Preliminary JMP presentation

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Research Agenda Overview

Essays on Investor Behavior

- *C1. Asymmetric Labor Income Risk: Implications for Risk-Taking in Financial Markets*
- *C2. Navigating Through Fear and Greed: The Experience-Driven Disposition Effect (Submitted)* (with Rong Liu, Yongjie Zhang, Jessica Wachter, Michael Kahana)
- *C3. When Risk Stops Mattering: Speculative Demand and Price Uncertainty in Housing Markets*

Side Projects

- *P1. Consumption under Constraints: Uncovering Inequality in Discretionary Spending*
- *P2. Tax-Induced Labor Supply Distortions: Evidence from Japan*

Asymmetric Labor Income Risk: Implications for Risk-Taking in Financial Markets

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Chapter 1: Research Question

Key Question

How do higher-order moments (variance and skewness) of labor income risk influence households' equity allocations?

- Standard Gaussian-income models cannot explain why higher income volatility sometimes coincides with greater equity holdings.
- Need to account for asymmetric (upside vs. downside) income shocks.

Literature Gaps

- Empirical focus on variance only (Betermier et al. 2012; Fagereng et al. 2018).
- Mixed evidence on covariance channels (Vissing-Jorgensen 2002; Calvet et al. 2014).
- The distribution of the risk (Skewness) is largely unaddressed in reduced-form studies.

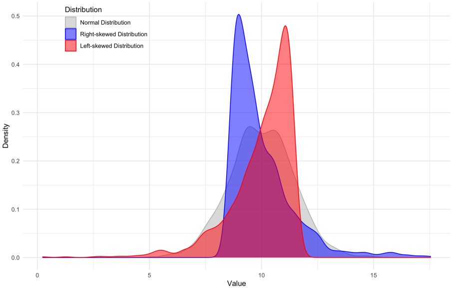
Labor Income Risk

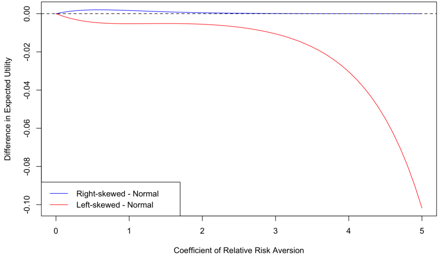
Connection to Guvenen et al. (2014 JPE)

- $\Delta y = m_{s,t} + \sigma_{s,t}\eta + \varepsilon_t^i$ with state s. η standardized shock with $N(0,1)$.
- The individual risk (ε_t^i) and the macro level risk ($m_{s,t} + \sigma_{s,t}\eta$) jointly determine the labor income risk faced by workers.
- My $\sigma_i^2 \leftrightarrow$ their ε_t^i; group skew $\upsilon_g \leftrightarrow$ cyclical $m_{s,t}$ and $\sigma_{s,t}$ are dependent on the state of the world.

- Income innovation: $\tilde{y}_{it} = \sigma_i, \upsilon_g$.
- $\sigma_i^2 = Var(\Delta e_{it})$: idiosyncratic variance by worker.
- $\upsilon_g =$ P90–P10 dispersion in edu$\times$industry group: captures skewness.
- Use $\sigma_i^2 \times \upsilon_g$ to separate scale and shape effects of the labor income risk.

Simulation Insight





- Same mean/variance, varying skewness (-2,0,2).
- Utility premium rises for right-skew, plummets for left-skew.
- More risk-averse: insensitivity to upside, high cost of downside.

Testable Hypotheses

1. Holding υ_g fixed, higher $\sigma_i^2 \rightarrow$ lower risky share.
2. Holding σ_i^2 fixed, more negative skew ($\mu_\varepsilon < 0$) $\rightarrow$ lower share.
3. Holding both fixed, higher risk aversion $\rightarrow$ lower share.
4. Both effects attenuate with higher wealth ($1/W, 1/W^2$ scaling).

Data & Measurement

- Nationally representative longitudinal survey of U.S. households.
- Monthly data on income, demographics, portfolio holdings.
- Sample: over 250,000 individuals directly holding stocks.

- **Variance**$_{i,t}$ $\Leftrightarrow$ σ_i^2: individual annual income-growth variance.
- **Skewness**$_{g,t}$ $\Leftrightarrow$ υ_g: cluster-level (education $\times$ industry) distribution asymmetry (P90-P50 vs. P50-P10).
- **Labor Risk**: Variance$_{i,t}$ $\times$ Skewness$_{g,t}$.

