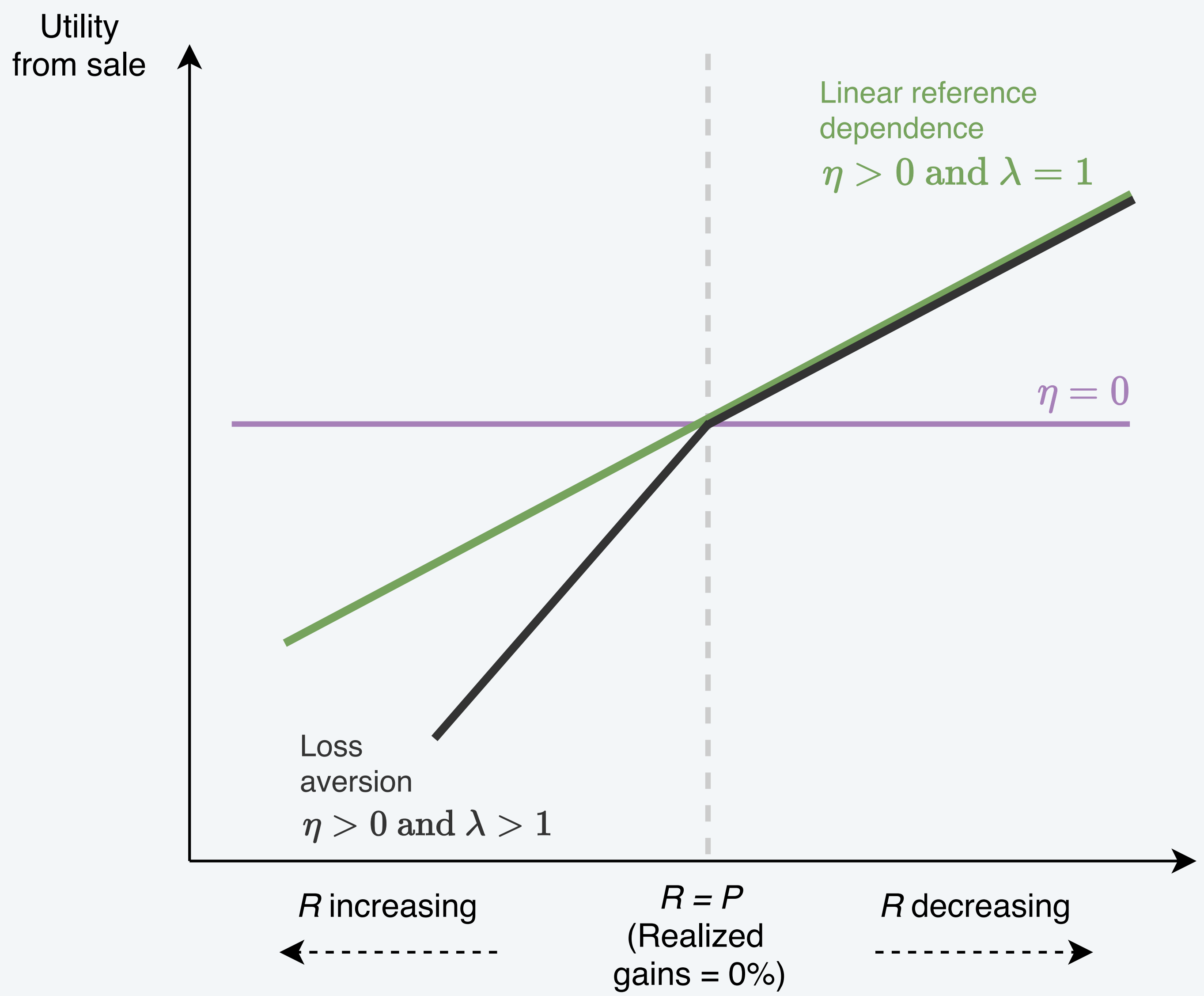
- $\theta \sim \mathrm{F}(\theta_{\min}, \theta_{\max})$ is "gain from trade/moving" (Stein, 1995), i.e., utility of move.
- φ is the cost of listing/search.
- δ adjustment to perceived demand concavity.

