Housing *Is* the Financial Cycle: Evidence from 100 Years of Local Building Permits

Gustavo S. Cortes
University of Florida

Cameron LaPoint
Yale SOM

SFS Cavalcade North America

Stevens Institute of Technology

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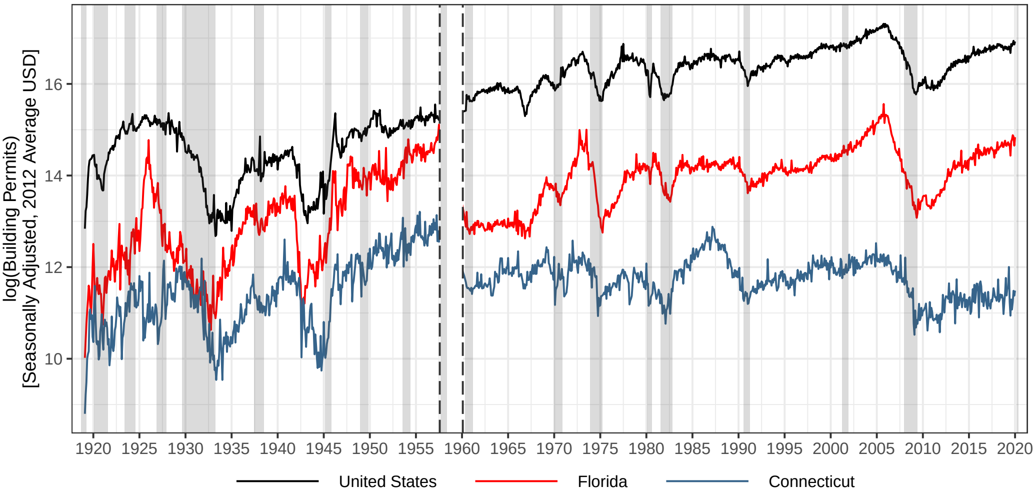
Why Housing Matters: An Old Question with New Data ▸ Literature

- A century-old, recurring observation among economists:
  - Long (1939): *"The building industry is probably the most strategic single factor in making or breaking booms and depressions"*
  - Leamer (2007): *"Housing IS the business cycle"*
- Striking empirical relations between housing and real/financial cycles:
  - Residential investment consistently forecasts GDP (Leamer, 2015)
  - It leads 10 out of 12 post-war recessions (including the Great Recession)
  - Real estate volatility explains the largest stock volatility spike in U.S. history and the Great Depression volatility puzzle (Cortes & Weidenmier, 2019)
  - "Twin bubbles": Housing peaks consistently precede stock market crashes
- **But we lack granular and historical evidence on the mechanisms:**
  - Geographic transmission of housing shocks is still unclear

What We Do: A Century of Local Residential Permits Data

1. ***Monthly* building permits for all U.S. states & 60 MSAs** (1919 – 2019)
   - Hand-collected + deep learning OCR from archival reports
   - First granular, nationwide housing database spanning the pre-1970s era
2. **Key Finding:** Building permit volatility consistently predicts financial stress
   - Strong predictor of stock and corporate bond return volatility
   - Works across over a dozen crisis episodes
   - Holds conditional on housing demand (pop. growth, leverage, disaster risk)
3. **Novel mechanism: Building permits as forward-looking signals**
   - Real estate developers have local information
   - Permits as a call option reveal beliefs about future fundamentals
   - Information flows from "Main Street" to "Wall Street"
   - Rationalized by extended version of Grossman & Stiglitz (1980) model

A Century of U.S. Building Permits Forecasts Crashes



Preview of Results

- Local **building permit growth (BPG) volatility** offers a new *monthly* factor for forecasting stock and bond markets
  - Heterogeneity: driven by building in more **supply elastic real estate markets** (the South and sand states) $\longrightarrow$ greater signal-to-noise in low regulation areas
  - Key example: BPG vol contains **early info about subprime crisis** which is unrelated to leverage growth $\longrightarrow$ first PC has $\approx 20\%$ incremental R^2
- **Firm cross-section:** local BPG exposure from plant network predicts individual stock return vol, even conditional on physical risks to production
  - Scope for designing strategies using BPG vol to hedge against **overbuilding risk** $\longrightarrow$ follow up paper focusing on house prices/return levels as outcomes
- **Quantitatively important relative to alternative explanations**
  - Horse-race exercise: adding lags of σ^{BPG} in elastic states beats lags of leverage in an incremental R^2 sense

Why Use Permits as a Forecasting Variable?

1. Permits are **continuously available at monthly frequency** with disaggregated, nationwide coverage over long time periods

2. Other readily available economic statistics are released with **long lags and often revised** between releases
   - Labor market statistics: QCEW has 5 month lag after quarter end, state-level BEA employment only quarterly starting in 2018
   - True also for forward-looking corporate variables like investment rates in 10-Qs, released with 1-2 month delays

3. **Permits are more forward looking** than other real estate indicators
   - House price indices reflect moving average of past transactions, only go back to 1970s across all geographies
   - Building completions lag permits at least one quarter for SFH, and >1 year for larger MFH CoreLogic Permits

Database Construction

Building Permits Data Sources

▸ Other Data

1. **Dun & Bradstreet's Review (1919 – 1957):** city-level permit values
   - Extend Cortes & Weidenmier (2019) to a much longer period ▸ Details ▸ Raw Data

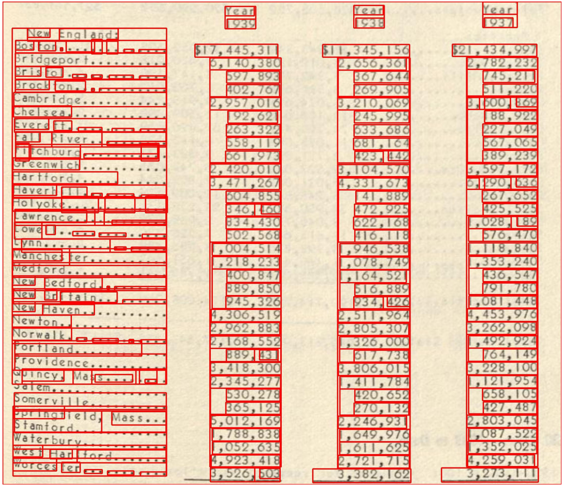
2. Bureau of Labor Statistics Construction Reports (various years, 1921 – 1953)
   - Annual data from legacy version of Census survey $\longrightarrow$ validation check

3. State and local government building permit surveys (1958 – 1960): bridge period between Dun's and Census ▸ Splicing

4. **Historical Census Building Permits Survey [BPS] (1960 – 1987)**
   ▸ BPS Details ▸ Raw Data ▸ MFH Permits

5. **Modern Census BPS (1988 – 2019):** modern data already downloadable from FRED/Census up to present

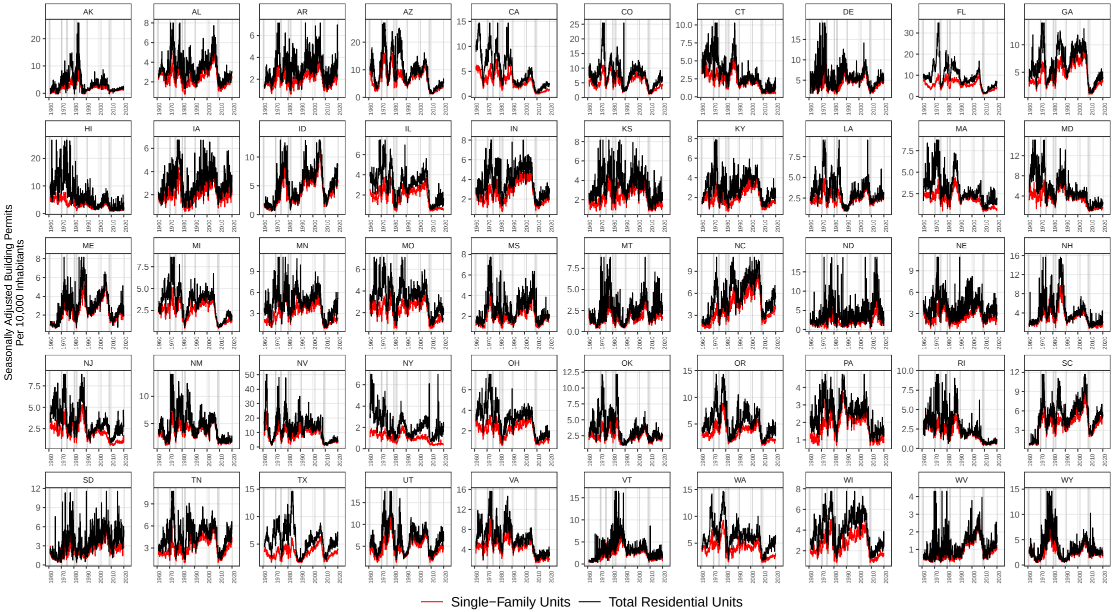
Digitization Process and OCR Techniques



	Year 1939	Year 1938	Year 1937
New England			
Boston	$17,445,311	$11,345,156	$21,434,997
Bridgeport	6,140,380	2,656,361	2,782,232
Bristol	597,893	367,644	745,211
Brockton	402,767	269,905	511,220
Cambridge	2,957,016	3,210,069	3,600,869
Chelsea	192,621	245,995	188,922
Everett	263,322	633,686	227,049
Fall River	558,119	681,164	567,065
Fitchburg	661,973	423,442	389,239
Greenwich	2,420,010	3,104,570	3,597,172
Hartford	3,471,267	4,331,673	6,290,636
Haverhill	604,855	141,889	267,652
Holyoke	346,460	472,925	425,525
Lawrence	834,430	622,168	1,028,189
Lowell	502,568	416,118	576,470
Lynn	1,004,514	1,946,538	1,118,840
Manchester	1,218,233	1,078,749	1,353,240
Medford	400,847	1,164,521	436,547
New Bedford	889,850	516,889	791,780
New Britain	945,326	934,426	1,081,448
New Haven	4,306,519	2,511,964	4,453,976
Newton	2,962,883	2,805,307	3,262,098
Norwalk	2,168,552	1,326,000	1,492,924
Portland	889,431	617,738	764,149
Providence	3,418,300	3,806,015	3,228,100
Quincy, Mass.	2,345,277	1,411,784	1,121,954
Salem	530,278	420,652	658,105
Somerville	365,125	270,132	427,487
Springfield, Mass.	5,012,169	2,246,931	2,803,045
Stamford	1,788,838	1,649,976	1,087,522
Waterbury	1,052,635	1,611,625	1,352,025
West Hartford	4,923,418	2,721,715	4,259,031
Worcester	3,526,503	3,382,162	3,273,111

- **Layout Parser**: optimize deep learning Python package for digitizing > 30k pages of tables
  - *k*-means clustering + GPUs to match training environment
  - > 2.5x speed improvement
- Quality control:
  1. Assign score to each page based on fraction of blocks identified
  2. For low-scored pages, hand-collect or ABBYY + Excel VBA
  3. **Check if row totals line up** (with rounding error tolerance)

Ex: Census · Ex: Dun's · Scoring Example


Seasonally Adjusted Building Permits
Per 10,000 Inhabitants
AK
AL
AR
AZ
CA
CO
CT
DE
FL
GA
HI
IA
ID
IL
IN
KS
KY
LA
MA
MD
ME
MI
MN
MO
MS
MT
NC
ND
NE
NH
NJ
NM
NV
NY
OH
OK
OR
PA
RI
SC
SD
TN
TX
UT
VA
VT
WA
WI
WV
WY
Single−Family Units
Total Residential Units

New Stylized Facts about Historical Housing Markets

1. **Per capita permits are procyclical and lead crashes**
   - Example: Florida permits peak 5 months before 1973 OPEC recession and 2 years before GFC
2. In most states, per capita **SFH permitting peaked in the 1970s** and collapsed following GFC $\longrightarrow$ consistent with drop in new housing supply
   - Use microdata to show SFH permit completion rates $> 80\%$ since 1990 $\Longrightarrow$ permits $\approx$ housing supply + beliefs about local fundamentals ▸ Map
3. Housing supply collapse concentrated in areas with **stringent land use laws**

- By focusing on quantities, we complement contemporaneous work which constructs other measures of historical housing market activity
  - Prices (Lyons *et al.* 2024); construction productivity (D'Amico *et al.* 2024)
  - Inflating permit quantities by proxies for project value matters little for forecasting $\longrightarrow$ predictability comes from information aggregation

Methodology

GARCH Model for Building Permit Growth (BPG) Volatility

- Building permit series available at monthly frequency
  - Seasonally adjust using Census's X-13 ARIMA-SEATS model ▸ X-13 ▸ Validation
- We follow Cortes & Weidenmier (2019) to extract volatility from BPG ▸ Define
- GARCH(1,1) for one-period ahead conditional volatility of local BPG, $\sigma^{BPG}_{s,t}$:

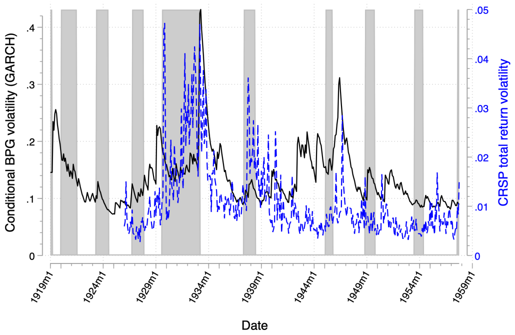
$$x_{s,t} = \theta_0 + \theta_1 \cdot x_{s,t-1} + \varepsilon_{s,t}, \text{ with } \varepsilon_t \sim \mathcal{N}(0, (\sigma^{BPG}_{s,t})^2) \text{ or } \varepsilon_t \sim t_\nu(\cdot)$$

$$(\sigma^{BPG}_{s,t})^2 = \alpha_0 + \alpha_1 \cdot \varepsilon^2_{s,t-1} + \alpha_2 \cdot (\sigma^{BPG}_{s,t-1})^2$$

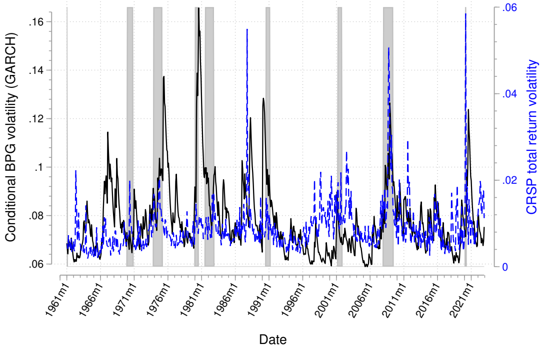
- $\alpha_i > 0$; $\alpha_1 + \alpha_2 < 1$: estimated via QMLE
- GJR-GARCH helps account for skewness in BPG distribution, but GARCH(1,1) is generally most stable ▸ Taxonomy ▸ Stability Simulations ▸ Skewness

BPG Vol Spikes Prior to Spikes in Stock Return Volatility

Dun's Review Period (1919 – 1957)



Census BPS Period (1961 – 2022)



- Conditional BPG volatility spikes with a <6 month lead relative to the stock market in 12 out of 15 NBER recessions ▸ Bond Vol ▸ Break Tests

Main Specification: Return Volatility and BPG Volatility

$$\sigma_t = \beta_0 + \underbrace{\delta_t}_{\text{seasonal dummies}} + \underbrace{\sum_{\tau=1}^{\tau^*} \beta_\tau \cdot \sigma_{t-\tau}}_{\text{autocorrelation}} + \underbrace{\sum_{\tau=1}^{\tau^*} \beta_{s,\tau} \cdot \sigma^{BPG}_{s,t-\tau}}_{\text{BPG volatility for locality } s} + \underbrace{\gamma'_s \cdot \sum_{p=1}^{p*} \mathbf{X}_{s,t-p}}_{\text{local controls}} + \varepsilon_t$$

- σ_t: Total return volatility for an asset class (e.g., stock or bond total returns).
- $\sigma^{BPG}_{s,t}$: One-period ahead conditional volatility (from GARCH) for locality s
- Seasonality δ_t or $\sigma_{t-1} \times \delta_t$: Accounts for asset market seasonality (Ogden 2003; Heston & Sadka 2008)
- Local controls $\mathbf{X_{s,t}}$: pop. growth, corporate or HH leverage ratios, disaster risk
- τ^*: lag order of $\tau^* = 12$ months for literature comparability (e.g., Schwert, 1989; Cortes & Weidenmier, 2019), but also AIC and BIC ($\tau^*_{AIC} = \tau^*_{BIC} = 1$)