Portfolio Choice Regression

$$Share_{i,t} = \alpha + \beta_1 Var_{i,t} + \beta_2 Skew_{g,t} + \beta_3 (Var_{i,t} \times Skew_{g,t}) + Controls + FE + \varepsilon$$

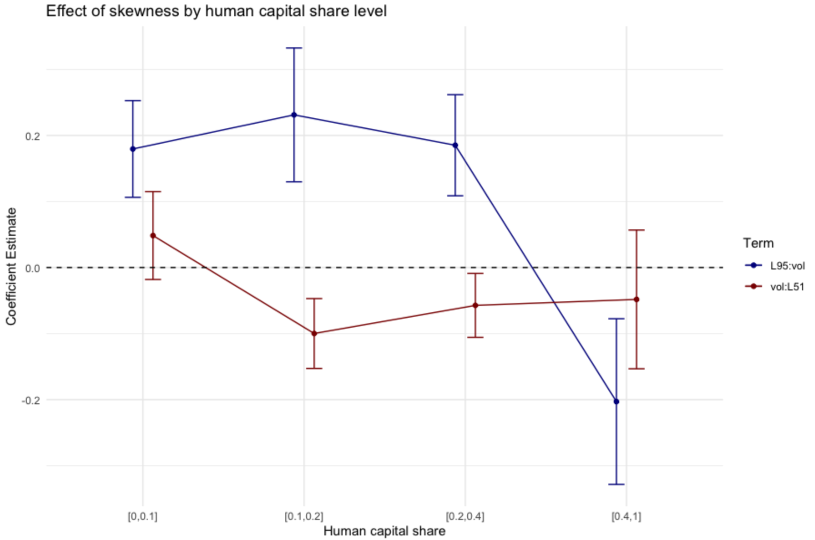
- Controls: age, gender, income, wealth, education, housing/unemployment status.
- Fixed effects: industry $\times$ year-month.

Skewness and asset allocation

	% Share of Assets Directly Invested in Stocks % $\in$ [0,100]					
	(1)	(2)	(3)	(4)	(5)	(6)
Opportunity (L9050)	0.323	-	0.316	0.120	-	0.152
	(3.668)	-	(3.593)	(1.346)	-	(1.678)
Disaster (L5010)	−0.246	-	−0.251	-	−0.211	−0.219
	(−3.332)	-	(−3.403)	-	(−2.822)	(−2.885)
Individual Risk (Variance)	-	0.076	0.076	**−0.084**	0.074	−0.059
	-	(4.628)	(4.621)	(−3.358)	(3.257)	(−2.222)
Opportunity Risk (L9050$\times$Var)	-	-	-	0.137	-	**0.173**
	-	-	-	(6.843)	-	(8.037)
Disaster Risk (L5010$\times$Var)	-	-	-	-	0.003	**−0.047**
	-	-	-	-	(0.190)	(−2.995)

All columns control for household characteristics and include industry fixed effects as well as year-month fixed effects. The total number of observations is 259,485.

Empirical Evidence for Downside Risk Aversion



Implications of Chapter 1

- Non-Gaussian risk distributions matter for household portfolios.
- Skewness measures vital for financial advice and retirement planning.
- Foundation for models incorporating third-moment preferences.

Navigating Through Fear and Greed: *The Experience-Driven Disposition Effect*

Tai Lo Yeung[*], Rong Liu[†], Jessica Wachter[‡], Michael Kahana[§], Yongjie Zhang[†]

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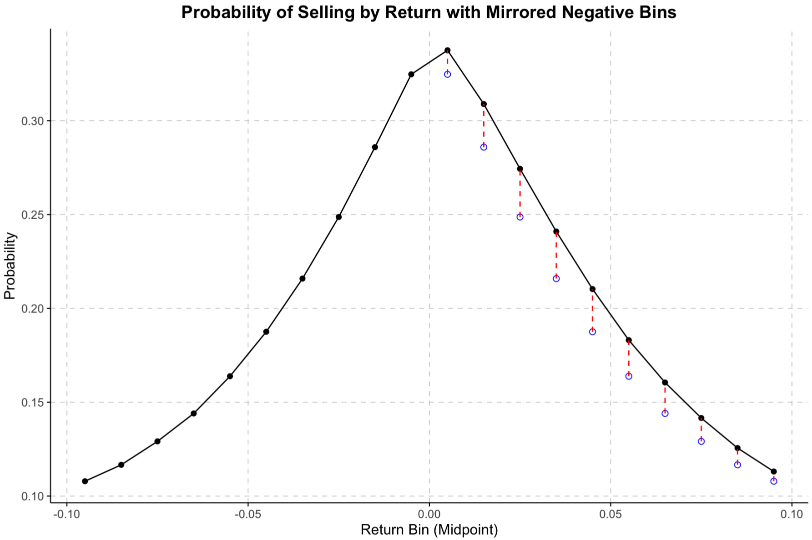
Chapter 2: Research Question

Key Question

How do the experiences of winning and losing in trading shape the behavioral biases of retail investors?