Reference dependence and loss aversion

- Utility function with reference dependence and loss aversion:

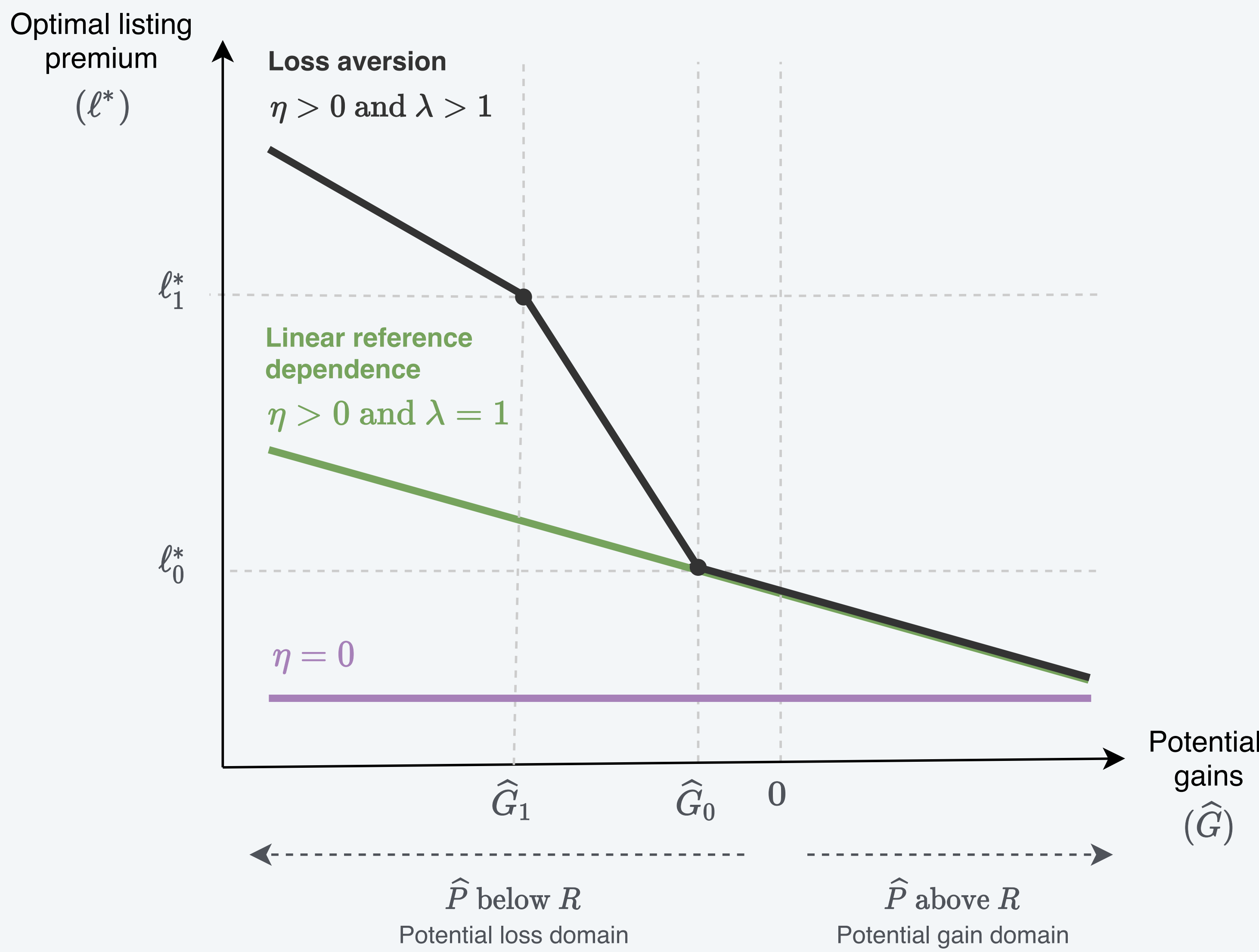
$$u = P + \eta G(\lambda 1_{G<0} + 1_{G\geq 0})$$

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



Optimal listing premia (ℓ^*)

- Solve for optimal listing premia under different utility specifications.
- Consider the state variable: *potential gains* $\widehat{G} = \widehat{P} - R$.
  - Maps to realized gains through listing and sale: $G(\ell^*) = \widehat{G} + \beta(\ell^*)$.