Firm Cross-Sectional Specification

- Extend main specification to cross-section of equities or bonds j

$$\sigma_{j,t} = \delta_t + \eta_j + \underbrace{\sum_{\tau=1}^{\tau_j^*} \beta_{j,\tau} \cdot \sigma_{j,t-\tau}}_{\text{own autocorrelation}} + \underbrace{\sum_{\tau=1}^{\tau_j^*} \varphi_{j,\tau} \times \left(\sum_{k \in \mathcal{J}} \omega_{k,t-\tau-1} \cdot \sigma_{k,t-\tau}^{BPG} \right)}_{\text{share-weighted exposure}} + \underbrace{\gamma' \cdot \mathbf{X_{j,t-1}}}_{\text{controls}} + \varepsilon_{j,t}$$

- ω_k: sales or employment shares across all plants k in firm's network of locations $\mathcal{J} \longrightarrow$ D&B Historical data from 1969 – 2019
  - Bartik-style shock with possibly time-varying weights on BPG vol exposure
  - Weights capture physical exposure to overbuilding risk neg. impacting demand for firm's products
- Firm-level controls $\mathbf{X_{j,t}}$: leverage, EBITDA, size/age bins, Tobin's Q
  - CRSP–Compustat merge based on matching names to create crosswalk between `gvkey` and DUNS

Main Results from Longitudinal Analysis

Post-1960s U.S. BPG Predicts Aggregate CRSP Returns

Cross-Section

$$r_{CRSP,t} = \alpha + \beta_1 \cdot r_{CRSP,t-1} + \beta_2 \cdot US\ BPG_{SFH,t-1} + \gamma' \cdot \mathbf{X_{t-1}} + \delta_t + \varepsilon_t$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$r_{CRSP,t-1}$	0.059	0.048	0.057	0.057	0.051	0.052	0.052	0.064	0.085
	(1.331)	(1.083)	(1.358)	(1.332)	(1.187)	(1.205)	(1.209)	(1.517)	(1.554)
$US\ BPG_{SFH,t-1}$		0.055***	0.055***	0.055***	0.053**	0.051**	0.052**	0.055**	0.050*
		(2.576)	(2.626)	(2.629)	(2.517)	(2.459)	(2.483)	(2.559)	(1.724)
Time sample	1960-2019	1960-2019	1960-2019	1960-2019	1960-2019	1960-2019	1960-2019	1960-2016	1980-2016
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
$CFRI_{t-p}$			✓	✓	✓	✓	✓	✓	✓
$PopGrowth_{t-p}$			✓	✓	✓	✓	✓	✓	✓
$CAPE_{t-1}$				✓					
$CAPE\ Yield_{t-1}$					✓	✓	✓	✓	✓
$IPGrowth_{t-p}$						✓	✓	✓	✓
$Leverage_{t-p}$							✓	✓	✓
$NVIX_{t-p}$								✓	✓
$DSCR_{t-p}$									✓
N	715	715	715	715	715	715	715	669	434
R^2	0.025	0.035	0.038	0.042	0.046	0.049	0.049	0.053	0.061

Notes: Permits for new single-family homes (SFH) used to construct $US\ BPG_{SFH,t-1}$ from the monthly Census BPS. *CFRI* refers to the commodity futures return index of Janardanan, Qiao, Rouwenhorst (2024).

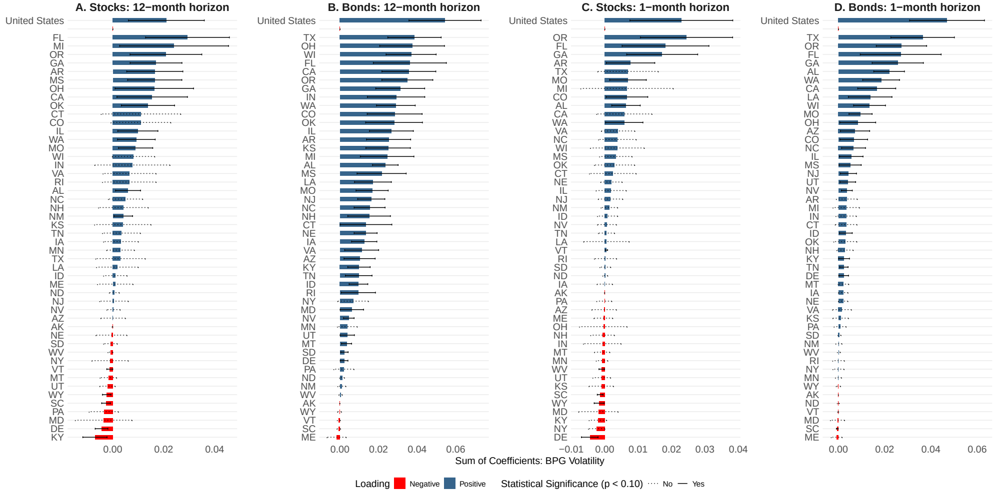
Post-1960s Aggregate U.S. BPG Vol Predicts Aggregate Return Vol

Asset Market:	Equities					Corporate Bonds				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
σ^{BPG}_{t-1}	0.088***	0.027**	0.026**	0.025**	0.064**	0.070***	0.036***	0.035***	0.033***	0.016***
	(2.82)	(2.45)	(2.47)	(2.39)	(2.57)	(4.68)	(3.76)	(3.40)	(3.18)	(3.77)
Time sample	1960-19	1960-19	1980-19	1980-16	2000-16	1960-19	1960-19	1980-19	1980-16	2000-16
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓	✓		✓	✓	✓	✓
$PopGrowth_{t-p}$		✓	✓	✓	✓		✓	✓	✓	✓
$Leverage_{t-p}$			✓	✓	✓			✓	✓	✓
$DSCR_{t-p}$			✓	✓	✓			✓	✓	✓
$IPGrowth_{t-p}$			✓	✓	✓			✓	✓	✓
$DisasterNVIX_{t-p}$				✓	✓				✓	✓
N	714	707	479	435	195	714	707	479	435	195
R^2	0.109	0.471	0.463	0.471	0.605	0.185	0.367	0.452	0.444	0.544

- Interpretation: 1 p.p. $\uparrow$ in σ^{BPG} associated with $\approx$ 30% $\uparrow$ in stock vol relative to its monthly avg. in the next month (true even outside GFC or GD)

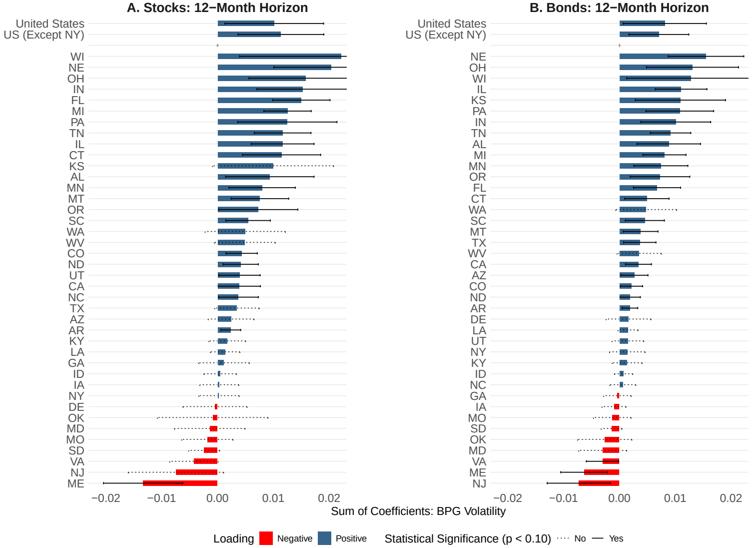
▸ SFH ▸ Dividend Vol ▸ More controls ▸ Pre-1960s stocks ▸ Pre-1960s bonds

Predictive Power of BPG Vol Driven by Supply Elastic States



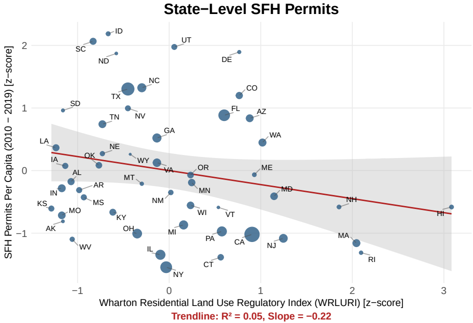
▸ SFH ▸ S-MFH ▸ L-MFH ▸ Controls ▸ GJR-GARCH ▸ Horse Race

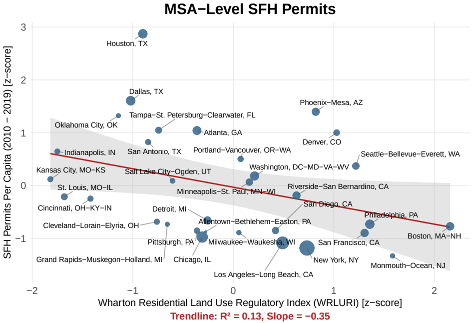
Similar Geographic/Industry Patterns Using Pre-1960s Data



Tightly Regulated Jurisdictions Issue Fewer SFH Permits

▸ Total permits





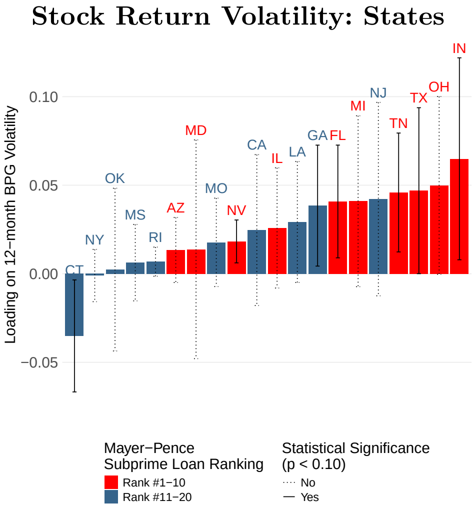
- Wharton Index (WRLURI) captures political economy constraints on new construction (e.g., voting procedures, # of steps in the approval process)
  - Use 2006 version from Gyourko, Saiz, Summers (2008) to avoid reverse causality
- Similar if use minimum lot size intensity (Bartik *et al.* 2024) ▸ AI-based index

BPG Volatility around the Global Financial Crisis

Loading on BPG Factor Greatest in Subprime Crisis States

- Focus of our paper is longitudinal to establish general pattern across different types of crisis episodes with different “root” causes
- However, some advantages to looking at the modern era...
  - House price data can be used to inflate up permitted homes Q from book to market value $\longrightarrow$ **predictive power dominated by Q rather than P**
  - Data on firms’ plant locations to do tests in cross-section of equities
- **Test:** Do building permit swings predict subprime mortgage crisis before defaults are widely known beyond loan servicers?
  - Mayer & Pence (2008): local share of SFH and small MFH mortgage loans in subprime pool as of 2005
  - Idea: BPG contains **soft information** about risk profile of borrowers, even conditional on build up in leverage

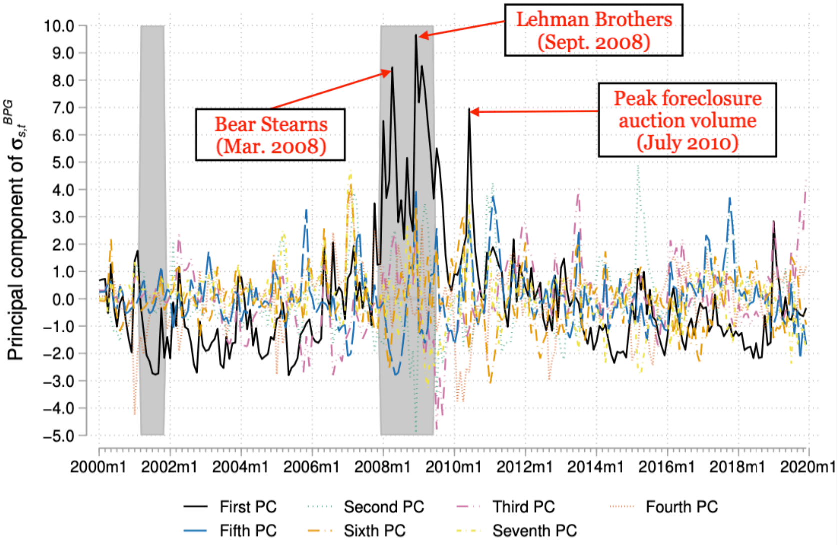
Loading on BPG Factor Greatest in Subprime Crisis States



- 7 out of top 10 states by factor loadings are also in the **top 10 in Mayer–Pence subprime ranking**
- All 20 Case-Shiller MSAs are ranked within top 60 subprime metros by loan share ▸ MSA Coefplots ▸ Bonds
- Areas with more flipping like Las Vegas predict downturn with longer leads (Chinco & Mayer 2016)
  - "Informed" investors drive longer-run BPG predictability

First Principal Component Tracks Major Events in GFC

▸ Full sample



Subprime Factor Only PC That Predicts Return Vol around GFC

Asset Market:	Equities				Corporate Bonds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PC^{(1)}_{t-1}$ ["subprime" factor]	0.0012***	0.0003**	0.0003**	0.0003**	0.0003***	0.0001***	0.0001***	0.0001***
	(2.78)	(2.09)	(2.06)	(2.27)	(4.45)	(2.51)	(2.44)	(2.64)
$PC^{(2)}_{t-1}$			−0.0003	−0.0003			−0.0001	−0.0001
			(1.41)	(1.35)			(1.54)	(1.63)
$PC^{(3)}_{t-1}$				0.0002				0.0001
				(0.82)				(1.36)
$PC^{(4)}_{t-1}$				0.0001				0.0000
				(0.28)				(0.55)
$PC^{(5)}_{t-1}$				−0.0002				−0.0001
				(0.77)				(1.47)
$PC^{(6)}_{t-1}$				0.0001				0.0001
				(0.53)				1.10
$PC^{(7)}_{t-1}$				0.0003				−0.0001
				(0.99)				(1.12)
Sample period	2000–2019	2000–2019	2000–2019	2000–2019	2000–2019	2000–2019	2000–2019	2000–2019
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓		✓	✓	✓
ΔHMDA $ originations			✓	✓			✓	✓
R^2	0.173	0.563	0.565	0.569	0.202	0.488	0.493	0.504
N	239	239	239	239	239	239	239	239

Predictive Power of Firms' Exposure to BPG Vol

Sectors

$$\sigma_{j,t} = \delta_t + \eta_j + \sum_{\tau=1}^{\tau_j^*} \beta_{j,\tau} \cdot \sigma_{j,t-\tau} + \sum_{\tau=1}^{\tau_j^*} \varphi_{j,\tau} \times \left(\sum_{k \in \mathcal{J}} \omega_{k,t-\tau-1} \cdot \sigma_{k,t-\tau}^{BPG} \right) + \gamma' \cdot \mathbf{X_{j,t-1}} + \varepsilon_{j,t}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\sigma_{j,t-1}^{BPG}$	0.0046**	0.0029**	0.0031**	0.0019*	0.0048**				
	(2.12)	(2.26)	(2.36)	(1.70)	(2.08)				
$\sum_{\tau=1}^{12} \sigma_{j,t-\tau}^{BPG}$						0.0079**	0.0057**	0.0062***	0.0100**
						(2.29)	(2.04)	(2.71)	(2.43)
Time sample	1989-2019	1989-2019	1989-2019	1989-2019	2000-2019	1989-2019	1989-2019	1989-2019	2000-2019
Share weights ω_k	Emp	Emp	Emp	Sales	Emp	Emp	Emp	Sales	Emp
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓	✓		✓	✓	✓
Firm controls			✓	✓	✓		✓	✓	✓
# of firms	2,067	2,066	1,865	1,865	1,280	1,865	1,713	1,713	1,174
N	157,040	156,907	135,808	135,808	73,832	132,342	117,345	117,345	65,348
Adj. R^2	0.31	0.40	0.43	0.43	0.35	0.33	0.42	0.42	0.35

Notes: Firm controls include *ex ante* firm size, age, EBITDA, Tobin's Q, leverage ratio, natural disaster risk exposure (SHELDUS). We focus our sample on 1989 – 2019, as plant location information is incomplete in earlier vintages of DnB.

Discussion of Mechanisms

Developers Concerned about Overbuilding Risk During Booms

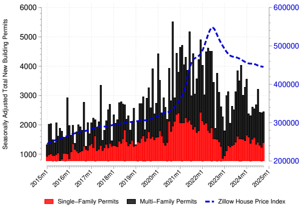
Source: *Wall Street Journal*, March 18, 2024.

