# The Demand for Safe Assets

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## Introduction and Motivation

- <u>Safe assets</u> appeal to a diverse range of investors, each with distinct investment horizons and preferences.
- No fundamental risk and information asymmetry, but **bid dispersion**; heterogeneity in valuations.
- **Q1**: How does demand heterogeneity affect the pricing of safe assets?
- **Q2**: Does issuance auction rules, bidder composition influence secondary market dynamics?
- This paper: heterogeneity in safe asset demand and its impact on bidding behavior and price dynamics.
- ► **Theory**: Heterogenous investment horizons in uniform-price double auction for a safe asset.
- **Empirics**: Unique data on Swiss Treasury auctions: demand heterogeneity, asset pricing implications.

# **Summary and Contributions**

**Mechanism**: Demand heterogeneity shapes bidding behavior and pricing of safe assets in the auctions. ► Tractable model of uniform-price double auction with heterogeneity in investment horizons; resale.

**Timing and preferences**: Three periods; bond issuance at auction t = 0, secondary market trading t = 1, bond pays off t = 2. Three types; n dealers, m long-term agents, competitive fringe.

**Theoretical framework** 

 $\blacktriangleright$  CARA utility  $u(W_2) = -\exp(-\gamma W_2)$ . Budget constraints for dealers and long-term agents

$$W_{j2} = (p_1^* - p_0)q_{j0} - \lambda_j q_{j0} - \frac{\kappa}{2}q_{j0}^2 + (1 - p_1^*)q_{j1}^* - \lambda_j q_{j1}^* - \frac{\kappa}{2}(q_{j1}^*)^2$$
(Dealers)  
$$W_{k2} = W_{k0} + (1 - p_0)q_{k0} - 2\left(\lambda_j q_{k0} + \frac{\kappa}{2}q_{k0}^2\right)$$
(Long-term)

► All agents; competitive secondary market;  $p_1^*$  and  $q_{i1}^*$  denote price and demand.

**Information structure**: Linear-quadratic setting (Vives (2011)).  $\lambda_i = \lambda + \varepsilon_i$ ,  $\lambda_k = \lambda + \varepsilon_k$  prior the auction; private information.  $\lambda \sim \mathcal{N}(\lambda, \sigma_{\lambda}^2)$ ;  $\varepsilon_j, \varepsilon_k \sim \mathcal{N}(0, \sigma_{\varepsilon}^2)$ ;  $\varepsilon_j, \varepsilon_k$  uncorrelated across agents.

**Primary market**: Only dealers and long-term agents. Multi-unit uniform-price auction. Strategies are price-contingent demand schedules  $\{q_{j0}(p_0)\}_{j=1}^n$ ,  $\{q_{k0}(p_0)\}_{k=1}^m$ ; **Bayes-Nash equilibrium**.

# **Demand Schedules and Predictions**

**Theory**: When horizons are heterogeneous, issuance process and bidder composition endogenously affect risk-return profile of assets; interaction of common <u>and</u> private values.

▶ Investment horizon determines incentive to learn from prices and exposure to demand risk. Three major takeaways:

(1) Investment horizons affect bidding and price dynamics: theory, empirics, and unique data. (2) Bidder composition key to auction design; not only <u>how</u> an asset is sold, but also <u>to whom</u>. ► Cost of a primary dealer system is the demand risk premium; benefit is enhanced liquidity. (3) Investment horizons link safe assets to demand risk; beyond credit and fundamental risk.

# Data and Institutional Setting

**Data**: 530 Swiss Treasury bond auctions from 1980 to 2023; maturities from two to fifty years. ► Uniform-price auctions; bidders submit price-quantity pairs; no formal primary dealer system.



**Equilibrium**: Equilibrium in the secondary market implies

$$p_1^* = 1 - \lambda - \kappa Q_a \qquad : \qquad q_{1i}^* = \lambda \kappa^{-1} - \lambda_i \kappa^{-1} + Q_a$$

▶ Bayes-Nash equilibrium; dealers (D) and long-term agents (L) submit linear schedules  $q_{j0} = b_D - a_D p_0 - c_D \lambda_j$  :  $q_{k0} = b_L - a_L p_0 - c_L \lambda_k$ ► Demand slopes  $a_L = \frac{1}{2}c_L$  and  $a_D = c_L \frac{2-m+\kappa(m-1)c_L}{2n(1-c_L\kappa)}$ .  $\boldsymbol{c} = (c_L, c_D)$  fixed-point of  $\boldsymbol{c} = f(\boldsymbol{c})$  $\boldsymbol{c} = \left(\frac{1 - \mu_{\lambda}^{p}(\boldsymbol{c})(\hat{\gamma}(\boldsymbol{c})\kappa^{-1} - 1)}{\kappa + \hat{\gamma}(\boldsymbol{c}) + d_{D}(\boldsymbol{c})} \cdot \frac{2n(1 - c_{L}\kappa)}{2 - m + \kappa(m - 1)c_{L}} \quad ; \quad \frac{\hat{\gamma}(\boldsymbol{c})\kappa^{-1} + 1 - \mu_{\lambda}^{\lambda}(\boldsymbol{c})(\hat{\gamma}(\boldsymbol{c})\kappa^{-1} - 1)}{\kappa + \hat{\gamma}(\boldsymbol{c}) + d_{D}(\boldsymbol{c})}\right)$ where  $d_D$ ,  $d_L$  slope of inverse residual supply; effective risk-aversion  $\hat{\gamma}(\mathbf{c}) = \frac{\gamma}{\sum_{\lambda}^{-1}(\mathbf{c}) + \gamma \kappa^{-1}}$ ; posterior distribution