Analytical solution | Discussion

Additional model predictions

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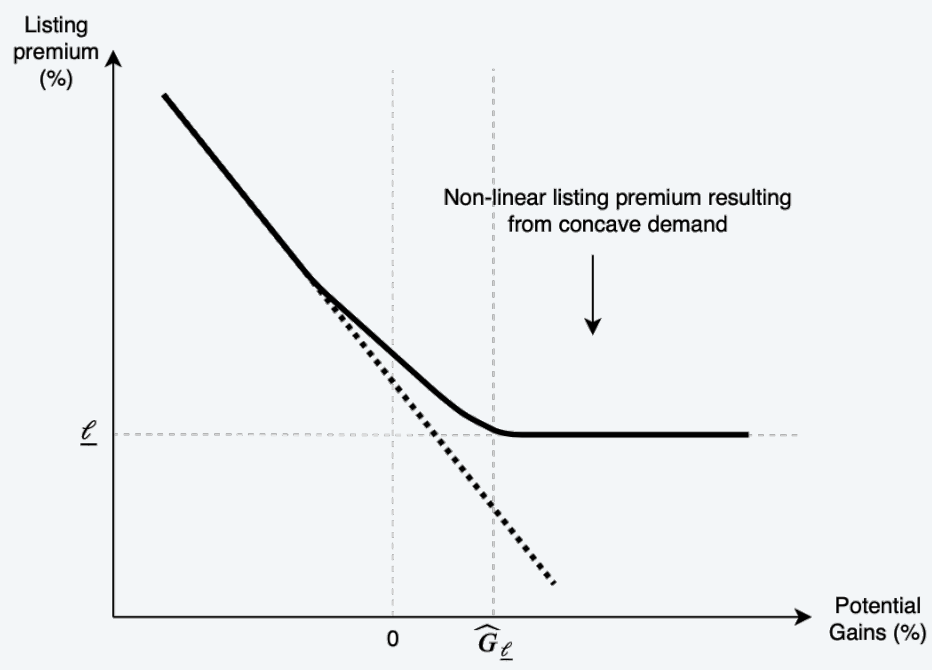
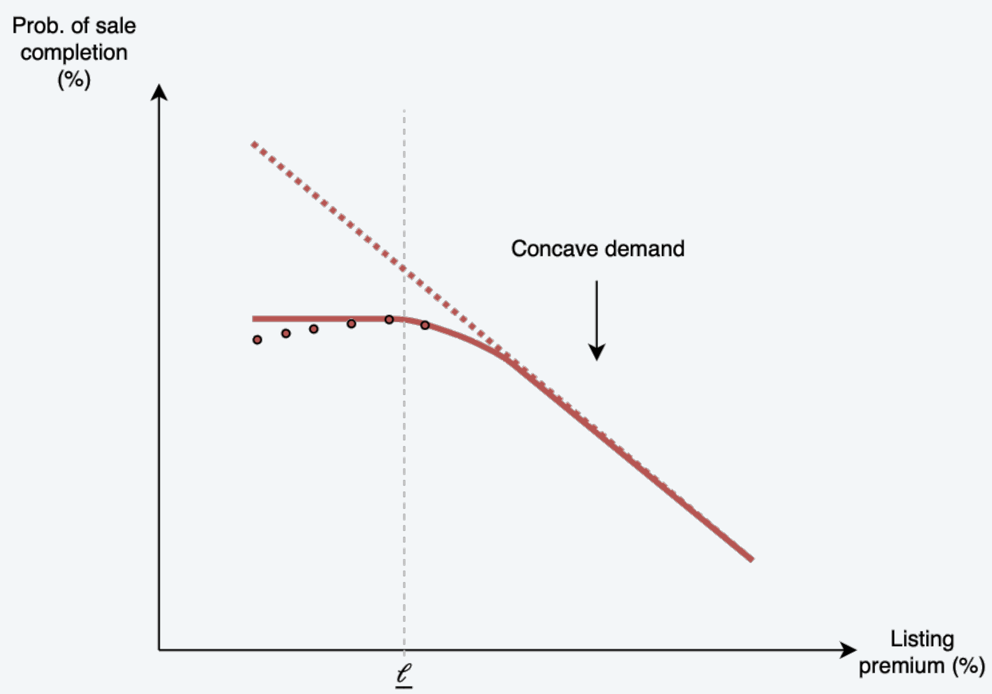
2. Extensive margin decision and heterogeneity:
   - ► Sellers with potential losses are less likely to list properties for sale.
   - ► Distribution of "gains from moving" in the population "smooths out" non-linearities and kinks. More details
3. Concave demand generates non-linearity of listing premium profile:
   - ► The seller understands that the chosen listing premium affects the final sales price, and time on the market.