- Waning demand in former hotspots for WFH nomads (e.g., Austin, TX)
- Echoes other episodes characterized by *ex post* evidence of overbuilding
  - 19th century land booms tied to crop yields: Glaeser (2013)
  - 1920s NYC skyscrapers: Barr (2010); Nicholas & Scherbina (2013)
  - 2000s housing cycle: Nathanson & Zwick (2018)
- Consistent with **rational disagreement** models (e.g., Grossman–Stiglitz)

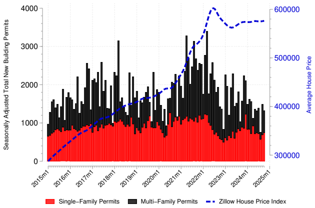
Permits Predict Price Corrections in WFH Nomad Cities

Rents

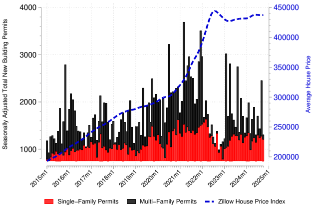
Austin, TX



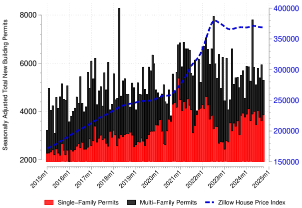
Denver, CO



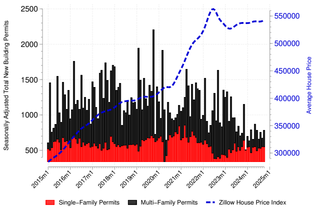
Nashville, TN



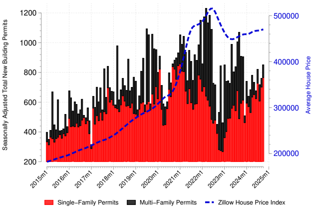
Dallas, TX



Portland, OR



Boise, ID



Rational Disagreement Model with BPG as Quasi-Public Signal

- Nest textbook real estate development option model (Geltner *et al.* 2014) into rational disagreement framework of Grossman–Stiglitz ▸ Other stories
- **Housing Development (Stage 1)** ▸ Details
  - Unit mass of housing market investors $i \in [0,1]$ spanning localities $s \in \{1,\ldots,\mathcal{S}\}$ (states, MSAs, counties)
  - Developable land is in fixed supply $T_s < 1$, and each investor can hold a permit on at most one parcel (akin to measures in Saiz 2010, Lutz & Sand 2023)
- **Financial Markets (Stage 2)** ▸ Details
  - Risky asset pays unknown dividend d in $t+1$
  - Unit mass of investors $j(s)$ in [0,1] in each locality s trading in t at p_t
  - Unitary asset market, so $p = p_s, \forall s$
  - Informed investors observe local BPG q_s as quasi-public signal of dividends

Main Testable Predictions from the Model

Details

1. Building permits proxy for local economic fundamentals
   - Strong local fundamentals $\mathbf{X_{s,t}}$ increase probability project is successful
   - Already well-established fact in the literature: Ghent & Owyang (2010); Strauss (2013); Howard *et al.* (2024) ✓
2. BPG pos. predicts risky asset price and return movements $\longrightarrow \partial p/\partial q_s > 0$

Cross-section Total Returns

3. Sign of comovement between BPG volatility and asset price or total return volatility is theoretically ambiguous but heterogeneous across localities
   - Comovement is positive for sufficiently small $\sigma^2_{q(s)}$ (e.g., Florida) ✓
4. **Signal precision of BPG depends on geographic and regulatory constraints on local real estate development** Result
   - Intuition: signal more informative in housing supply elastic markets ✓

Conclusion: BPG Vol As a New Factor

- New evidence from **100 years of local building permits** data in favor of longstanding hypothesis that housing is the financial cycle
    - Predictability holds across almost all recession episodes
    - True for both equities and corporate bonds
    - Holds conditional on possible confounding housing demand-side factors
- Local **building permit growth (BPG) volatility** offers a new *monthly* factor for forecasting asset volatility, returns, prices
    - Larger, supply unconstrained real estate markets (the South and "sand states") consistently lead the stock market at 1-month to 12-month horizons
    - At firm level, BPG factor unrelated to other physical sources of risk
- Future applications of our data to study questions related to local housing supply and **macroprudential housing policy**

THANK YOU!

SSRN paper downloadable here

$\downarrow\downarrow$

https://papers.ssrn.com/abstract=4855353

Literature at Intersection of Macro-Finance and Housing

- **Origins of financial cycles**
  - Officer (1973); Schwert (1989); Greenwood & Hanson (2013); Giglio, Kelly, Pruitt (2016); Manela & Moreira (2017); Jordà *et al.* (2019); Greenwood *et al.* (2022); Calomiris & Jaremski (2023); Kuvshinov (2024)
- **Housing markets as a leading indicator of the business cycle**
  - Stock & Watson (1991, 2010); Leamer (2007, 2015); Case, Quigley, Shiller (2005); Ghent & Owyang (2010); Goetzmann & Newman (2010); Glaeser (2013); Strauss (2013); Gjerstad & Smith (2014); Nathanson & Zwick (2018); Cortes & Weidenmier (2019); Gao, Sockin, Xiong (2020); LaPoint (2022)
- **Drivers of historical real boom-bust episodes**
  - Leverage: Schularick & Taylor (2012); Jordà, Schularick, Taylor (2013); Mian, Sufi, Verner (2017, 2020); Müller & Verner (2023)
  - Non-Rational Beliefs: Kindleberger (1978); Shiller (1981, 2006); Greenwood & Shleifer (2014); Baron & Xiong (2017); Barberis et al. (2018)
  - Rational beliefs: Garber (1990, 2000); Pástor & Veronesi (2006)

Our contributions to the literature

- **Origins of financial cycles**
- **Housing markets as a leading indicator of the business cycle**
- **Drivers of historical real boom-bust episodes**

Our contributions

1. New evidence favoring the longstanding hypothesis that housing *is* the financial cycle after all + microfounded mechanism as to why.
2. New longitudinal database of *local* building permits $\longrightarrow$ opens door for variety of applications to understanding housing markets.

Data Appendix

Supplementary Data Sources

Go Back

1. CRSP Stock Database (1926 – 2019): WRDS
   - CRSP–Compustat merge for firm balance sheet controls
2. Corporate bond market data:
   - DOW Corporate Bond Index: GFD/Finaeon (1915 – 2019)
   - Issue-level data: SDC Refinitiv (1990s – 2019)
3. Dun *&* Bradstreet's DUNS Marketing Identifier (1969 – 2019): plant-level locations, employment, sales $\longrightarrow$ match firms to Compustat
4. **CoreLogic *Building Permits* microdata (1990 – 2019):** use panel dimension to examine completion rates + completion times
5. Modern house and land price index data:
   - S&P Case–Shiller (1988 – 2019): available for 20 MSAs
   - State-level Zillow HVI (2000 – 2019)

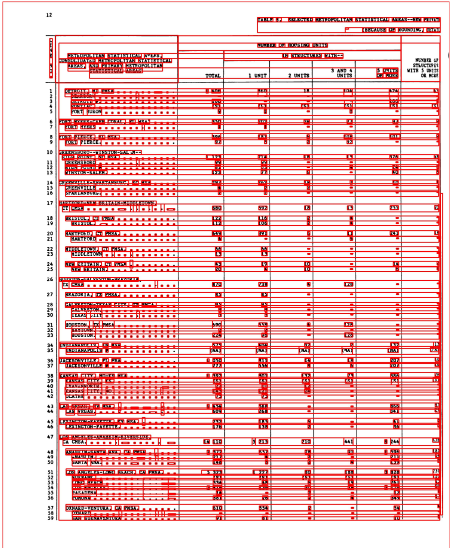
Sources of Census Building Permit Survey Reports

Go back

- Census Building Permit Survey (BPS) conducted continuously at the monthly frequency from 1959:M5 to present
  - Available at the state and local levels from 1960:M5 onward
  - For 1959:M5 – 1960:M4, we obtain state and MSA-level permits by aggregating up from counties
- For 1960 – 1987, Census BPS reports not digitized and held in archives, various academic and Federal Depository Libraries
  - State-level monthly report PDFs for 1970 – 1987 obtained directly from Census
  - Bulk of remaining monthly reports downloaded from HathiTrust
  - We obtained reports not in HathiTrust from the CT Federal Depository Library
- BPS survey follows a consistent format over time, but MSA and county geographic coverage changes, especially from 1960s to 1970s

Example: Layout Parser in Action on Census Documents

Go back



- Example from Table 3 (permit counts) of March 1986 Census Building Permits Survey for MSAs
- LP identifies "blocks" in red
  - Akin to "tokens" or separated chunks of characters
- Use GPUs and increase contrast to better match training dataset consisting of more historical texts

Example: Output from Layout Parser for Census

◂ Go back

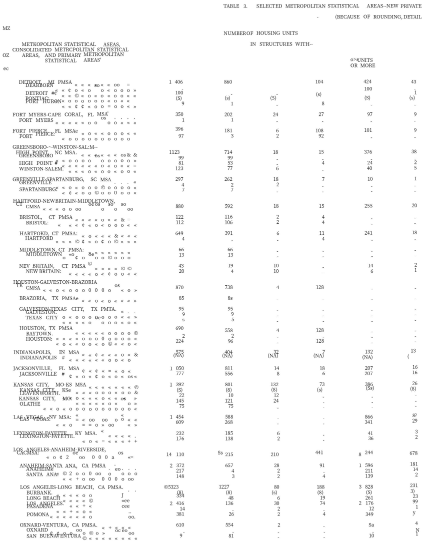


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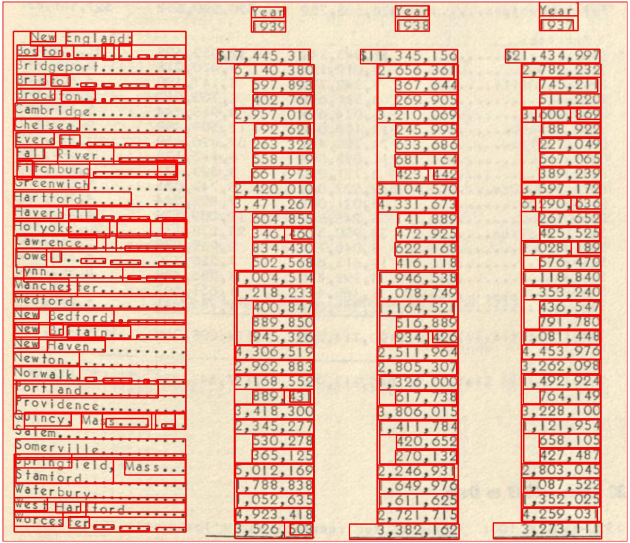
TABLE 3. SELECTED METROPOLITAN STATISTICAL AREAS--NEW PRIVATE

(BECAUSE OF ROUNDING, DETAIL

LINE NO.	METROPOLITAN STATISTICAL AREAS, CONSOLIDATED METROPOLITAN STATISTICAL AREAS, AND PRIMARY METROPOLITAN STATISTICAL AREAS[1]	NUMBER OF HOUSING UNITS					NUMBER OF STRUCTURES WITH 5 UNITS OR MORE
		TOTAL	IN STRUCTURES WITH-- 1 UNIT	2 UNITS	3 AND 4 UNITS	5 UNITS OR MORE	
1	DETROIT, MI PMSA	1 406	860	18	104	424	43
2	DEARBORN	-	-	-	-	-	-
3	DETROIT #	100	-	-	-	100	1
4	PONTIAC	(S)	(S)	(S)	(S)	(S)	(S)
5	PORT HURON	9	1	-	8	-	-
6	FORT MYERS-CAPE CORAL, FL MSA[3]	350	202	24	27	97	9
7	FORT MYERS	1	1	-	-	-	-
8	FORT PIERCE, FL MSA	396	181	6	108	101	9
9	FORT PIERCE	97	3	2	92	-	-
10	GREENSBORO--WINSTON-SALEM--HIGH POINT, NC MSA	1 123	714	18	15	376	38
11	GREENSBORO	99	99	-	-	-	-
12	HIGH POINT #	81	53	-	4	24	2
13	WINSTON-SALEM	123	77	6	-	40	5
14	GREENVILLE-SPARTANBURG, SC MSA	297	262	18	7	10	1
15	GREENVILLE	4	2	2	-	-	-
16	SPARTANBURG	7	7	-	-	-	-
17	HARTFORD-NEW BRITAIN-MIDDLETOWN, CT CMSA	880	592	18	15	255	20
18	BRISTOL, CT PMSA	122	116	2	4	-	-
19	BRISTOL	112	106	2	4	-	-
20	HARTFORD, CT PMSA	649	391	6	11	241	18
21	HARTFORD	4	-	-	4	-	-
22	MIDDLETOWN, CT PMSA	66	66	-	-	-	-
23	MIDDLETOWN	13	13	-	-	-	-
24	NEW BRITAIN, CT PMSA	43	19	10	-	14	2
25	NEW BRITAIN	20	4	10	-	6	1
26	HOUSTON-GALVESTON-BRAZORIA, TX CMSA	870	738	4	128	-	-
27	BRAZORIA, TX PMSA	85	85	-	-	-	-
28	GALVESTON-TEXAS CITY, TX PMSA	95	95	-	-	-	-
29	GALVESTON	9	9	-	-	-	-
30	TEXAS CITY	5	5	-	-	-	-
31	HOUSTON, TX PMSA	690	558	4	128	-	-
32	BAYTOWN	2	2	-	-	-	-
33	HOUSTON	224	96	-	128	-	-
34	INDIANAPOLIS, IN MSA	575	404	32	7	132	13
35	INDIANAPOLIS #	(NA)	(NA)	(NA)	(NA)	(NA)	(NA)
36	JACKSONVILLE, FL MSA	1 050	811	14	18	207	16
37	JACKSONVILLE #	777	556	8	6	207	16
38	KANSAS CITY, MO-KS MSA	1 392	801	132	73	386	26
39	KANSAS CITY, KS	(S)	(S)	(S)	(S)	(S)	(S)
40	LEAVENWORTH	22	10	12	-	-	-
41	KANSAS CITY, MO	145	121	24	-	-	-
42	OLATHE	75	75	-	-	-	-
43	LAS VEGAS, NV MSA	1 454	588	-	-	866	87
44	LAS VEGAS	609	268	-	-	341	29
45	LEXINGTON-FAYETTE, KY MSA	232	185	6	-	41	3
46	LEXINGTON-FAYETTE	176	138	2	-	36	2
47	LOS ANGELES-ANAHEIM-RIVERSIDE, CA CMSA	14 110	5 215	210	441	8 244	678
48	ANAHEIM-SANTA ANA, CA PMSA	2 372	657	28	91	1 596	181
49	ANAHEIM	217	4	2	-	211	14
50	SANTA ANA	148	3	2	4	139	2
51	LOS ANGELES-LONG BEACH, CA PMSA	5 323	1 227	80	188	3 828	231
52	BURBANK	(S)	(S)	(S)	(S)	(S)	(S)
53	LONG BEACH	334	48	6	19	261	23
54	LOS ANGELES	2 416	136	30	74	2 176	99
55	PASADENA	14	-	2	-	12	1
56	POMONA	381	26	2	4	349	17
57	OXNARD-VENTURA, CA PMSA	610	554	2	-	54	4
58	OXNARD	-	-	-	-	-	-
59	SAN BUENAVENTURA	91	81	-	-	10	1

Example: Layout Parser in Action on *Dun's Review*

◂ Go back



	Year 1939	Year 1938	Year 1937
New England:			
Boston	$17,445,311	$11,345,156	$21,434,997
Bridgeport	6,140,380	2,656,361	2,782,232
Bristol	597,893	367,644	745,211
Brockton	402,767	269,905	511,220
Cambridge	2,957,016	3,210,069	3,600,869
Chelsea	192,621	245,995	188,922
Everett	263,322	633,686	227,049
Fall River	558,119	681,164	567,065
Fitchburg	661,973	423,442	389,239
Greenwich	2,420,010	3,104,570	3,597,172
Hartford	3,471,267	4,331,673	6,290,636
Haverhill	604,855	141,889	267,652
Holyoke	346,460	472,925	425,525
Lawrence	834,430	622,168	1,028,189
Lowell	502,568	416,118	576,470
Lynn	1,004,514	1,946,538	1,118,840
Manchester	1,218,233	1,078,749	1,353,240
Medford	400,847	1,164,521	436,547
New Bedford	889,850	516,889	791,780
New Britain	945,326	934,426	1,081,448
New Haven	4,306,519	2,511,964	4,453,976
Newton	2,962,883	2,805,307	3,262,098
Norwalk	2,168,552	1,326,000	1,492,924
Portland	889,431	617,738	764,149
Providence	3,418,300	3,806,015	3,228,100
Quincy, Mass.	2,345,277	1,411,784	1,121,954
Salem	530,278	420,652	658,105
Somerville	365,125	270,132	427,487
Springfield, Mass.	5,012,169	2,246,931	2,803,045
Stamford	1,788,838	1,649,976	1,087,522
Waterbury	1,052,635	1,611,625	1,352,025
West Hartford	4,923,418	2,721,715	4,259,031
Worcester	3,526,503	3,382,162	3,273,111