 $\lambda \mid p_0, \lambda_j \sim \mathcal{N}\left(ar{\mu}_\lambda(oldsymbol{c}) + \mu_\lambda^\lambda(oldsymbol{c})\lambda_j + \mu_\lambda^p(oldsymbol{c})p_0 \quad ; \quad \Sigma_\lambda(oldsymbol{c})
ight)$ 

**Implications**: Model nests **pure private** values (n = 0) and **pure common** values (m = 0).

- ► Asymmetry; dealers and long-term agents respond differently to demand uncertainty  $\sigma_{\lambda}$ .
- ► Bidder composition impacts first and second moment of post-auction capital gain.





► We observe **bidder identities**; separate large banks from pension funds and foreign investors.

# **Bidding Behavior and Heterogeneity in Demand Schedules**

► Average demand schedule has four bid steps; represents 6.09% of total bid volume. ► Very elastic demand schedules (log units); auctions typically cheaper than secondary market.

	Ν	Mean	SD	Min	Median	Max
Bid steps	8'699	4.15	4.11	1.00	3.00	38.00
Bid share	8'699	6.09	10.56	0.00	1.59	92.71
Allotted share	8'699	6.09	11.62	0.00	1.19	98.56
Log elasticity	2'279	5.08	0.99	0.56	5.18	7.50
Spread	3'482	0.02	0.12	-1.45	0.02	3.94

► Substantial heterogeneity in level (spread) and slope (log elasticity) of demand schedules.



(a) Private values; common values; intermediate cases.

- $\blacktriangleright$  Dealers only penalize demand uncertainty; use prices to learn about uncertain capital gain  $p_1^* p_0$ .
- ► An increase in demand risk flattens demand curves; effect is stronger for dealers.

# **Bidding Behavior and Demand Risk**

**Bond volatility**: <u>Less elastic</u> demand schedules in response to higher return volatility  $\sigma_{i-21,i}$ .

► Effect **stronger** for short-term oriented large banks; consistent with the theory.

	Log demand elasticity			
$\sigma_{j-21,j}$	-1.58***	-1.23***	-0.48**	-0.55***
	(0.15)	(0.15)	(0.19)	(0.20)
$\sigma_{j-21,j} \times 1{\{Bank\}_i}$		$-0.58^{***}$	$-0.56^{***}$	$-0.47^{***}$
		(0.13)	(0.12)	(0.12)
Controls	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Macro	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Adj. $R^2$	0.25	0.27	0.30	0.33
N	993	993	993	993

### **Return Predictability**

► Lower elasticities for longer duration bonds; inventory risk (Greenwood & Vayanos (2014)).

	Log demand elasticity			
Maturity	[2, 10)	[10, 15)	[15, 20)	[20, 50]
Large banks	5.293	5.055	4.757	4.272
Cantonal banks	5.533	5.505	4.671	4.565
Foreign banks	5.767	5.624	4.808	4.442
Non-finance companies	—	4.883	4.851	4.440
Regional banks	5.865	5.454	4.603	4.177

► Decline in elasticity **positively** predicts post-auction bond returns (Albuquerque et al. (2024)).

► Decline for banks predicts up to two days ahead; for long-term investors up to <u>one month</u> ahead.

	$rx_{j,j+1}$	$rx_{j,j+2}$	$rx_{j,j+5}$	$rx_{j,j+21}$
$\bar{\beta}_{i}^{others}$	-0.20**	-0.22***	-0.36***	-0.69**
5	(0.09)	(0.08)	(0.10)	(0.27)
$ar{eta}_{j}^{banks}$	$-0.24^{***}$	$-0.14^{*}$	-0.11	0.06
0	(0.08)	(0.09)	(0.13)	(0.25)
Adj. $R^2$	0.13	0.07	0.04	0.04
N	234	240	238	220

#### References

► Albuquerque, R., Cardoso-Costa, J. M., & Faias, J. A. (2024). Price elasticity of demand and risk-bearing capacity in sovereign bond auctions. Review of Financial Studies, 37 (10), 3149–3187.

► Greenwood, R., & Vayanos, D. (2014). Bond supply and excess bond returns. Review of Financial Studies, 27 (3), 663–713.

► Vives, X. (2011). Strategic supply function competition with private information. Econometrica, 79 (6), 1919–1966.

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