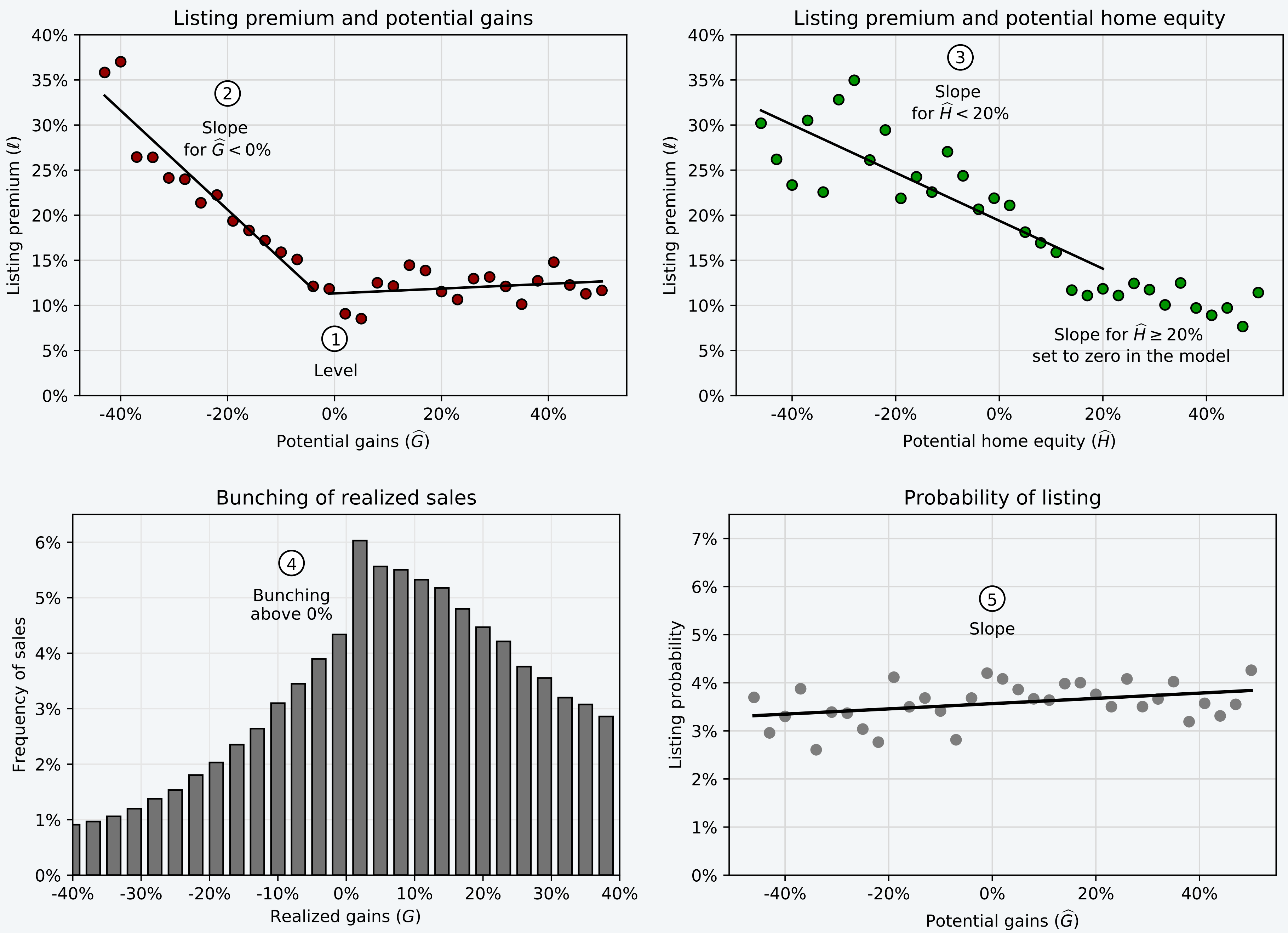


Exploit cross-regional variation for identification

Structural estimation: Work in progress

Matching empirical moments