Example: Output from Layout Parser for *Dun's Review*

Go back

	Year 1939	Year 1$38	Year 1937
New England:			
BOS EON "erie sa ake s we Sate	$17,445,311	$11,345,156	$21,434,997
Bridgeport....cceees	6,140,380	2,656,361	2,782,232
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EVERC TH.	263,322	633,686	227,049
Fall River... S252 St a	558,119	681,164	567,065
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Greenwich 3.02505	2,420,010	3,104,570	$,597,172
Herttord......	3,471,267	4,331,673	6, 290, 636
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	530,278	420,652	658,105
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Details on Scoring Quality of OCR Output

Go back

	x_1	y_1	x_2	y_2	block_type	text	id	score
0	0	0	2422	3292	rectangle		0	-1
1	1381	86	2372	168	rectangle		1	-1
2	1381	86	2372	168	rectangle		2	-1
3	1381	86	2368	110	rectangle		3	-1
4	1381	87	1465	109	rectangle	TABLE	4	52.5215
5	1483	88	1511	110	rectangle	3	5	93.745506
6	1549	87	1680	109	rectangle	SELECTED	6	93.745506
7	1696	87	1895	110	rectangle	METROPOLIT	7	96.277077
8	1912	86	2093	109	rectangle	STATISTICAL	8	93.089775
9	2111	86	2267	108	rectangle	AREAS--NEW	9	91.174957
10	2283	87	2368	109	rectangle	PRIVATE	10	96.741982
11	1857	141	2372	168	rectangle		11	-1
12	1857	143	1875	150	rectangle	-	12	0
13	1950	142	2077	166	rectangle	(BECAUSE	13	95.490311
14	2094	141	2127	163	rectangle	OF	14	96.607399
15	2144	142	2280	168	rectangle	ROUNDING,	15	95.613129
16	2298	142	2372	164	rectangle	DETAIL	16	96.516464
17	950	185	2158	265	rectangle		17	-1
18	950	185	2158	265	rectangle		18	-1
19	950	185	2158	265	rectangle		19	-1
20	950	185	2158	265	rectangle		20	95
21	1200	266	2158	319	rectangle		21	-1
22	1200	266	2158	319	rectangle		22	-1
23	1200	266	2158	319	rectangle		23	-1
24	1200	266	2158	319	rectangle		24	95
25	255	200	270	414	rectangle		25	-1
26	255	200	270	414	rectangle		26	-1
27	255	200	270	414	rectangle		27	-1
28	259	405	267	414	rectangle	ec	28	32.35474
29	255	338	270	386	rectangle	OZ	29	85.155327
30	255	200	270	304	rectangle	MZ	30	8.830643
31	762	2582	898	2701	rectangle		31	-1
32	762	2582	898	2701	rectangle		32	-1
33	762	2582	898	2701	rectangle		33	-1

- LP places each block on the coordinate grid and classifies it
  - Block type = "rectangle" $\longrightarrow$ tabular format
  - Set a rotation angle to account for the fact that scans are off-centered
- Each block then receives a "score" for its quality
  - Tesseract API confidence level
- We drop any output from blocks with score $= -1$ (blanks) or < 90 and hand-collect leftovers

Building Permit Value Growth: Price × Quantity

- Main measure: log of local **Building Permit Growth (BPG)**

$$x_{s,t+1} = \Delta \log(V_{s,t+1}), \quad \text{with } V_{s,t} = P_{s,t} \times Q_{s,t} = \sum_{i=1}^{N} p_{i,s,t}$$

- $V_{s,t}$: building permit value for <u>new</u> residential units
  - Depends on quantity ($Q_{s,t}$) and average value per permit index ($P_{s,t}$)
  - $P_{s,t}$ is an index capturing average value per permit ($p_{i,s,t}$)
  - $Q_{s,t}$ depends on demand and supply factors (e.g., demand for new properties, availability of developable land, land use regulations)
- Ideally would observe option value $\mathbb{E}_t[V^*_{s,t+1}] \longrightarrow$ focus on $Q_{s,t}$ BPS Definition
- Geographic units (s) based on data availability across boom-bust cycles (e.g., D&B: 164 largest cities since 1919; Census BPS: 60 MSAs since 1960)

Caution with Using Census Valuation Numbers

Go back

"Because of the nature of the building permit application process, valuations may frequently differ from the true cost of construction. Any attempt to use these figures for inter-area comparisons of construction volume must, at best, be made cautiously and with broad reservations."

— **U.S. Census Bureau**,

Residential Building Permits Survey Documentation, Master Compiled Data Set

↪ We focus on quantities and use standard house price indices at the correct geographic level for the modern period 1990s onward

"Some building permit jurisdictions close their books a few days before the end of the month, so that the time reference for permits is not in all cases strictly the calendar month."

↪ Focus on SFHs, which are less likely to be strategically timed.

Seasonally Adjusting Raw Permit Series

Go back

- Census reports seasonally adjusted permit series for 1988 onward but no longitudinal adjustment factor series

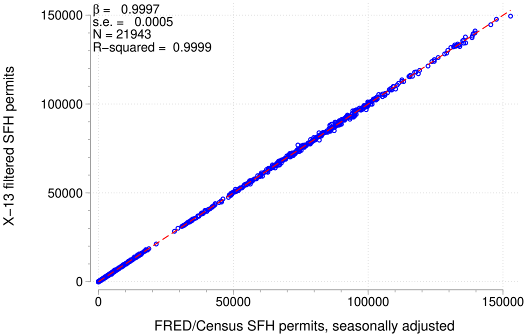
- We apply the Census **X-13 ARIMA-SEATS model** (Linux machine) to each of our longer-run time series for each state/MSA
  - We modify Fortran source code to accommodate longer time series
  - Almost exactly match Census seasonally adjusted series for both SFH and total permits in modern period for each location
  - **For our X-13 filtered SFH permits, avg. correlation of 99.999% with Census series during modern period**

- Small differences due to default location-specific ARIMA intercept
  - Avg. level gap between the SFH series of $\approx 0.23\%$ (median $= 0\%$)

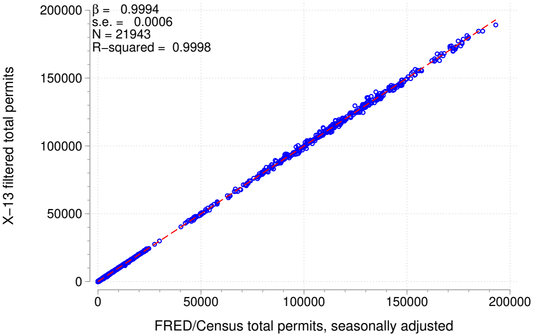
Matching Seasonally Adjusted Series Using X-13 Filter

Go back

Single-family home permits



Total private residential permits



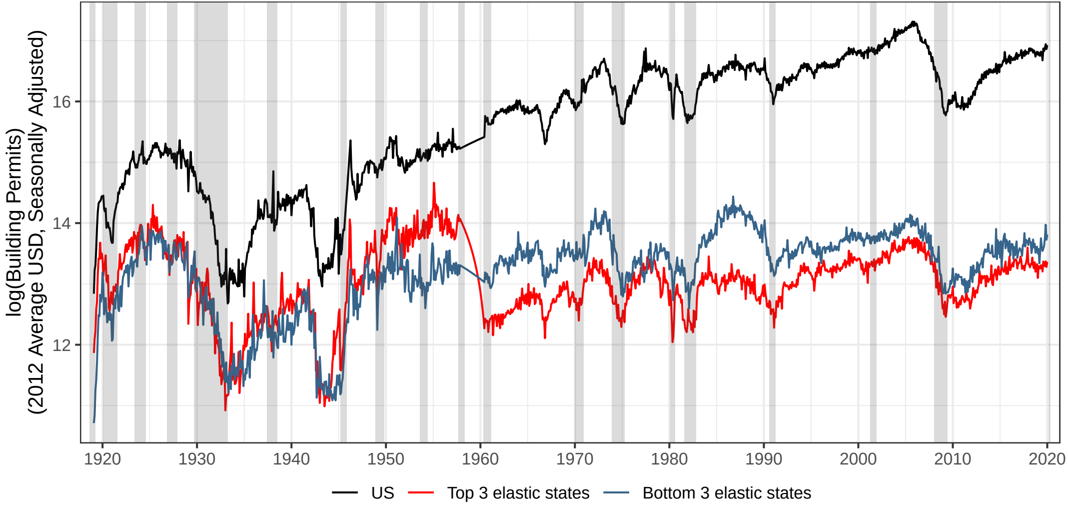
How We Splice Together Permit Series

Go back

- Small gap between our two main permits data sources
  - *Dun's Review* ceased publishing permits tables after Oct. 1957
  - Census Bureau took over Building Permits Survey in May 1959, subsuming the semi-annual surveys conducted by the BLS
- Use New York State Construction and Real Estate Census, which has permit valuations bridging this period
  - Includes SFH and MFH $\implies$ roughly matches the totals reported in Census and *Dun's Review* during overlapping months
- We then perform the following steps:
  1. Deflate to 2012 dollars using Shiller's (2015) long-run CPI series
  2. Seasonally adjust each data source's series using the X-13 filter
  3. Interpolate backwards using a VAR(1) model with NYS data as the input

100 Years of Building Permits with Interpolated Gap

Go back

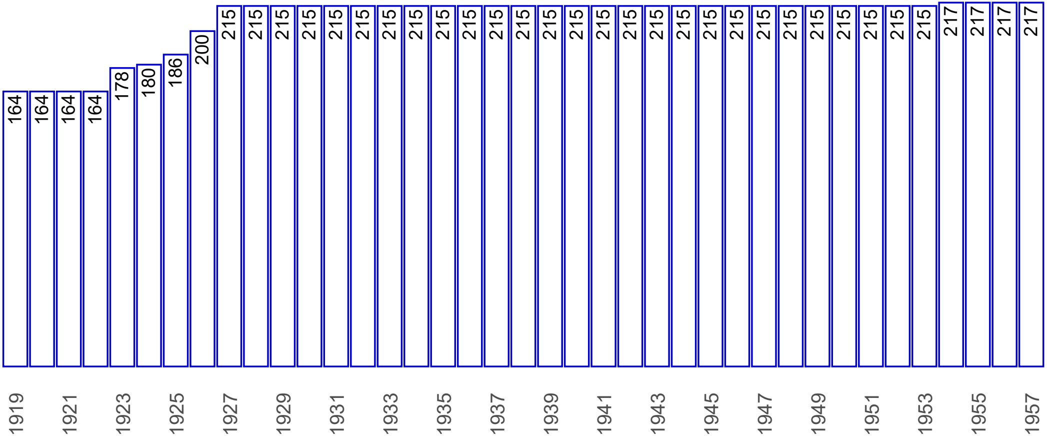


Dun's Review Coverage and Sources

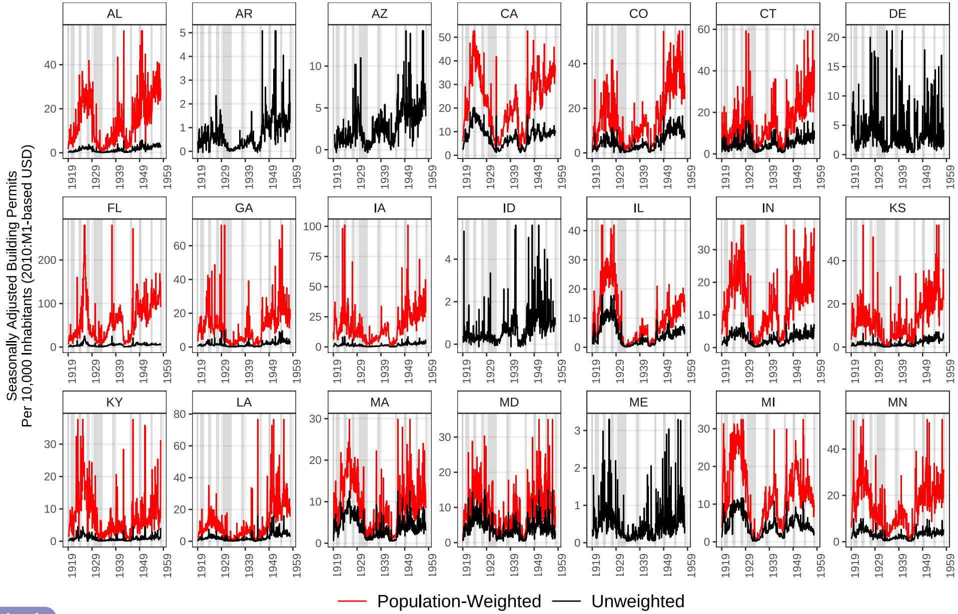
Go back

- *Dun's Statistical Review* was an economic and financial monthly publication reporting permit valuations (construction cost approach)
  - Data shared with BLS Construction Reports $\longrightarrow$ cross-validated to check for errors in digitization
  - Matches "total" series reported later in Census BPS
- Still not in the public domain, so we scanned these from the collection of volumes at the University of Illinois Library
  - Extend Cortes & Weidenmier (2019), who digitized tables for 1928 – 1938
- Steps to harmonize geographic unit definition across *Dun's* and Census:
  1. Aggregate permits within each city to the state level
  2. Inflate up by inverse population weight in each year = total population of surveyed cities relative to total state population
  3. Run X-13 seasonal adjustment on resulting series

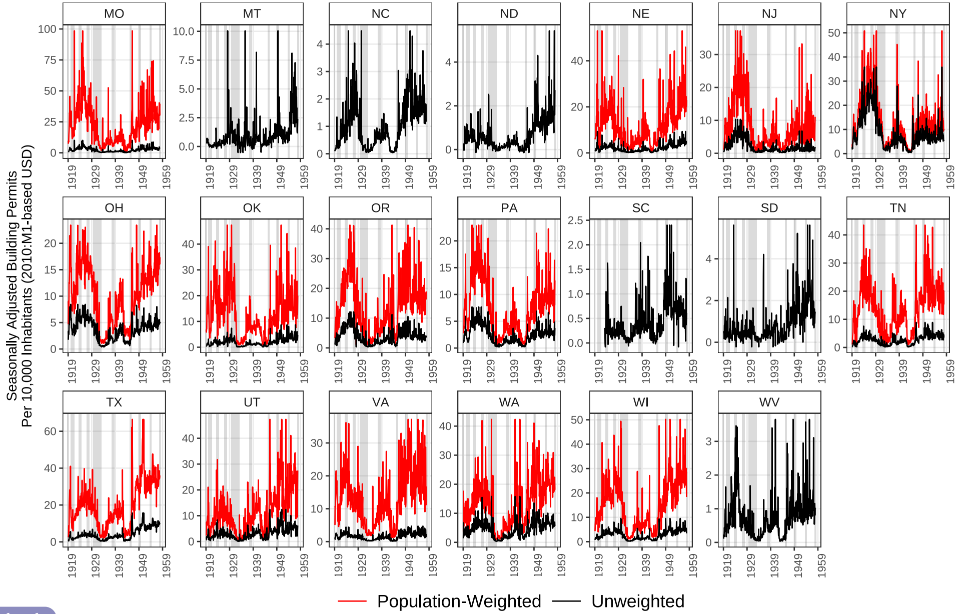
Number of Cities Reporting Building Permits in *Dun's Review*



Go back

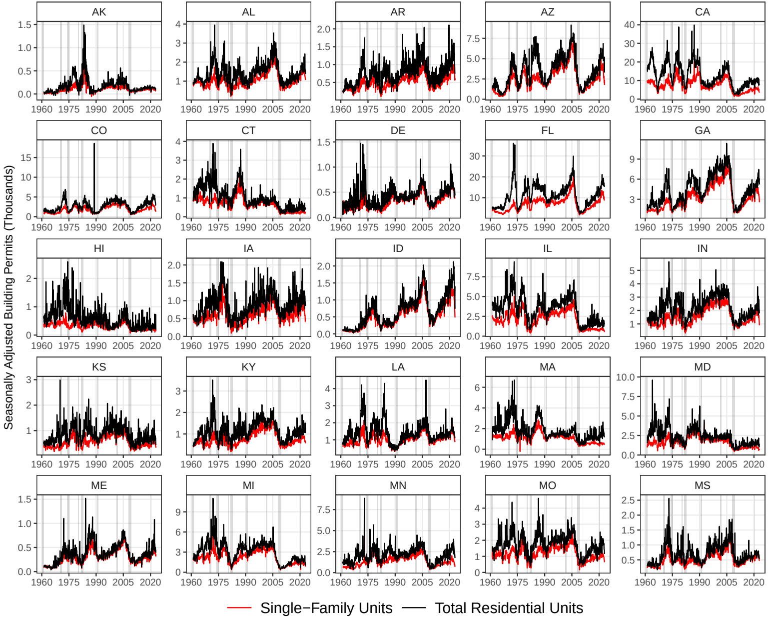

AL
AR
AZ
CA
CO
CT
DE
FL
GA
IA
ID
IL
IN
KS
KY
LA
MA
MD
ME
MI
MN
Seasonally Adjusted Building Permits
Per 10,000 Inhabitants (2010:M1-based USD)
1919
1929
1939
1949
1959
Population-Weighted
Unweighted