- Mainstream studies measure market experience by the number of trades and argue that as experience increases, the associated bias decreases. (List (QJE, 2003; AER, 2011); Seru, Shumway, and Stoffman (RFS, 2010))
- Under a learning framework, evidence suggests that individuals acquire information differently from positive versus negative experiences (Kuhnen, 2015 JF).

Depicting the Disposition Effect



Data & Episode Definition

Data Sample

We construct a nationally representative sample of approximately 190,000 Chinese individual investors.

- **Period:** July 2013 to February 2016.
- **Selection:** Only investors who opened accounts after the beginning of our observation period, ensuring complete portfolio records.

Portfolio Evaluation

When a stock is sold, we calculate the paper return for all remaining (unsold) stocks in that investor's portfolio. The idea is that if an investor sells one stock, there is a deliberate choice to hold onto the others—reflecting an evaluation of their entire portfolio at that moment.

Constructing Trading Episodes

1. **New Position Start:**
   - Each time a stock is purchased, it initiates a new trading episode.
2. **Position Termination:**
   - A position ends upon the first sale (full or partial) of the stock.
   - It also creates a corresponding trading experience that can be either positive or negative depending on the return.
3. **Partial Sale Implication:**
   - Even if only part of the holdings is sold, the initial episode ends and a new episode begins for any remaining shares.
4. **Methodological Reference:**
   - Follows the approach of Seru, Shumway, and Stoffman (RFS, 2010).

Investor A Portfolio Timeline

$t = 0$

No holdings.

$t = 1$

Buy:
AAPL: 100 @ \$240
AMD: 100 @ \$100
NVDA: 100 @ \$120
QCOM: 100 @ \$150
TSLA: 100 @ \$260

$t = 2$

Sell:
TSLA 100 @ \$270
Hold:
AAPL: 100 @ \$220,
AMD: 100 @ \$110
NVDA: 100 @ \$150,
QCOM: 100 @ \$140

$t = 3$

Sell:
AAPL 100 @ \$210,
AMD 100 @ \$120
Hold:
NVDA: 100 @ \$200,
QCOM: 100 @ \$170

Time

Panel Data Record from Trading

$t = 1$**:** Recorded in raw data but **excluded** from panel analysis.

$t = 2$ **Investor A**

Stock	Gain	Sale	Exp
TSLA	1	1	0
AAPL	0	0	0
AMD	1	0	0
NVDA	1	0	0
QCOM	0	0	0

$t = 3$ **Investor A**

Stock	Gain	Sale	Exp
AAPL	0	1	1 (W)
AMD	1	1	1 (W)
NVDA	1	0	1 (W)
QCOM	1	0	1 (W)

Percentage of Gains Realized (PGR) and Losses Realized (PLR):

The PGR for Investor A at $t = 2$ is $\frac{1}{3}$, the PLR is $\frac{0}{2}$;
at $t = 3$ the PGR is $\frac{1}{3}$ and the PLR is $\frac{1}{1}$.

What is the Disposition Effect and Why It Is Not Rational?

- At $t = 2$: $PGR > PLR \Rightarrow$ disposition effect observed.
- At $t = 3$: $PGR < PLR \Rightarrow$ no disposition effect.

In rational models, a positive or negative paper balance should not matter—only your assessment of the present value of future returns. As noted by previous researchers, this phenomenon can equivalently be expressed by estimating the regression below and finding $\beta_1 > 0$:

$$\text{Sale}_{i,j,t} = \beta_0 + \beta_1 \, \text{Gain}_{i,j,t} + \varepsilon_{i,j,t},$$

where $\text{Sale}_{i,j,t}$ is a dummy variable indicating whether the stock was sold, and $\text{Gain}_{i,j,t}$ is a dummy indicating whether the stock was trading at a gain. It can easily be verified that $\beta_1 = PGR - PLR$.