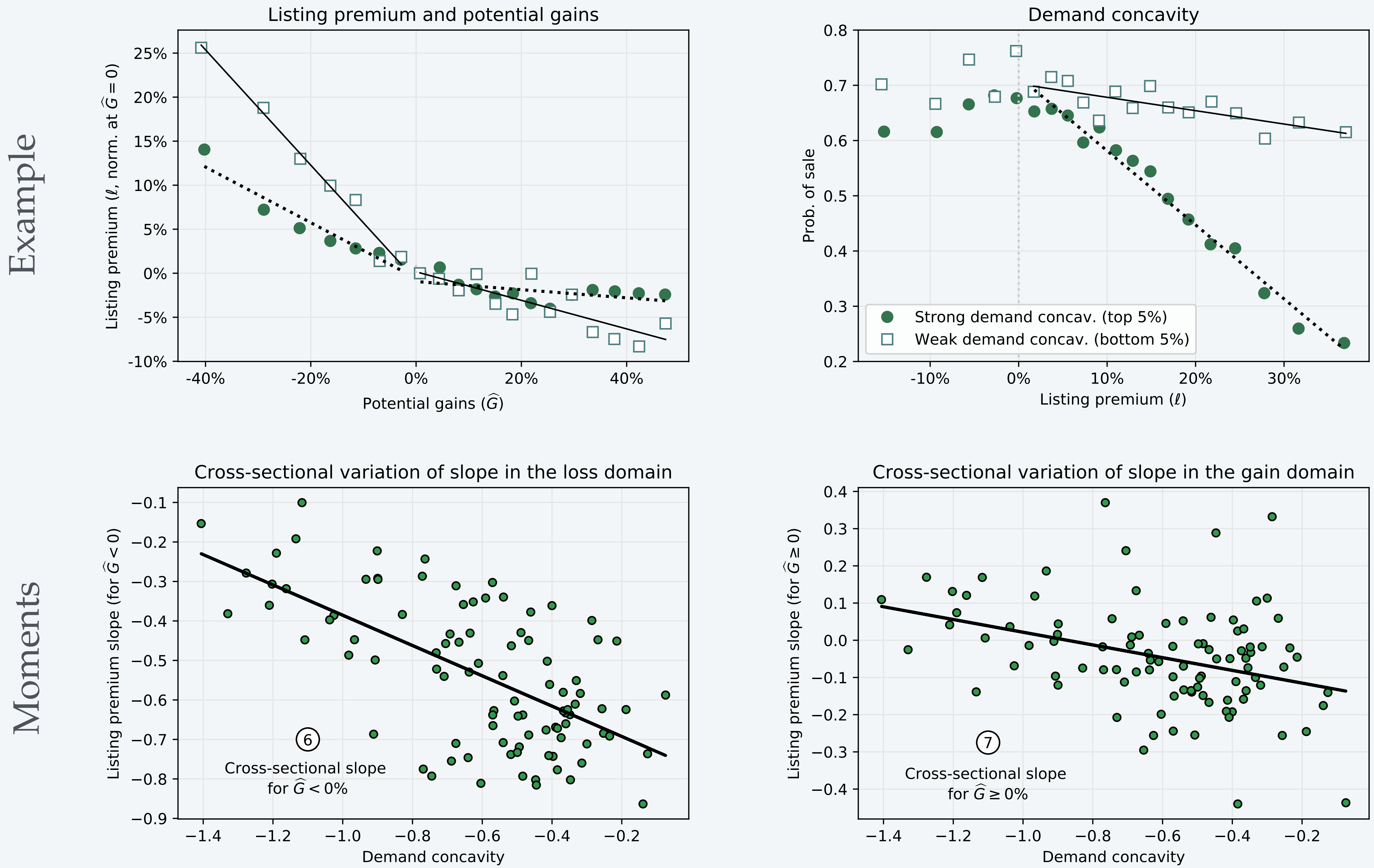
- Average listing premium for different levels of potential gains and home equity, excess bunching at $G = 0\%$, and probability of listing.