Go back

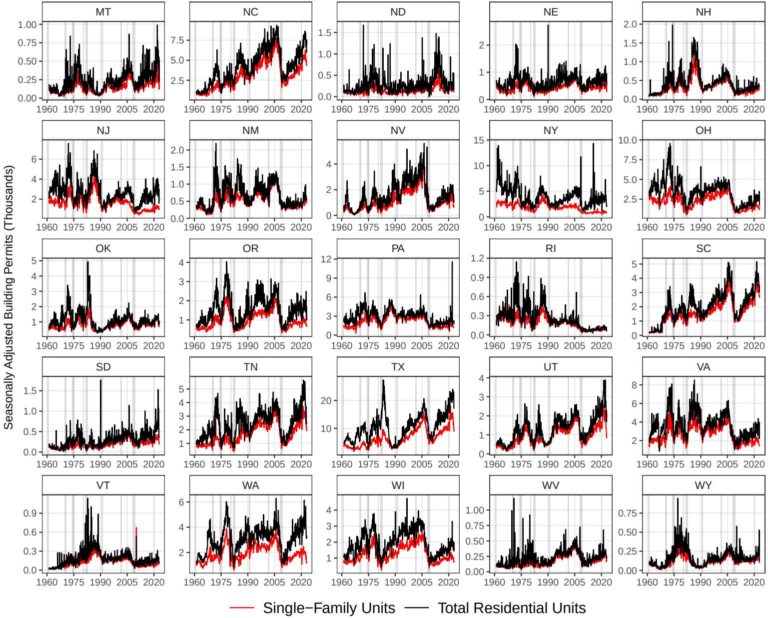


Seasonally Adjusted Building Permits
Per 10,000 Inhabitants (2010:M1-based USD)
MO
MT
NC
ND
NE
NJ
NY
OH
OK
OR
PA
SC
SD
TN
TX
UT
VA
WA
WI
WV
1919
1929
1939
1949
1959
Population-Weighted
Unweighted

Go back


Seasonally Adjusted Building Permits (Thousands)
AK
AL
AR
AZ
CA
CO
CT
DE
FL
GA
HI
IA
ID
IL
IN
KS
KY
LA
MA
MD
ME
MI
MN
MO
MS
1960 1975 1990 2005 2020
Single−Family Units
Total Residential Units

▸ Go back


Seasonally Adjusted Building Permits (Thousands)
MT
NC
ND
NE
NH
NJ
NM
NV
NY
OH
OK
OR
PA
RI
SC
SD
TN
TX
UT
VA
VT
WA
WI
WV
WY
1960 1975 1990 2005 2020
Single−Family Units
Total Residential Units

Go back

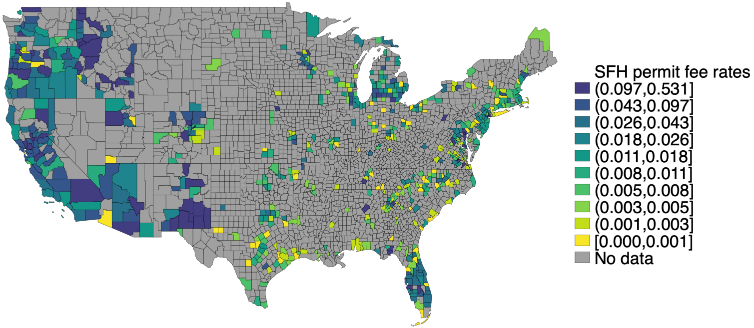
Accounting for "Blips" in the Multi-Family Series

Go back

- **Hypothesis:** multi-family permits better predict return volatility and at longer horizons given time to build and investor composition
  - More likely to be institutional investors building at scale, with geographical diversification of properties $\longrightarrow$ pro forma forecasts at acquisition stage
  - Average time to build is 388 days for MFH *vs.* 193 days for SFH
- **Problem:** multi-family development more sensitive to state/local tax incentive schemes $\longrightarrow$ bunching around tax year ends
  - Qualitatively similar results, but noisier BPG conditional volatility
- Some clear examples in our data:
  - NYC 421a property tax exemption reforms in July 2008 and 2015 (Soltas, 2022)
  - California's Proposition 13 in June 1978

Permit Fees Are Small Fraction of Total Construction Costs

Go back

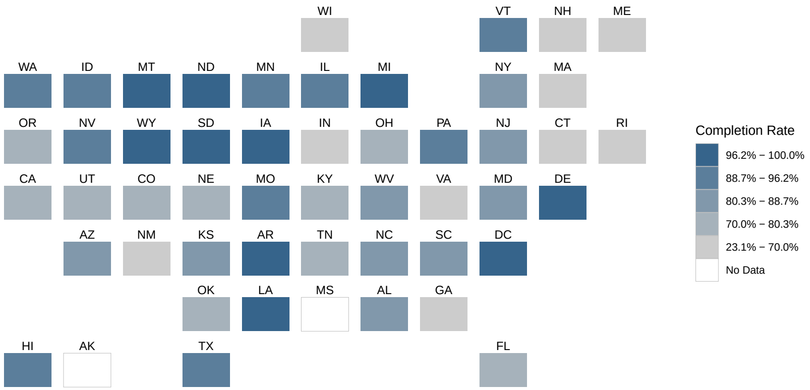


Source: Horton *et al.* (2024): "Property Tax Policy and Housing Affordability," *National Tax Journal*.

- Fees on new SFH permits $< 1\%$ in the median county; exceed 10% in some pockets of California
- City planning rules very sticky, unlikely to be correlated with local economic conditions at high frequency $\longrightarrow$ component of supply elasticity

Greater 12-Month Unconditional Completion Rates for Residential Permits in Low Regulatory States

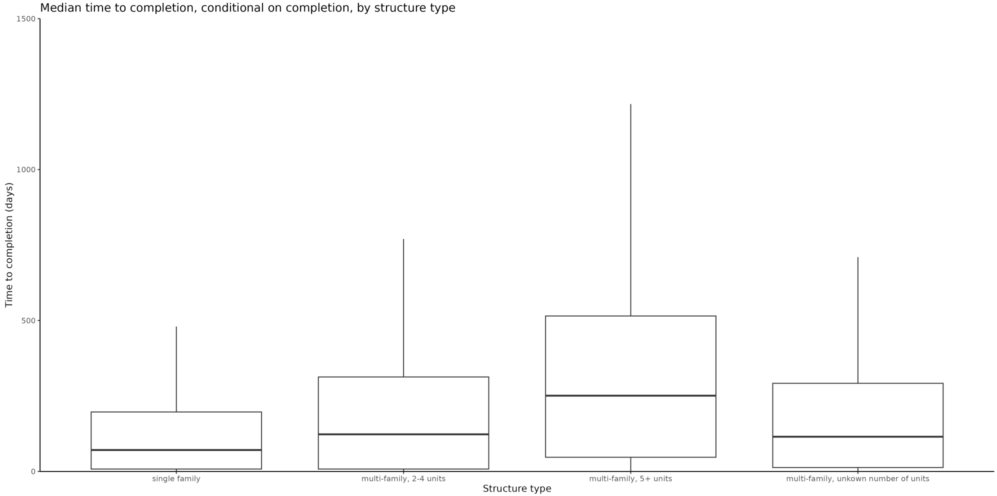
Go back



- Completion rates slightly counter-cyclical in nationwide but more pro-cyclical in low-regulation areas Fees Time Series

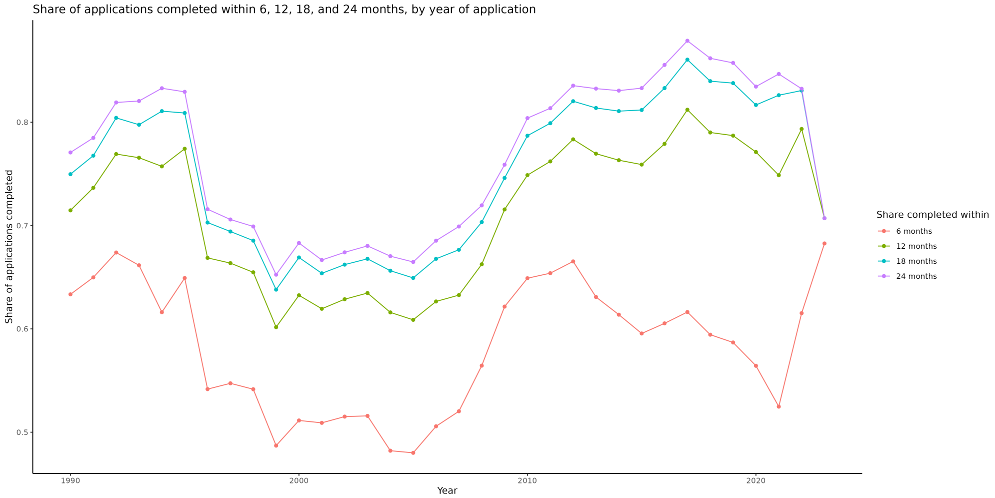
Conditional Time from Permit to Completion by Property Type

▸ Go back



Time from Permit to Completion Varies Over Business Cycle

Go back



Choosing GARCH Specifications

Taxonomy of GARCH Models

Go back

- We explore three main classes of GARCH models common in the literature:

  1. GARCH(1,1) (e.g., Bollerslev, 1986; Chan, Chan, and Karolyi, 1991):
  $\sigma_t^2 = \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2 + \alpha_2 \cdot (\sigma_{t-1}^{BPG})^2$
  2. GJR-GARCH (Glosten, Jagannathan, and Runkle, 1993):
  $\sigma_t^2 = \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2 + \alpha_2 \cdot (\sigma_{t-1}^{BPG})^2 + \gamma \cdot \varepsilon_{t-1}^2 \cdot \mathbb{1}\{\varepsilon_{t-1} < 0\}$
  3. E-GARCH (Nelson, 1991):
  $$\ln(\sigma_t^{BPG})^2 = \alpha_0 + \alpha_1 \cdot \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}^{BPG}}\right) + \alpha_2 \cdot \ln(\sigma_{t-1}^{BPG})^2 + \gamma \cdot \left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}^{BPG}}\right| - \sqrt{\frac{2}{\pi}}\right)$$

- We show E-GARCH does not yield global solutions for aggregate permits data, and GJR-GARCH usually does not yield a unique solution

- Headline results robust to using either GARCH or GJR-GARCH or normal vs. t-stat innovations ε_t

Parameter Restrictions for GARCH Simulations

Go back

Simulation Version 1

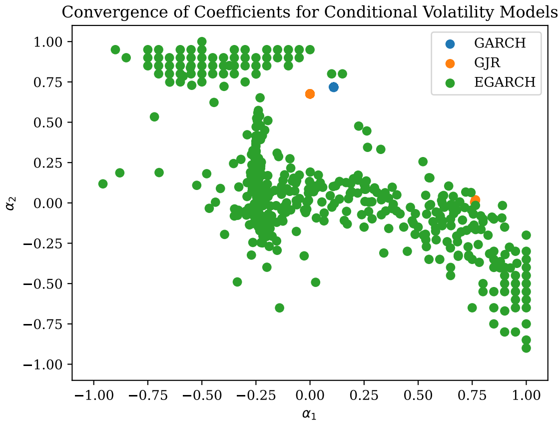
- GARCH specs:
  - Optimization constraint: $\alpha_1 + \alpha_2 < 1$
  - Starting values constraint: select two random non-negative values satisfying $\alpha_1 + \alpha_2 = 0.9$
  - Parameter domain: $\alpha_0 > 0; 0 < \alpha_1 < 1; 0 < \alpha_2 < 1$
- GJR-GARCH specs:
  - Optimization constraint: $\alpha_1 + \alpha_2 + \gamma/2 < 1$
  - Starting values constraint: select three random non-negative values satisfying $\alpha_1 + \alpha_2 + \gamma = 0.9$
  - Parameter domain: $\alpha_0 > 0; 0 < \alpha_1 < 1; 0 < \alpha_2 < 1; 0 < \gamma < 1$

Simulation Version 2

- GARCH specs:
  - Optimization constraint: $\alpha_1 + \alpha_2 < 1$
  - Starting values constraint: select two random non-negative values satisfying $\alpha_1 + \alpha_2 = 0.999$
  - Parameter domain: $\alpha_0 > 0; 0 < \alpha_1 < 1; 0 < \alpha_2 < 1$
- GJR-GARCH specs:
  - Optimization constraint: $\alpha_1 + \alpha_2 + \gamma/2 < 1$
  - Starting values constraint: select three random non-negative values satisfying $\alpha_1 + \alpha_2 + \gamma = 0.999$
  - Parameter domain: $\alpha_0 > 0; 0 < \alpha_1 < 1; 0 < \alpha_2 < 1; 0 < \gamma < 1$

Stability of GARCH(1,1) to Starting Value Choice

Go back



- Fit demeaned U.S. aggregate permit series according to Simulation V1
  - `basinhopping` routine in Python
- Draw with replacement 10,000 starting values $\alpha_i \in [-1, 1]$ and estimate via QMLE
- **GARCH(1,1)** always converges to the same parameter values $(\widehat{\alpha}_1, \widehat{\alpha}_2)$
- **GJR-GARCH** and **E-GARCH** do not yield global solutions

Convergence and Parameter Stability across GARCH Models

Go back

A. Single-Family Homes vs. Total Private Residential Permits: Simulation Version 2

	Single-Family Homes Permits				*Total Private Residential Permits*			
	Convergence Rate	N. Unique Solutions	Convergence Rate	N. Unique Solutions	Convergence Rate	N. Unique Solutions	Convergence Rate	N. Unique Solutions
GARCH	0.9876	44	0.9984	4	0.9984	2	0.9999	2
GJR-GARCH	0.9457	7	0.9986	14	0.9976	5	0.9996	3
E-GARCH	0.9974	11	0.9998	7	0.9992	6	1	1
Sample	1960 – 2019	1960 – 2019	1980 – 2019	1980 – 2019	1960 – 2019	1960 – 2019	1980 – 2019	1980 – 2019

B. Comparing Simulation Version Results in the Post-2000s Period

	U.S. Building Permits: $P \times Q$			
	Simulation Version 1		Simulation Version 2	
	Convergence Rate	N. Unique Solutions	Convergence Rate	N. Unique Solutions
GARCH	0.9999	4	0.9999	4
GJR	0.9997	20	1	16
E-GARCH	0.3907	3859	0.9979	4
Sample	2000 – 2023	2000 – 2023	2000 – 2023	2000 – 2023

Notes: Convergence rate is defined as the fraction of starting parameter draws for which the optimization routine converges to a solution. A unique solution is defined up to five decimal places.

High pairwise correlations across GARCH model estimates

Go back

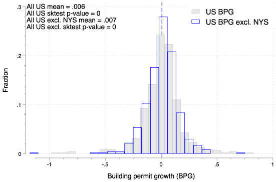
Series	Sample Period	Corr($\sigma_{\text{GAR}}, \sigma_{\text{GJR}}$)	Corr($\sigma_{\text{GAR}}, \sigma_{\text{EGR}}$)	Corr($\sigma_{\text{GJR}}, \sigma_{\text{EGR}}$)
SFH Permits	1960 – 2019	0.8115	0.9538	0.8282
SFH Permits	1980 – 2019	0.8899	0.9754	0.8829
Total Permits	1960 – 2019	0.8590	0.6854	0.5439
Total Permits	1980 – 2019	0.9162	0.7866	0.6840

Notes: For each unique solution $[\widehat{\alpha}_1, \widehat{\alpha}_2]$ obtained from each GARCH model, compute average pairwise correlations across solutions between two models.