Quantifying Losing Experiences

Definition:

$$\text{Losing Experiences}_{i,t} = \sum_{T=0}^{t-1} \mathbf{1}\{\text{return}(s,j)_T < -X\}$$

where $\mathbf{1}\{\cdot\}$ indicates a loss for investor i at time T for stock j.

This measure continuously updates as new transactions occur, ensuring that an investor's current decisions reflect the full history of their loss experiences.

Model Specification

$$\text{Sale}_{i,j,t} = \alpha + \beta_1 \cdot \text{Gain}_{i,j,t} + \beta_2 \cdot \text{Experience}_{i,t} + \beta_3 \cdot \left(\text{Gain}_{i,j,t} \times \text{Experience}_{i,t}\right) + \varepsilon_{i,j,}$$

- $\text{Gain}_{i,j,t}$ equals 1 if stock j (for investor i on day t) is at a gain, and 0 otherwise. β_1 measures the extra likelihood of selling when the stock is winning.
- $\text{Experience}_{i,t}$ counts the trades made by investor i before day t. β_2 reflects how accumulated experience alters the selling probability.
- β_3 captures the how experience affects disposition effect.

Put simply, the regression specification is analogous to the method used in Chang et al. (2016), which was developed based on Odean (1998).

Expected Probability of Sale

- When $G_{i,j,t} = 0$ (loss),

$$\mathbb{E}[\text{Sale} \mid G = 0, E = e] = \alpha + \beta_2\, e.$$

- When $G_{i,j,t} = 1$ (gain),

$$\mathbb{E}[\text{Sale} \mid G = 1, E = e] = \alpha + \beta_1 + \beta_2\, e + \beta_3\, e.$$

Difference (Gain vs. Loss) at a given experience level e:

$$\Delta(e) = \underbrace{\left[\alpha + \beta_1 + \beta_2 e + \beta_3 e\right]}_{\mathbb{E}[\text{Sale}|G=1,E=e]} - \underbrace{\left[\alpha + \beta_2 e\right]}_{\mathbb{E}[\text{Sale}|G=0,E=e]} = \beta_1 + \beta_3\, e.$$

Interpretation

$\Delta(e)$ is the "disposition effect" (the extra propensity to sell a stock at a gain vs. a loss) *as a function of* the investor's experience level e.

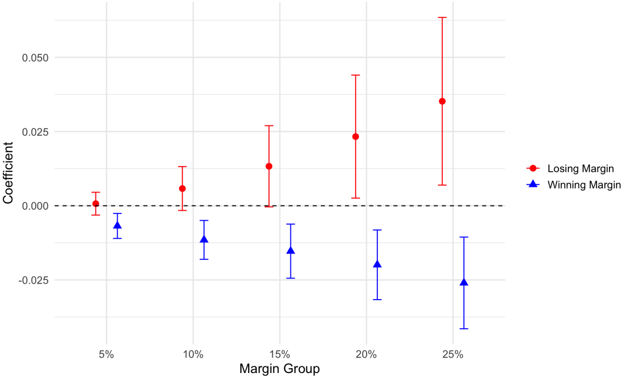
Empirical result: main result

Table: The Behavioral Bias in Trading Experience

	Sale $\times$ 100	
($X \geq 5\%$)	**Losing Experiences**	**Winning Experiences**
Gain	2.4765***	2.6628***
	(4.34)	(4.79)
Experience	0.0162***	0.0103
	(3.12)	(1.50)
Gain $\times$ Experience	**0.0007**	**$-$0.0068***
	(0.30)	(-2.66)
Constant	8.4384***	8.5822***
	(36.15)	(33.86)
Cluster investor-time-stock	YES	YES
Observations	43,649,867	43,649,867
R-squared	0.138	0.138
Individual FE	YES	YES
Stock FE	YES	YES
Time FE	YES	YES

Empirical result: main result

Figure: Effects of Different Levels of Significance on the Disposition Effect



Notes. These figures display the coefficients for Gain × Experience from Table 1 across varying levels of significance. The error bars represent the 90% confidence intervals.

Risk-Averse Investors

- Foundational studies (Malmendier & Nagel, 2011) show that while negative experiences can have a long-lasting dampening effect on risk-taking, that effect is mitigated for those with inherently higher risk tolerance.