Estimated moments

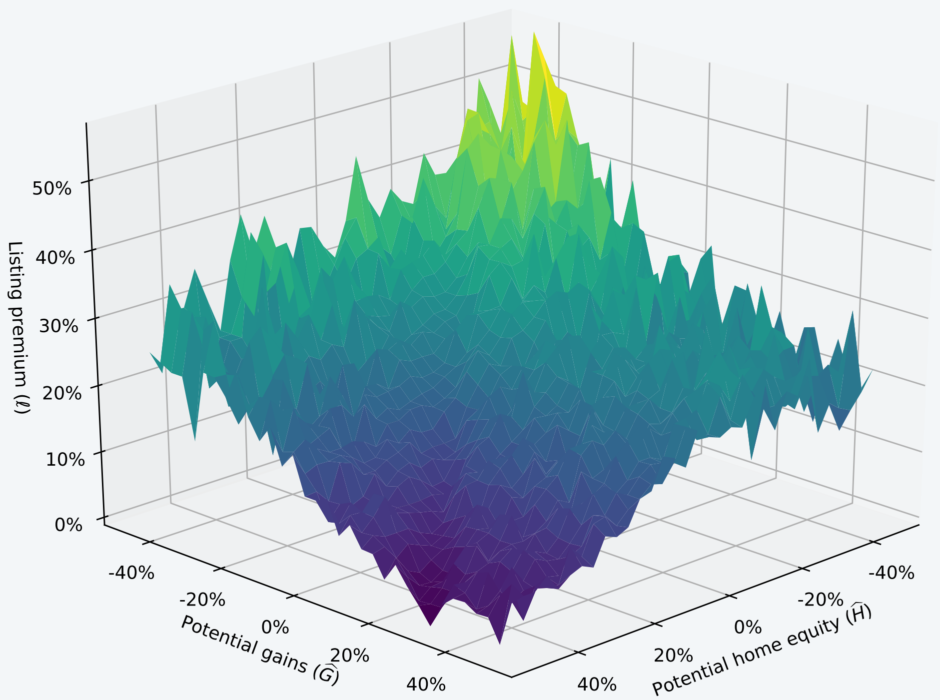
Matching empirical moments: Demand concavity

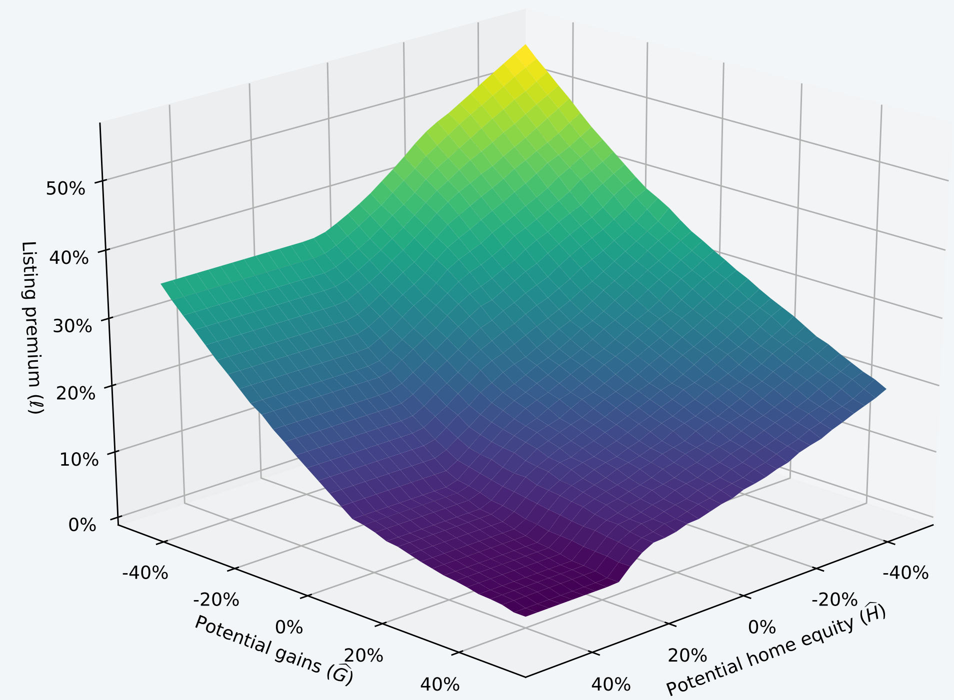
► Relationship between the slope of the listing premium and demand concavity across 98 municipalities of Denmark.