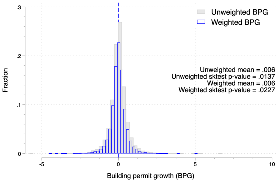
GJR-GARCH Accommodates Skewness in BPG

A. U.S. BPG in *Dun's*

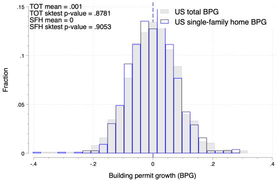
◂ Go back



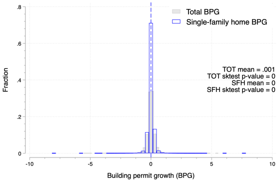
B. Cross-Sectional BPG in *Dun's*



C. U.S. BPG in Census BPS



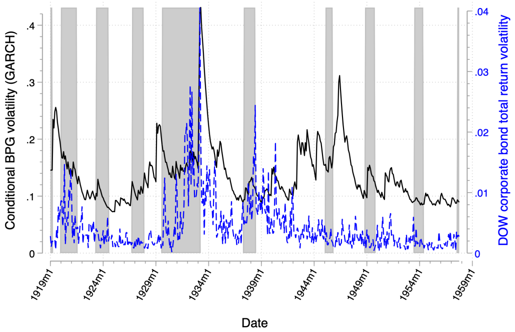
D. Cross-Sectional BPG in Census BPS



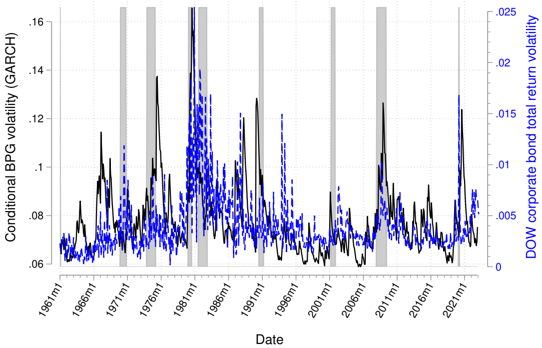
Additional Results and Robustness

BPG Vol Also Spikes Prior to Spikes in Bond Return Volatility

Dun's Review Period (1919 – 1957)



Census BPS Period (1961 – 2022)



- Break in BPG and bond total return volatility after late-1980s Savings & Loan Crisis (Stock & Watson 2010) Go Back

Similar Aggregate Predictability of BPG Vol using SFH Series

Go back

Asset Market:	Equities					Corporate Bonds				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
σ^{BPG}_{t-1}	0.074***	0.024**	0.022**	0.022**	0.049**	0.076***	0.044***	0.040***	0.038***	0.015***
	(2.60)	(2.40)	(2.49)	(2.41)	(2.18)	(6.07)	(4.48)	(4.54)	(4.28)	(3.99)
Time sample	1960-19	1960-19	1980-19	1980-16	2000-16	1960-19	1960-19	1980-19	1980-16	2000-16
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓	✓		✓	✓	✓	✓
$PopGrowth_{t-p}$		✓	✓	✓	✓		✓	✓	✓	✓
$Leverage_{t-p}$			✓	✓	✓			✓	✓	✓
$DSCR_{t-p}$			✓	✓	✓			✓	✓	✓
$IPGrowth_{t-p}$			✓	✓	✓			✓	✓	✓
$DisasterNVIX_{t-p}$				✓	✓				✓	✓
N	714	707	479	435	195	714	707	479	435	195
R^2	0.095	0.470	0.462	0.471	0.599	0.258	0.391	0.471	0.463	0.543

Pre-1960s U.S. BPG Vol Predicts Stock Return Vol

Go back

Sample Period:	Full Time Period					Great Depression Era				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
σ^{BPG}_{t-1}	0.036**	0.013**	0.013**	0.013**	0.017***	0.037**	0.020***	0.021***	0.021***	0.020***
	(2.52)	(2.37)	(2.39)	(2.41)	(2.94)	(2.46)	(2.85)	(3.18)	(3.13)	(3.00)
Time sample	1926-57	1926-57	1926-57	1926-57	1926-57	1928-38	1928-38	1928-38	1928-38	1928-38
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓	✓		✓	✓	✓	✓
$PopGrowth_{t-p}$		✓	✓	✓	✓		✓	✓	✓	✓
$MktLeverage_{t-p}$		✓	✓	✓	✓		✓	✓	✓	✓
$IPGrowth_{t-p}$			✓	✓	✓			✓	✓	✓
$DisasterNVIX_{t-p}$				✓	✓				✓	✓
$WarNVIX_{t-p}$					✓				✓	✓
N	381	381	381	381	381	131	131	131	131	131
R^2	0.102	0.618	0.618	0.620	0.631	0.147	0.613	0.614	0.615	0.629

- Quantitatively similar predictability of σ^{BPG} compared to post-1960s era (stock return vol $\uparrow$ in modern period)

Pre-1960s U.S. BPG Vol Predicts Bond Return Vol

Go back

Sample Period:	Full Time Period					Great Depression Era				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
σ_{t-1}^{BPG}	0.021^{***}	0.009^{**}	0.009^{**}	0.009^{**}	0.011^{**}	0.030^{***}	0.017^{**}	0.021^{***}	0.021^{***}	0.021^{***}
	(2.72)	(2.11)	(2.10)	(2.12)	(2.54)	(3.31)	(2.39)	(3.02)	(2.95)	(2.97)
Time sample	1919-57	1925-57	1925-57	1925-57	1925-57	1928-38	1928-38	1928-38	1928-38	1928-38
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓	✓		✓	✓	✓	✓
$PopGrowth_{t-p}$		✓	✓	✓	✓		✓	✓	✓	✓
$MktLeverage_{t-p}$		✓	✓	✓	✓		✓	✓	✓	✓
$IPGrowth_{t-p}$			✓	✓	✓			✓	✓	✓
$DisasterNVIX_{t-p}$				✓	✓				✓	✓
$WarNVIX_{t-p}$					✓				✓	✓
N	465	393	393	393	393	131	131	131	131	131
R^2	0.090	0.515	0.516	0.518	0.525	0.142	0.527	0.541	0.542	0.543

- Quantitatively similar predictability of σ^{BPG} compared to post-1960s era (bond return vol $\downarrow$ in modern period)

Predictability Also Holds for CRSP Dividend Volatility

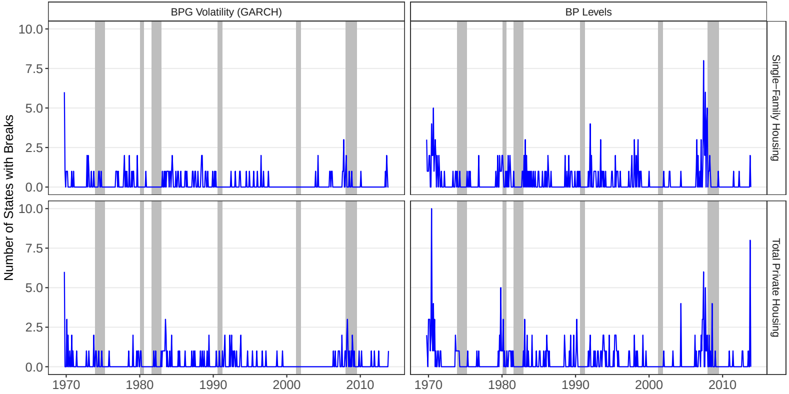
Go back

Dividend Vol	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ^{BPG}_{t-1}	0.0016***	0.0014***	0.0012***	0.0007***	0.0014***	0.0007***	0.0005**	0.0004*
	(6.51)	(6.08)	(5.18)	(3.95)	(5.60)	(3.74)	(2.10)	(1.91)
Time sample	1960-19	1960-19	1960-19	1980-19	1960-19	1980-16	2000-19	2000-16
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓	✓	✓	✓	✓
$PopGrowth_{t-p}$			✓	✓		✓		✓
$Leverage_{t-p}$			✓	✓		✓		✓
$DSCR_{t-p}$				✓		✓		✓
$IPGrowth_{t-p}$				✓		✓		✓
$WarNVIX_{t-p}$					✓	✓		✓
N	714	714	707	479	670	435	239	195
R^2	0.374	0.378	0.460	0.496	0.395	0.496	0.191	0.238

- Larger R^2 for bonds due to predictability of interest rates by housing starts
  - Monetary policy response to inflation passing through to bond coupon rates (e.g. Ludvigson & Ng 2009)

Bai–Perron Structural Break Tests: SFHs *vs.* Total Residential

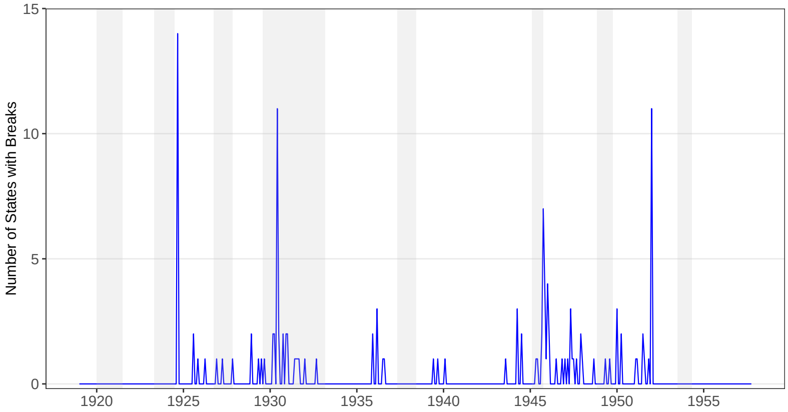
Go back



- Level breaks more common than volatility breaks
- Modal state has 2 breaks in its level series

Bai–Perron Structural Break Tests: Dun's Sample

Go back

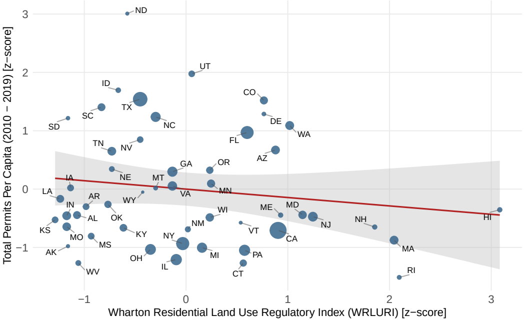


- Early evidence of pre-Great Depression financial distress in 1924–1925
  - Florida break date of 1924M9 consistent with permits containing soft information about failure of Manley-Anthony banking chain (Calomiris & Jaremski 2023)

Tightly Regulated Jurisdictions Issue Fewer Total Permits

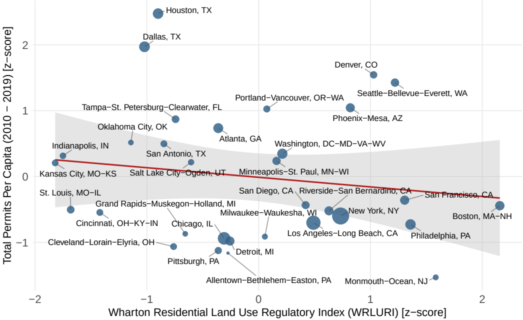
Go back

State-Level Total Residential Permits



Trendline: R^2 = 0.02, Slope = −0.14

MSA-Level Total Residential Permits

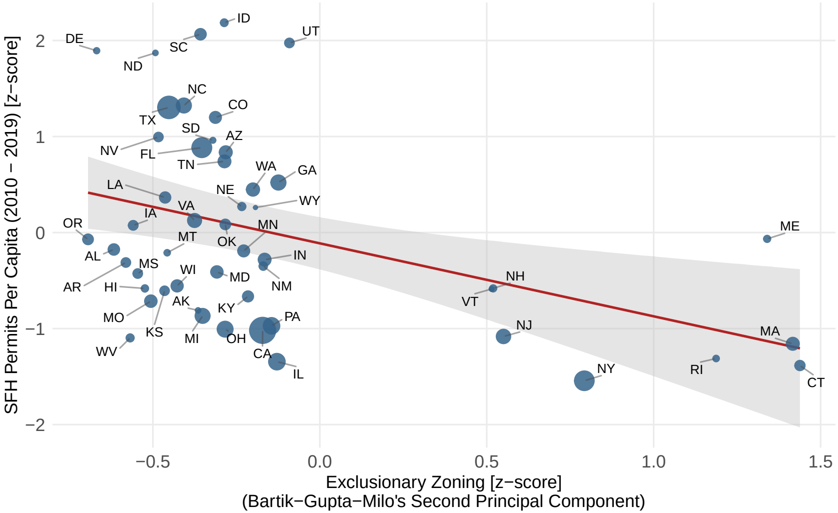


Trendline: R^2 = 0.02, Slope = −0.15

- Relationship weaker for total permits given that most zoning/land use restrictions in Wharton index more binding for SFHs

Permits vs. Exclusionary Zoning: Bartik, Gupta, Milo (2024)

Go back



Trendline: R^2 = 0.08, Slope = −0.28

Agg. BPG Vol Regressions: Controls for Commodities and Mortgages

Asset Market:	Equities					Corporate Bonds				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
σ^{BPG}_{t-1}	0.028^{***}	0.028^{**}	0.031^{**}	0.046^{**}	0.045^{**}	0.036^{***}	0.037^{***}	0.040^{***}	0.017^{***}	0.017^{***}
	(2.59)	(2.52)	(2.45)	(2.12)	(2.10)	(3.87)	(3.59)	(3.31)	(3.25)	(3.29)
Time sample	1960-19	1960-19	1980-16	2000-19	2000-19	1960-19	1960-19	1980-16	2000-19	2000-19
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged comm. return vol.		✓	✓				✓	✓		
Other controls$_{t-p}$			✓					✓		
ΔHMDA applications				✓					✓	
ΔHMDA $ originations					✓					✓
N	714	714	435	239	239	714	714	435	239	239
R^2	0.469	0.469	0.474	0.568	0.567	0.370	0.370	0.444	0.506	0.507

Notes: Total residential permits data used to construct σ^{BPG}_{t-1} from the monthly Census BPS. Commodity excess return index from Janardanan, Qiao, & Rouwenhorst (2024). Monthly HMDA series c/o Neil Bhutta (Philly Fed). Go back

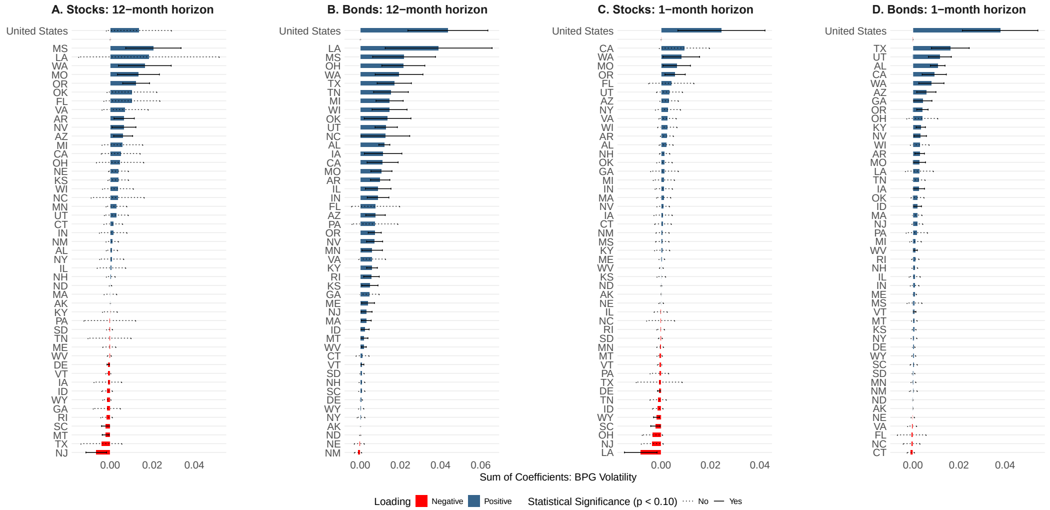
Post-1960s Agg. U.S. SFH BPG Vol Predicts Agg. Return Vol

Asset Market:	Equities					Corporate Bonds				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
σ^{BPG}_{t-1}	0.074***	0.024**	0.022**	0.022**	0.049**	0.076***	0.044***	0.040***	0.038***	0.015***
	(2.60)	(2.40)	(2.49)	(2.41)	(2.18)	(6.07)	(4.48)	(4.54)	(4.28)	(3.99)
Time sample	1960-19	1960-19	1980-19	1980-16	2000-16	1960-19	1960-19	1980-19	1980-16	2000-16
Monthly dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged asset return vol.		✓	✓	✓	✓		✓	✓	✓	✓
$PopGrowth_{t-p}$		✓	✓	✓	✓		✓	✓	✓	✓
$Leverage_{t-p}$			✓	✓	✓			✓	✓	✓
$DSCR_{t-p}$			✓	✓	✓			✓	✓	✓
$IPGrowth_{t-p}$			✓	✓	✓			✓	✓	✓
$DisasterNVIX_{t-p}$				✓	✓				✓	✓
N	714	707	479	435	195	714	707	479	435	195
R^2	0.095	0.470	0.462	0.471	0.599	0.258	0.391	0.471	0.463	0.543

Notes: Single family home (SFH) permits data used to construct σ^{BPG}_{t-1} from the monthly Census BPS. Go back