Dependent Variable: ($\geq$ 5%)	**Sale $\times$ 100** **Losing Experiences**	**Winning Experiences**
Gain	3.5185***	3.9991***
	(4.59)	(5.30)
Experiences	0.0233***	0.0212*
	(2.86)	(1.73)
Gain $\times$ Experiences	-0.0041	-0.0376***
	(-0.40)	(-2.97)
Constant	9.2246***	9.3532***
	(32.64)	(32.22)
Observations	1,821,417	1,821,417
R-squared	0.154	0.154
Individual FE	Yes	Yes
Stock FE	Yes	Yes
Time FE	Yes	Yes

Risk-Seeking Investors

- Empirical findings (Weber et al., 2013) directly link lower risk aversion with less drastic portfolio shifts in bear markets and faster reversion to pre-crisis allocations.

Dependent Variable: ($\geq$ 5%)	**Sale $\times$ 100** **Losing Experiences**	**Winning Experiences**
Gain	2.4658***	2.5992***
	(4.72)	(4.99)
Experiences	-0.0007	0.0015
	(-0.14)	(0.79)
Gain $\times$ Experiences	0.0003	-0.0019
	(0.41)	(-1.41)
Constant	8.3213***	8.1784***
	(24.12)	(40.05)
Observations	1,837,938	1,837,938
R-squared	0.138	0.138
Individual FE	Yes	Yes
Stock FE	Yes	Yes
Time FE	Yes	Yes

By Age

- Korniotis and Kumar (2011, REStat) find that younger investors are more prone to behavioral trading patterns, suggesting they are more easily influenced by recent experiences or prominent market events.

Dependent Variable:	**Sale** $\times$ **100**			
	Winning Experiences		**Losing Experiences**	
($\geq$ 5%)	**Age** $\leq$ 36	**Age** $>$ 36	**Age** $\leq$ 36	**Age** $>$ 36
Gain	2.6811***	2.7416***	2.2559***	2.5895***
	(4.20)	(5.28)	(3.20)	(4.91)
Trade Experiences	0.0463***	0.0050	0.0411***	0.0119**
	(10.13)	(0.79)	(7.84)	(2.20)
Gain $\times$ Trade Experiences	-0.0146***	-0.0056**	0.0069	-0.0004
	(-3.44)	(-2.41)	(0.80)	(-0.24)
Constant	8.3983***	8.3170***	8.4804***	8.1246***
	(38.34)	(32.56)	(34.08)	(34.15)
Fixed Effects:				
Individual FE	Yes	Yes	Yes	Yes
Stock ID FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster investor-time-stock	Yes	Yes	Yes	Yes
Observations	19,396,148	24,253,718	19,396,148	24,253,718
R-squared	0.145	0.133	0.145	0.133

By Age

Dependent Variable:	Sale $\times$ 100			
	Winning Experiences		Losing Experiences	
($\geq$ 30%)	**Age** $\leq$ 36	**Age** $>$ 36	**Age** $\leq$ 36	**Age** $>$ 36
Gain	2.5167***	2.6390***	2.1219***	2.5320***
	(4.27)	(5.23)	(3.40)	(4.90)
Experiences	0.4885***	0.0204	0.2394***	0.0664***
	(6.97)	(0.24)	(5.95)	(3.47)
Gain $\times$ Experiences	-0.1148***	-0.0284***	0.2153***	0.0273*
	(-3.79)	(-2.78)	(3.31)	(1.84)
Constant	8.9037***	8.4814***	9.0450***	8.3613***
	(42.16)	(36.46)	(41.24)	(45.00)
Fixed Effects:				
Individual FE	Yes	Yes	Yes	Yes
Stock ID FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster investor-time-stock	Yes	Yes	Yes	Yes
Observations	19,283,245	24,105,619	19,283,245	24,105,619
R-squared	0.146	0.134	0.146	0.134

Implications of Chapter 2

- Unlike most previous literature states, experience can attenuate behavioral biases, while negative experiences can amplify them.
- Behavioral asset-pricing models could include experience-based updating.
- Platforms could introduce a new mechanism that prompts traders to enhance their decision-making processes.

When Risk Stops Mattering:
Speculative Demand and Price Uncertainty in Housing Markets

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Key Question

During housing bubbles, does speculative demand weaken or reverse the usual negative relationship between idiosyncratic volatility (IVOL) and expected returns?

Empirical Consensus

- *Higher* IVOL $\rightarrow$ *Lower* returns.
- Real-estate studies likewise find *negative* price-uncertainty premia.