Level effects | Theoretical mechanism | Instrument

Model fit and estimated parameters



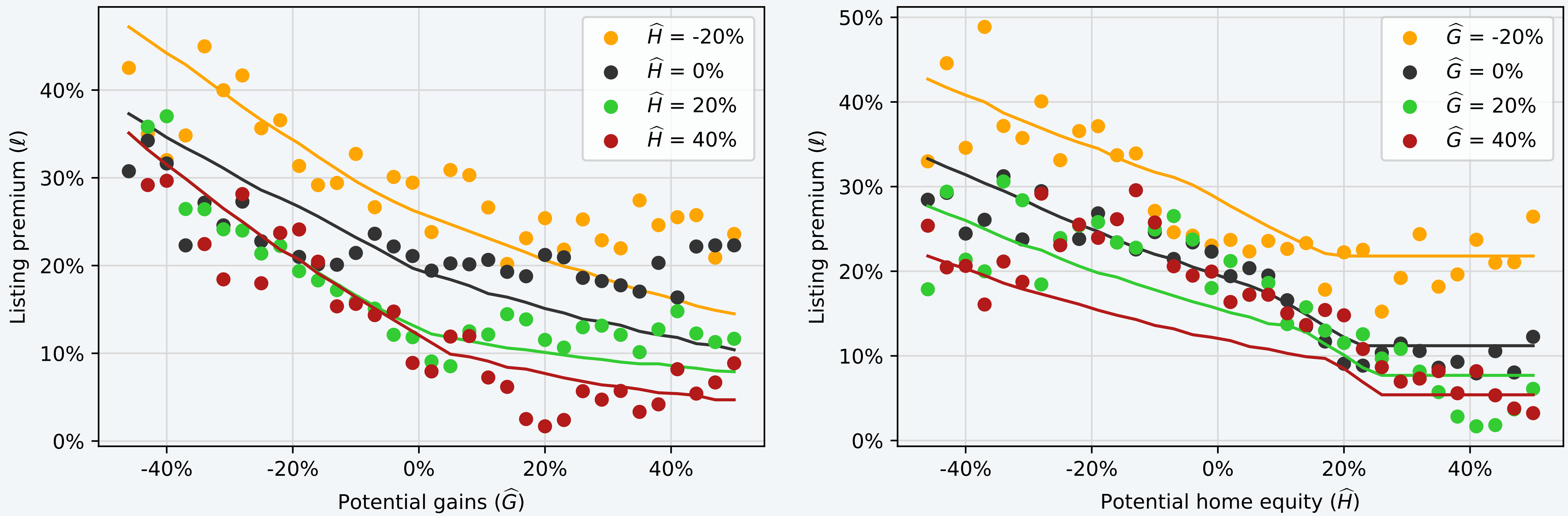


Reference dependence	η	=	0.981***	(0.312)
Loss aversion	λ	=	1.525***	(0.422)
Down-payment constraint	μ	=	1.035***	(0.140)
Distrib. of moving shocks	θ_{min}	=	0.228	(0.186)
	θ_{max}	=	1.037***	(0.174)
Cost of listing/search	φ	=	0.039	(0.040)
Adjustment to concavity	δ	=	−0.093***	(0.025)

- 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 cannot explain flattening out of listing premia-potential gains relationship as home equity constraint tightens.
- Similarly, it appears as if a household's propensity to engage in "fishing" behavior kicks in at a level of potential home equity that is influenced by potential gains.

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.