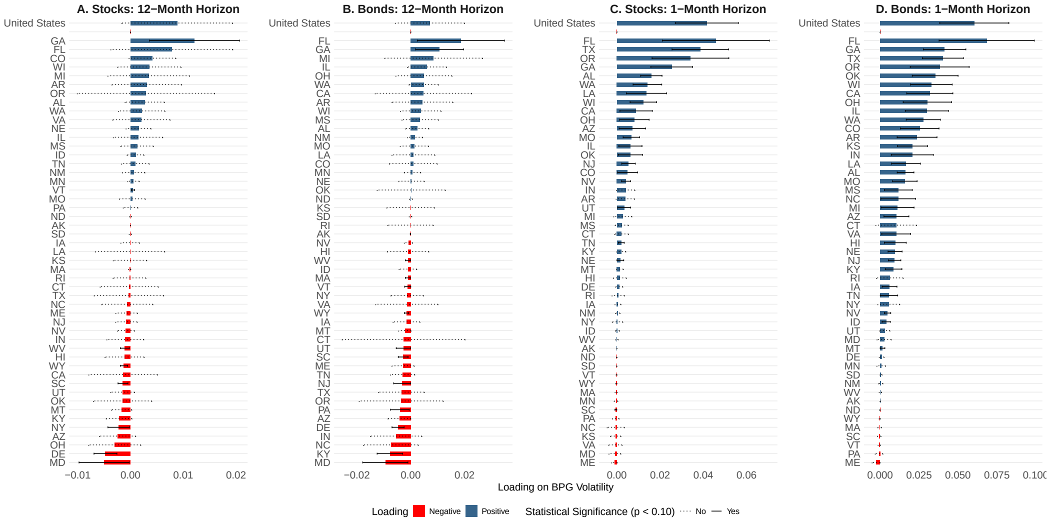
Controlling for Local Leverage + Pop. Growth

Go back



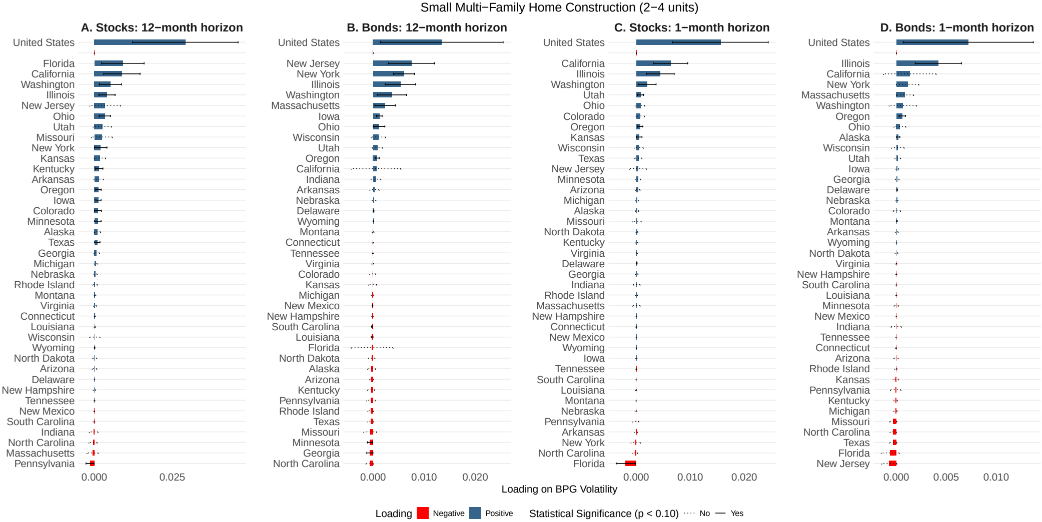
Robustness to Using GJR-GARCH

Go back



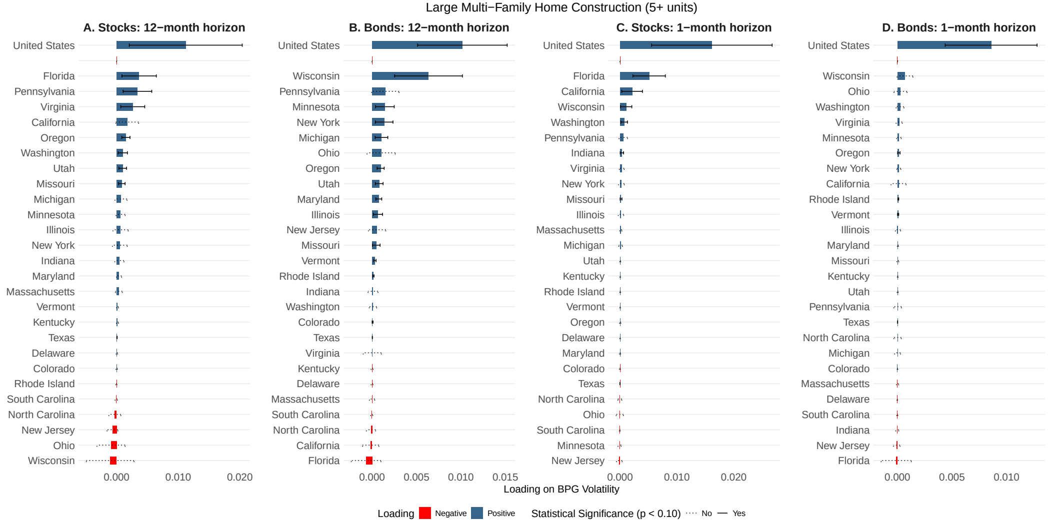
Predictability Using Small Multi-Family Housing (S-MFH)

Go back



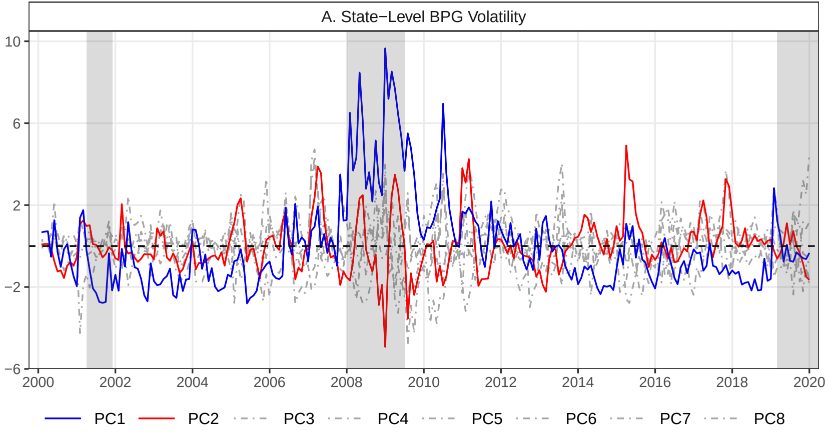
Predictability Using Large Multi-Family Housing (L-MFH)

Go back



First PC of σ_s^{BPG} Identifies "Subprime" Factor: States

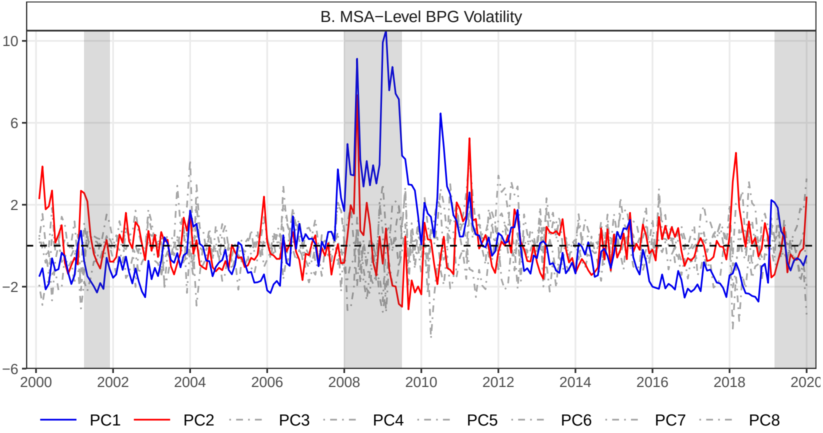
Go back



- First PC explains 24% of variation in σ_s^{BPG}

First PC of σ_s^{BPG} Identifies "Subprime" Factor: MSAs

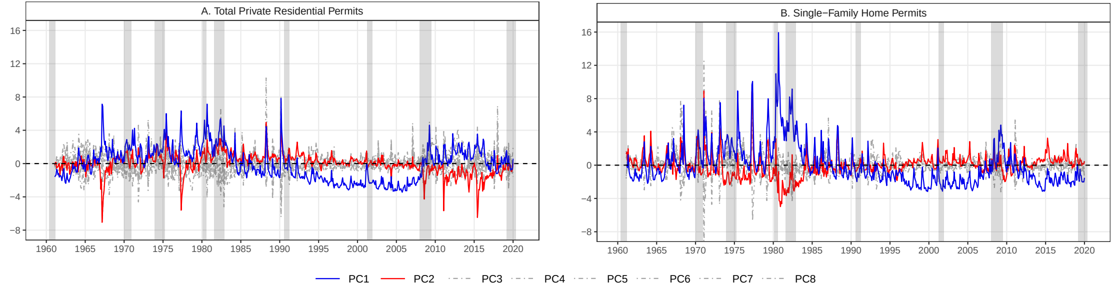
Go back



- Sharper peaks in PC1 when zoom in to MSA level

PCA of BPG Vol over Full Census Period (1961 – 2019)

Go back

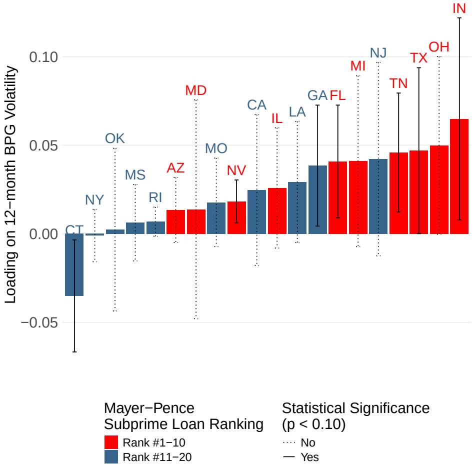


- First PC dominated by input supply shocks (e.g., OPEC) when we include the full Census sample period

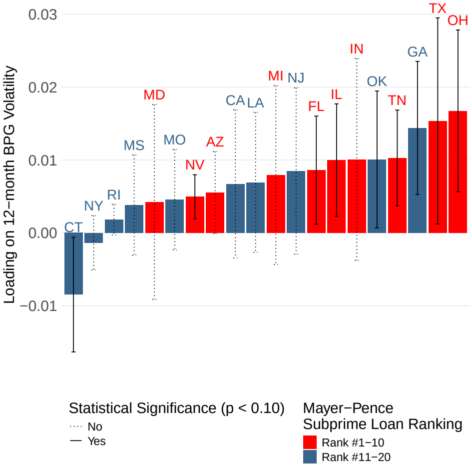
Loading on BPG Factor Greatest in Subprime Crisis States

Go back

Stock Return Volatility: States

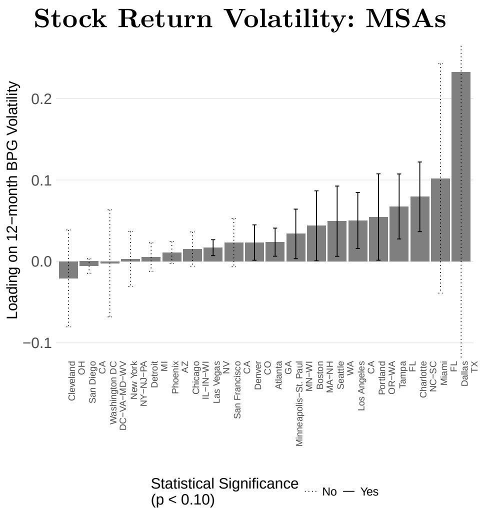


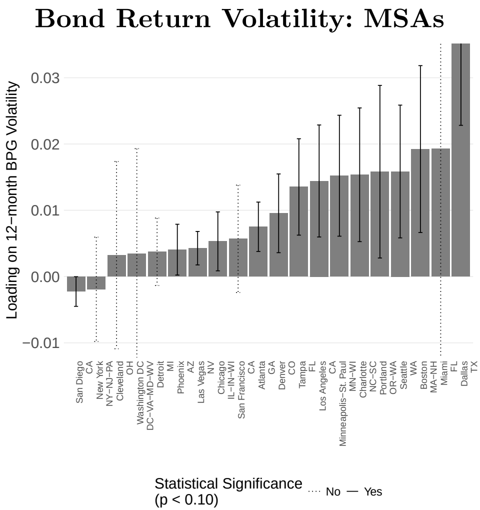
Bond Return Volatility: States



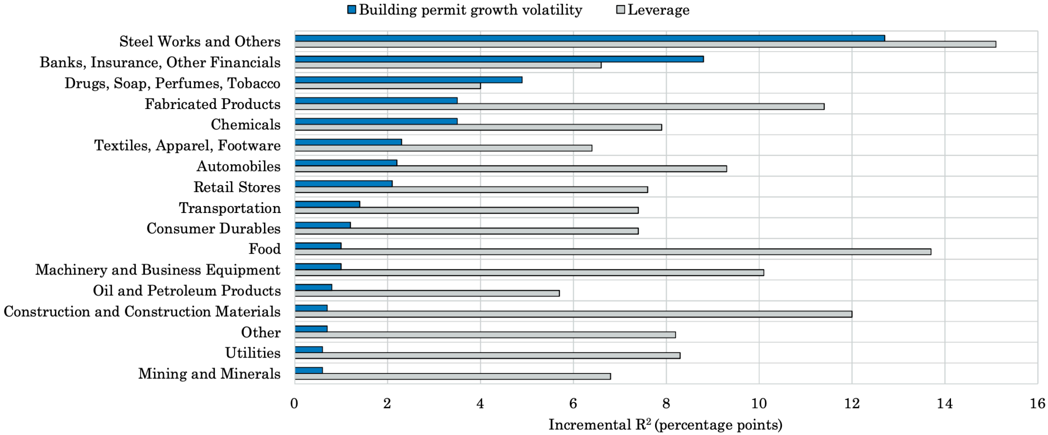
Loading on BPG Factor Greatest in Subprime Crisis MSAs

Go back



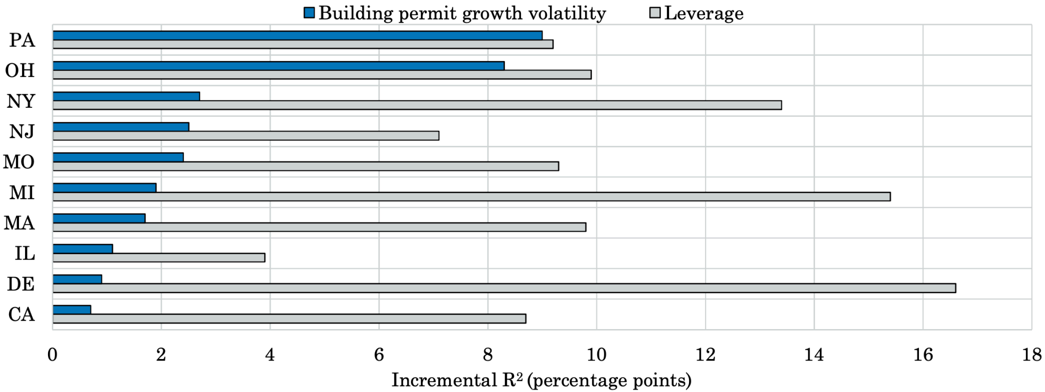


Financial + Heavy Manufacturing Sectors Drive Predictability



Notes: Figure 6 from Cortes & Weidenmier (2019, *RFS*). Go back

Industrialized States Important Around Depression Vol Spike



Notes: Figure 8 from Cortes & Weidenmier (2019, *RFS*).