This Paper

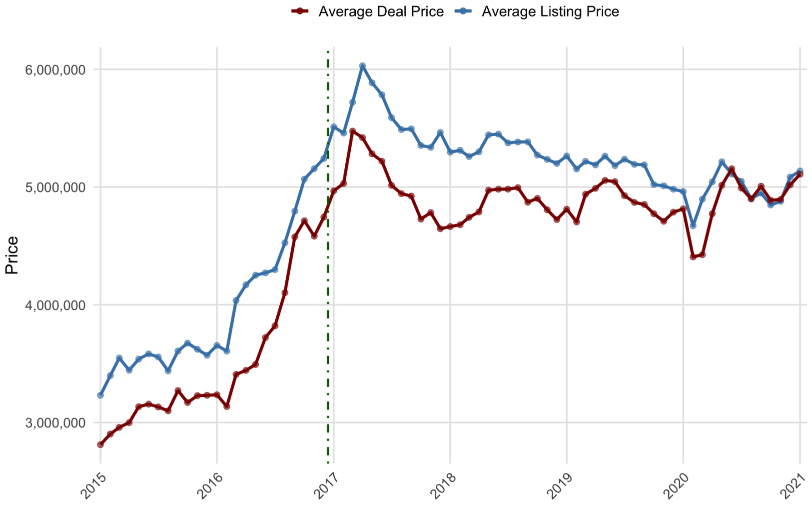
- Focus on 2015–16 Beijing bubble—an extreme IVOL surge.
- Ask: *How* do buyers respond to listing-level uncertainty under hype?
- Do they price in risk, or does feverish demand "flatten" the IVOL premium?

Data: Beijing Housing Listings (2010–2021)

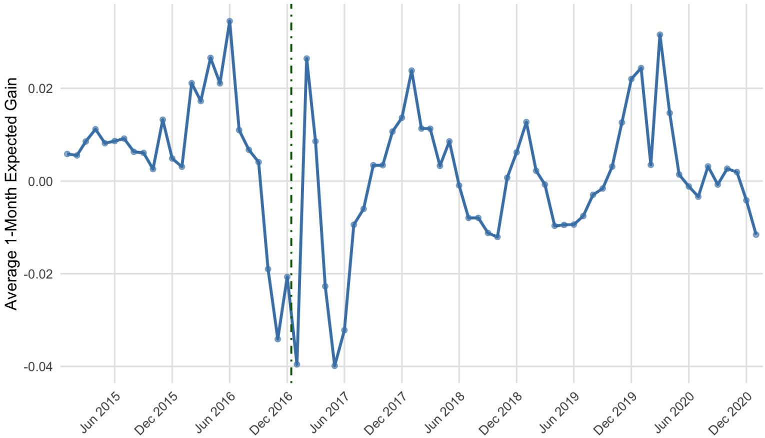
- 578,264 resale listings from 3,500 gated communities.
- Hedonic regression residuals squared yield ex-ante IVOL.
- The expected return is the difference between the listing price and the average transaction price in the same community last month.