- In industrialized states, BPG vol permits "as good" as leverage in predicting stock return vol ▸ Go back

Signal Precision Also Negatively Correlated with Supply Inelasticity

- Estimate $\sigma_t \sim \sum_{k=1}^{12} \sigma_{t-\tau}^{BPG} \longrightarrow \{\beta_\tau^{BPG}, \sigma(\beta_\tau^{BPG})\}$ Go back
  - $corr(1/\sigma(\beta_1^{BPG}), WRLURI) = -17\%$ for stocks, -22% for bonds
  - $corr(1/\sigma(\sum_\tau \beta_\tau^{BPG}), WRLURI) = -19\%$ for stocks, -21% for bonds
  - Similar neg. correlations with generative AI-based index of local zoning features from Bartik, Gupta, Milo (2024)
- Negligible correlation with (un)available land measures (Saiz, 2010)
  - $\implies$ construction costs rather than physical constraints determine permitting within city centers on the margin
  - Similar correlations to WRLURI if zoom into counties (Lutz & Sand, 2023)
- **Consistent with model framework:** signal precision is greater in places where permits are free to respond to beliefs about local economic conditions

Why Is (Local) Housing the Financial Cycle? ▸ Go Back

Main result: local building permit growth volatility consistently predicts return volatility at 12-month horizons

- Driven by most supply elastic housing markets
- Predictability can be neg. in high σ^{BPG} states with inelastic supply

Alternative explanations:

1. **Leverage cycles:** similar predictability even when mortgages uncommon
   - Results hold conditional on HH and corporate leverage ratios
2. Reforms/political upheavals: more slow-moving than monthly permits
   - Very little change in Wharton Index over last 20 years
3. **Physical risks:** results hold conditional on disaster component of NVIX or SHELDUS realized disaster severity measures
4. Demographics/migration: holds conditional on population growth, plus steady decline in inter-state migration (Kaplan & Schulhofer-Wohl 2017)

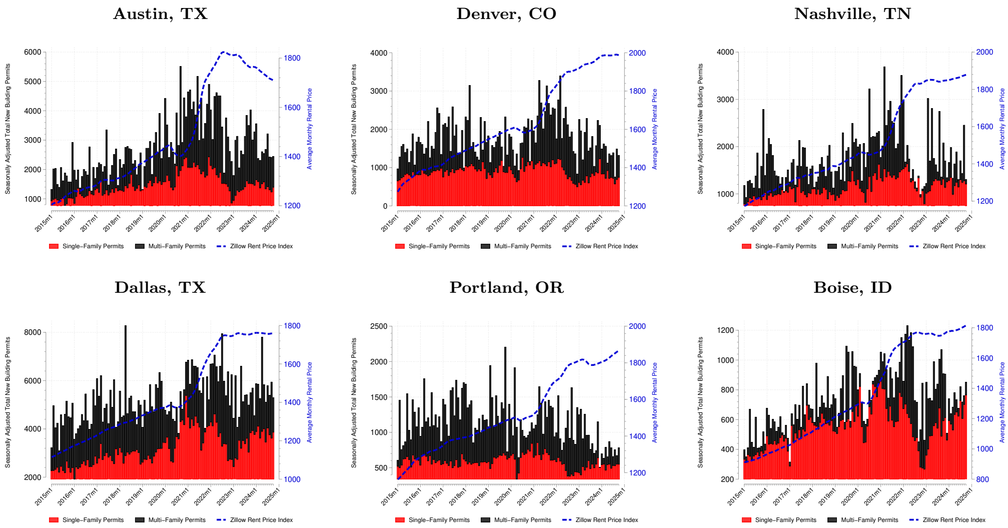
Why Is (Local) Housing the Financial Cycle? (Redux) ▸ Go Back

Other alternative (dynamic) explanations:

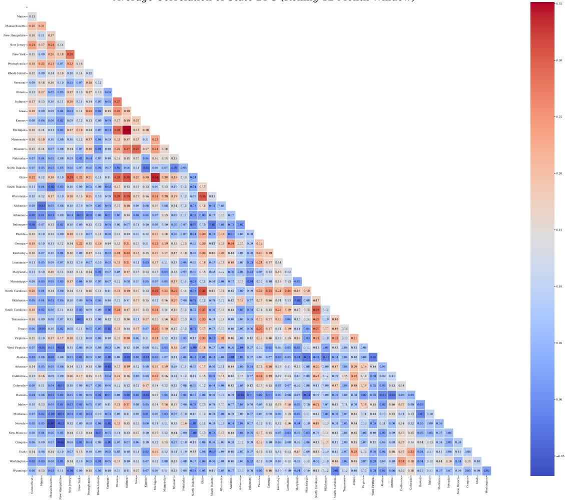
1. **Option value of waiting:** in times of economic uncertainty, developers delay or forgo construction projects altogether (McDonald & Siegel 1986)
   - Testable prediction: permitting should taper off during times of increasing BPG vol. or (housing) return vol. (Bulan, Mayer, Somerville 2009)
   - Some evidence of this in the permits microdata for MFH but not for SFH!
   - SFH permit completion times and rates flat during run-up to 2008 ▸ Result
2. **Extrapolative beliefs:** investors may place excess weight on ΔP_{t-k}, with housing market "wavering" before the stock market
   - If extrapolative, based on house price growth (capital gains = return for SFH)?
   - P × Q decomposition of permit values in modern era shows that nearly all predictability of BPG for financial markets driven by ΔQ rather than ΔP

Permits Predict Rental Price Corrections in WFH Cities

▸ Go back



Average Correlation of State BPG (Rolling 12-Month Window)



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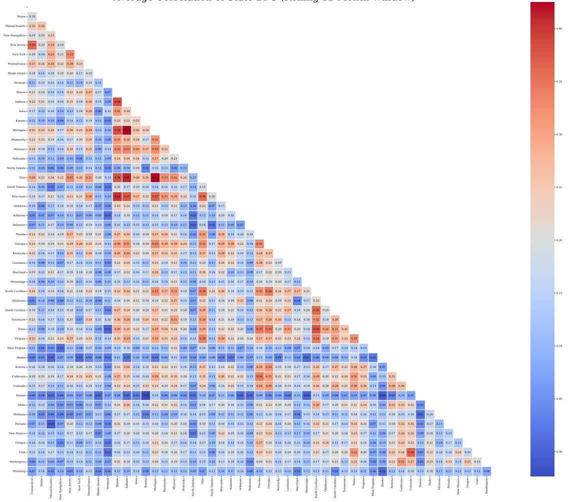

Asset Pricing Tests

SFH BPG Generates Return Premium of ≈ 6%

Go Back

Specification	MKTRF	SMB	HML	RMW	CMA	UMD	SFH	TOT
FF3	6.858 (0.001)	3.297 (0.030)	-1.452 (0.283)					
FF3 + UMD	6.868 (0.001)	3.404 (0.023)	-1.131 (0.382)			1.81 (0.392)		
FF5	6.506 (0.002)	3.501 (0.018)	-1.536 (0.250)	-0.632 (0.552)	-0.945 (0.323)			
FF5 + UMD	6.614 (0.001)	3.6 (0.014)	-1.425 (0.276)	-0.575 (0.584)	-1.079 (0.249)	2.304 (0.271)		
FF3 + SFH	6.612 (0.002)	3.34 (0.027)	-1.294 (0.336)				6.432 (0.101)	
FF3 + UMD + SFH	6.866 (0.001)	3.275 (0.027)	-1.38 (0.296)			2.354 (0.267)	6.466 (0.100)	
FF5 + SFH	6.635 (0.001)	3.347 (0.023)	-1.441 (0.277)	-0.746 (0.478)	-0.841 (0.375)		6.363 (0.101)	
FF5 + UMD + SFH	7.068 (0.001)	3.073 (0.034)	-1.423 (0.280)	-0.585 (0.579)	-1.126 (0.227)	2.941 (0.160)	6.129 (0.114)	
FF3 + TOT	6.627 (0.001)	3.357 (0.026)	-1.265 (0.340)					4.648 (0.252)
FF3 + UMD + TOT	6.696 (0.001)	3.321 (0.026)	-1.398 (0.289)			2.014 (0.340)		5.015 (0.217)
FF5 + TOT	6.555 (0.002)	3.542 (0.016)	-1.561 (0.237)	-0.538 (0.608)	-0.824 (0.381)			4.353 (0.275)
FF5 + UMD + TOT	6.638 (0.001)	3.393 (0.019)	-1.307 (0.321)	-0.461 (0.660)	-1.091 (0.243)	3.000 (0.150)		5.103 (0.198)

Factor premium estimates using the Fama MacBeth 2-pass technique on CRSP. We use 38,423 publicly traded securities.

BPG Very Weakly Correlated with FF5 Factors + Momentum

Go Back

Factor	SMB	HML	RMW	CMA	UMD	TOT	SFH
MKTRF	0.277	-0.248	-0.223	-0.389	-0.142	0.054	0.104
SMB		-0.061	-0.349	-0.104	-0.037	0.074	0.110
HML			0.072	0.691	-0.198	-0.036	-0.025
RMW				-0.039	0.102	-0.014	-0.009
CMA					-0.035	-0.060	-0.060
UMD						-0.026	-0.041
TOT							0.852

BPG Largely Orthogonal to FF5 Factors + Momentum

Go Back

BPG Type	Intercept	MKTRF	SMB	HML	RMW	CMA	UMD	R^2
SFH	0.003	0.148	0.237	0.002				0.018
	(0.306)	(0.070)	(0.038)	(0.987)				
	0.003	0.138	0.237	-0.019			-0.055	0.019
	(0.250)	(0.120)	(0.037)	(0.874)			(0.501)	
	0.002	0.145	0.271	0.056	0.153	-0.127		0.020
	(0.367)	(0.107)	(0.029)	(0.735)	(0.308)	(0.606)		
	0.003	0.136	0.274	0.025	0.166	-0.107	-0.059	0.021
	(0.312)	(0.153)	(0.026)	(0.885)	(0.258)	(0.659)	(0.464)	
TOT	0.003	0.059	0.181	-0.075				0.007
	(0.199)	(0.488)	(0.146)	(0.554)				
	0.004	0.048	0.181	-0.095			-0.054	0.008
	(0.179)	(0.597)	(0.146)	(0.486)			(0.594)	
	0.004	0.040	0.192	0.017	0.049	-0.208		0.009
	(0.178)	(0.655)	(0.157)	(0.929)	(0.750)	(0.435)		
	0.004	0.033	0.195	-0.009	0.060	-0.191	-0.051	0.009
	(0.173)	(0.734)	(0.153)	(0.962)	(0.684)	(0.464)	(0.602)	

Monthly regression of US BPG series on French-Frama factors and UMD. The regressions were conducted with n=678. The HAC p-values are shown in parentheses.

Model Appendix

Model Primitives

Go back

- Nest textbook real estate development option model into rational disagreement framework of Grossman–Stiglitz

- **Housing Development (Stage 1)**
  - Unit mass of housing market investors $i \in [0,1]$ spanning localities $s \in \{1,\ldots,\mathcal{S}\}$ (states, MSAs, counties)
  - Developable land is in fixed supply $T_s < 1$, and each investor can hold a permit on at most one parcel (akin to measures in Saiz 2010, Lutz & Sand 2023)

- **Financial Markets (Stage 2)**
  - Risky asset pays unknown dividend d in $t+1$
  - Unit mass of investors $j(s)$ in [0,1] in each locality s trading in t at p_t
  - Unitary asset market, so $p = p_s, \forall s$

Building Permits as a Real Option (1)

Go back

- Simple **real option value theory (OVT)** model of building permits
- Value of holding entitled land = earnings potential – construction costs at *highest and best use* (Titman, 1985; Geltner, 2014)
- Expected value of exercised option depends on success probability $f(\mathbf{X_{s,t}})$, construction cost, $C_{i,s,t+1}$, and market value of building + land, $B_{i,s,t+1} + L_{i,s,t+1}$

$$\mathbb{E}_t[V^*_{i,s,t+1}] = f(\mathbf{X_{s,t}}) \cdot \mathbb{E}_t[B_{i,s,t+1} + L_{i,s,t+1}] - C_{i,s,t+1} \tag{1}$$

- For simplicity, construction costs paid in period $t+1$, but known in t
- If successful, property valued at its market price: $(B_{i,s,t+1} + L_{i,s,t+1})$
- $\mathbf{X_{s,t}}$: time-varying factors of project success (e.g., macro fundamentals, local weather, regulatory shocks)

Building Permits as a Real Option (2)

Go back

- Replacement cost approach to valuing buildings $\Longrightarrow$ $B_{i,s,t+1} = C_{i,s,t+1}, \forall i$
  - Standard way of valuing building permits (e.g., Dun & Bradstreet's)
  - Assumes teardown costs + admin fees included in $C_{i,s,t+1}$
- Suppose that housing production is Cobb–Douglas, so land values are proportional to the attached structure's value: $L_{i,s,t} = \varphi \cdot B_{i,s,t}$
  - Reflects how tax assessor's offices value properties

$$\mathbb{E}_t[V^*_{i,s,t+1}] = \Big(\varphi_{i,s} \cdot f(\mathbf{X_{s,t}}) + (f(\mathbf{X_{s,t}}) - 1)\Big) \cdot C_{i,s,t+1} \quad (2)$$

$$V_{i,s,t} = \max\{0, \mathbb{E}_t[V^*_{i,s,t+1}]\} \quad (3)$$

- Davis & Heathcote (2007): estimate $\varphi = 0.56$ over $1975 - 2006$

$\Longrightarrow$ 0.64 break-even probability for buying permit

Building Permits as Public Signals in an Island Economy (1)

▸ Go back

- Observed permitting activity in island s is $Q_{s,t} = \int_i \mathbb{1}\{V_{i,s,t} > 0\} \cdot di \leq T_s$
- BPG $q_{s,t} \equiv \Delta \log Q_{s,t}$ forms public signal for local factors $\mathbf{X_{s,t}}$
  - Influence both the value of the permit but also other risky assets like stocks
  - Main Street to Wall Street: $Q_{s,t}$ informative about local performance of firms and willingness to invest in area $\longrightarrow f(\mathbf{X_{s,t}})$
  - Growth rates rather than levels to avoid truncated distributions (Yuan, 2005)
- Embed this problem into a standard Grossman & Stiglitz (1980) two-period setup with a risky asset (e.g., stocks, corporate bonds)
  - Stock pays a risky dividend and is subject to noise trading $\longrightarrow$ asset supply $A = m + u$ with $u \sim \mathcal{N}(0, \sigma_u^2)$
  - Asymmetric information: informed investors observe $Q_{s,t}$, while uninformed investors do not $\longrightarrow$ rational disagreement

Building Permits as Public Signals in an Island Economy (2)

Go back

- Suppose in each period informed investors observe a new $q_{s,t}$ and then try to forecast asset prices according to:

$$q_s = d + \varepsilon_s \quad \text{with } \varepsilon_s \sim \mathcal{N}(0, \sigma^2_{q(s)})$$

- Standard CARA-linear demand system would yield risky asset price of form:

$$p_s = \phi_0(s) + \phi_q(s) \cdot (q_s + \phi_u(s) \cdot u), \forall s \tag{4}$$

- ϕ_q loading on public signal from permits q_s and $\phi_q \cdot \phi_u$ loading on noise
- Coefficients $\phi(s) > 0$ are functions of signal precision: $\kappa_{q(s)} = 1/\sigma^2_{q(s)}$
  - Coefficients vary by locality through fraction of informed investors λ_s and BPG volatility $\sigma_{q(s)} \longrightarrow$ heterogeneous predictability in the data

Proposition Equilibrium

Equilibrium Definition

Go back

Noisy Rational Expectations Equilibrium

A noisy rational expectations equilibrium (NREE) is a price function $p(\{q_s\}_{s=1}^{\mathcal{S}}, u)$ and set of demand functions $x_{j(s)}$ for the informed (I) and uninformed (U) investors $j(s)$ with information set $\omega_{j(s)}$ satisfying:

$$\textit{Portfolio optimization: } x_{j(s)} = \frac{\mathbb{E}[d|\omega_{j(s)}] - (1+r)\cdot p}{\gamma \cdot Var[d|\omega_{j(s)}]} \tag{5}$$

$$\textit{Market clearing: } \sum_{s=1}^{\mathcal{S}} \Big[\lambda_s \cdot x_I(q_s, p(q_s,u)) + (1-\lambda_s)\cdot x_U(p(q_s,u))\Big] = m + u \tag{6}$$

$$\textit{No cross-market arbitrage (law of one price): } p_s = p, \forall s \tag{7}$$

Equilibrium Pricing Function

Go back

Proposition 1: Equilibrium Pricing Function

The price function which satisfies the three conditions for a noisy rational expectations equilibrium is linear in the local signal q_s and noise u and follows:

$$p = \phi_0(s) + \phi_q(s) \cdot (q_s + \phi_u(s) \cdot u), \forall s \tag{8}$$

Moreover, $\phi_q(s) > 0$ and $\phi_u(s) < 0$, regardless of the coefficient of absolute risk aversion γ, so the asset price loads positively on building permit growth in each locality and negatively on noise.

- Standard linear pricing function follows from CARA pricing kernel + normally distributed signals

Comparative Statics

Go back

$$\text{Transformed price signal: } \tilde{p} = \frac{p - \phi_0(s)}{\phi_q(s)} = q_s + \phi_u(s) \cdot u \tag{9}$$

Corollary 1: Comparative Statics

Given the equilibrium price function and the definition of the transformed price signal in (9):

1. Let σ_p^2 denote the variance of the equilibrium risky asset price. $\partial\sigma_p^2/\partial\sigma_{q(s)}^2$ has an ambiguous sign, but is positive for sufficiently small local BPG volatilities $\sigma_{q(s)}^2$.
2. Normalize the *ex ante* risky asset price to be $p_t = 0$, so that the total return can be written as $r_A = p_{t+1} + d_{t+1}$, with variance $\sigma_r^2 = \sigma_p^2 + (1 + 2\phi_{q(s)}) \cdot \sigma_d^2$. Then $\partial\sigma_r^2/\partial\sigma_{q(s)}^2$ has an ambiguous sign, but is positive for sufficiently small local BPG volatilities $\sigma_{q(s)}^2$.