Trading Platform

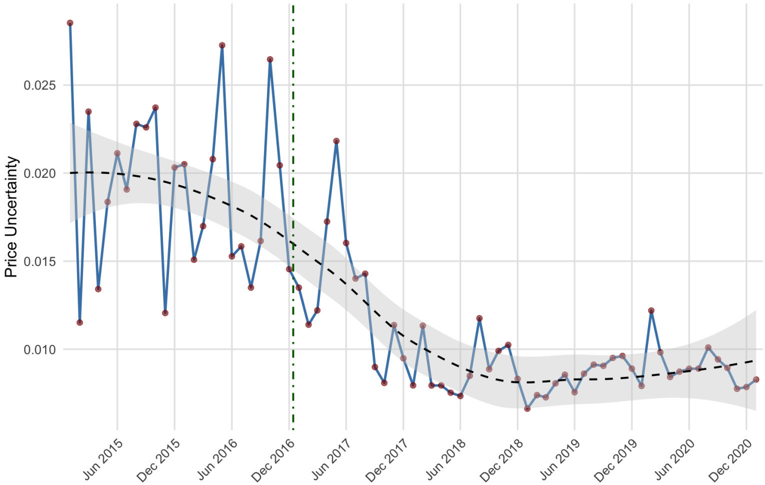
Boom–Bust Timeline



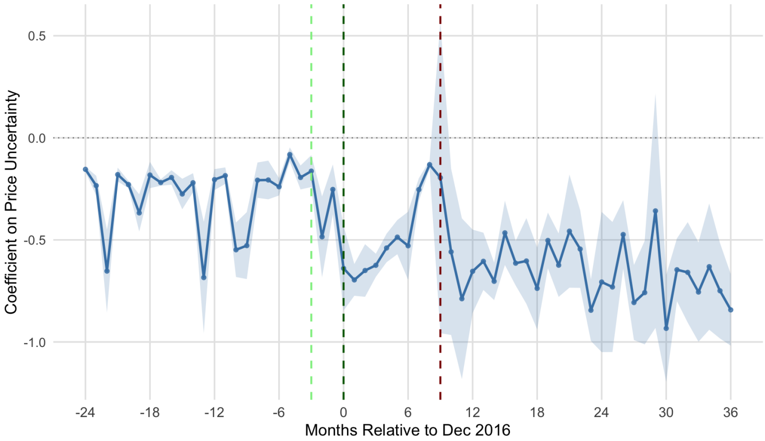
Expected Raw Return Overtime



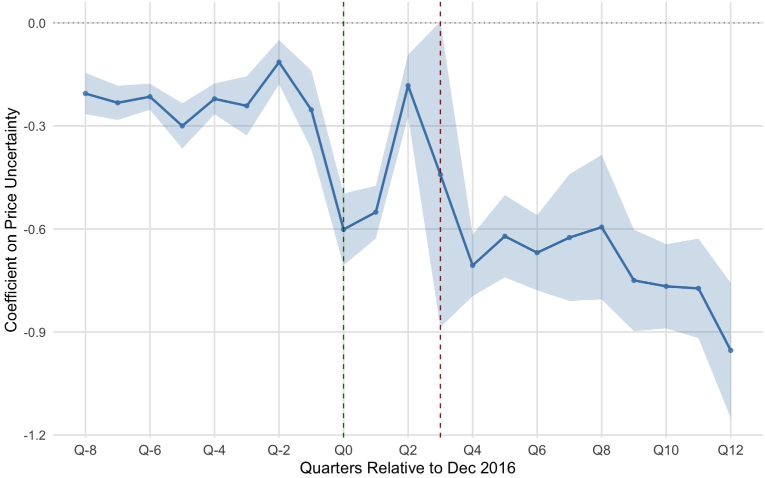
Price Uncertainty Overtime



When Risk Stops Mattering



At Quarterly Level



DiD: Price Uncertainty → Raw 1M Return

	(1)	(2)	(3)
Dep. var.:	Raw Expected Return (1-month)		
Price uncertainty	-0.170^{***}	-0.172^{***}	-0.173^{***}
	(0.020)	(0.020)	(0.020)
Post–2016-12-14	-0.0068^{***}	-0.0048	-0.0047
	(0.0013)	(0.0034)	(0.0034)
Unc. × Post	-0.241^{**}	-0.237^{**}	-0.240^{**}
	(0.088)	(0.087)	(0.088)
Fixed effects			
Community	Yes	Yes	Yes
Year–month	No	Yes	Yes
CZ	No	Yes	Yes
Floor	No	No	Yes
Construction type	No	No	Yes
R^2_{within}	0.078	0.078	0.079
Adj. R^2	0.085	0.097	0.098
Observations		385 818	

Clustered standard errors (community) in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Price Uncertainty and Listing Popularity

	(1)	(2)
	Dep. var.: Number of Followers	
Price uncertainty	-5.899^{***}	1.089^{***}
	(0.710)	(0.234)
Post–2016-12-14	—	-2.015
		(1.084)
Unc. × Post	—	-4.237^{***}
		(1.256)
Fixed effects		
Community	No	Yes
Year–month	No	Yes
CZ	No	Yes
Floor	No	Yes
Construction type	No	Yes
Adj. R^2	0.000	0.069
Within R^2	—	0.00001
Observations	578 264	

Std. errors clustered by community in (2); IID in (1).
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Popularity Dummies

- **House–level popularity**

$$\text{POPULAR\_HOUSE}_i = \mathbf{1}\left\{\, \text{FOLLOWER}_i > P_{75}\big(\text{FOLLOWER}\big) \,\right\}.$$

A listing is "popular" if its follower count exceeds the 75^{th} percentile of the *entire* follower distribution (threshold $=$ `$p75_fol`).

Key intuition: `POPULAR_HOUSE` identifies hot listings within the city.

Listing Premium & Supply Share

- **Raw listing premium (log points)**

$$\text{ListingPrem}_{i,t} = \text{asinh}\big(\widetilde{P}^{\text{post}}_{i,t}\big) - \text{asinh}\big(\underbrace{\overline{\widetilde{P}}^{\text{post}}_{c(i),t}}_{\text{community–month mean}}\big).$$

$\widetilde{P}$ is the quality–adjusted ("raw") price per m^2; subtracting the community-month mean isolates a seller's mark-up (or discount) relative to peers.

- **Supply share**

$$\text{SupplyShare}_{c,t} = \frac{N^{\text{list}}_{c,t}}{\sum_{c'} N^{\text{list}}_{c',t}}, N^{\text{list}}_{c,t} = \text{number of active listings in } c \text{ at } t.$$

Measures a community's share of total market inventory in month t.

Popularity and Raw Expected Return

	(1)	(2)	(3)
	Dep. var.: Raw Expected Return (1-month)		
Popular house (*PH*)	0.0064***	0.0127***	0.0128***
	(0.0015)	(0.0014)	(0.0014)
Post–2016-12-14	0.0039***	0.0029	0.0028
	(0.0008)	(0.0033)	(0.0033)
$PH \times$ Post	−0.0354***	−0.0418***	−0.0417***
	(0.0016)	(0.0015)	(0.0015)
Fixed effects			
Community	Yes	Yes	Yes
Year–month	No	Yes	Yes
CZ	No	No	Yes
Floor	No	No	Yes
Construction type	No	No	Yes
Adj. R^2	0.016	0.029	0.028
Within R^2	0.009	0.008	0.008
Observations		385 818	

Std. errors clustered by community.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Popularity and Listing Premium

	(1)	(2)	(3)
	Dep. var.: ln(Listing Premium)		
Popular house (*PH*)	0.0083***	0.0094***	0.0093***
	(0.0007)	(0.0008)	(0.0008)
Post–2016-12-14	0.0063***	0.0042*	0.0042*
	(0.0002)	(0.0018)	(0.0018)
$PH \times$ Post	−0.0249***	−0.0264***	−0.0263***
	(0.0008)	(0.0009)	(0.0008)
Fixed effects			
Community	Yes	Yes	Yes
Year–month	No	Yes	Yes
CZ	No	No	Yes
Floor	No	No	Yes
Construction type	No	No	Yes
Adj. R^2	−0.006	−0.005	−0.006
Within R^2	0.0067	0.0069	0.0068
Observations		578 264	

Std. errors clustered by community.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Listing Premium and Listing Popularity

	(1)	(2)	(3)
	Dep. var.: Number of Followers		
ln(Listing Premium)	12.84^{***}	13.30^{***}	11.60^{***}
	(1.52)	(1.46)	(1.42)
Post–2016-12-14	29.90^{***}	-1.98	-2.14^{*}
	(0.38)	(1.09)	(1.08)
ln(Prem) $\times$ Post	-127.42^{***}	-127.94^{***}	-121.56^{***}
	(5.80)	(5.78)	(5.52)
Fixed effects			
Community	Yes	Yes	Yes
Year–month	No	Yes	Yes
CZ	No	No	Yes
Floor	No	No	Yes
Construction type	No	No	Yes
Adj. R^2	0.049	0.064	0.073
Within R^2	0.030	0.005	0.005
Observations		578 264	

Std. errors clustered by community in all columns.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Market Share and Listing Premium

	(1)	(2)	(3)
	Dep. var.: ln(Listing Premium)		
Supply share (*SS*)	0.053	0.917**	0.904**
	(0.036)	(0.326)	(0.325)
Post–2016-12-14	−0.00018*	−0.00168	−0.00170
	(0.00008)	(0.00181)	(0.00181)
$SS \times$ Post	−0.487**	−1.019**	−1.003**
	(0.180)	(0.320)	(0.319)
Fixed effects			
Community	Yes	Yes	Yes
Year–month	No	Yes	Yes
CZ	No	No	Yes
Floor	No	No	Yes
Construction type	No	No	Yes
Adj. R^2	−0.012	−0.012	−0.013
Within R^2	1.7×10^{-5}	5.3×10^{-5}	5.2×10^{-5}
Observations		578 264	

Supply share = community's share of active listings in month t.
Std. errors clustered by community in all columns.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Implications of Chapter 3

- Ex-ante IVOL monitoring offers an early bubble warning indicator.
- Soft policy signals, such as verbal warnings, can effectively reinstate risk sensitivity, but their effectiveness is limited in the long run.
- Macro-prudential frameworks should integrate listing-level IVOL and popularity metrics.

Future Research Directions

- Cross-market tests of soft vs. hard policy signals in bubble contexts.
- Incorporate network and spatial effects into trading and housing search behavior.

Thank You

Suggestion?

`tlyeungae.github.io`