The Demand for Safe Assets[1]

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Abstract

We model a uniform-price auction for safe assets where dealers trade in both primary and secondary markets, while long-term investors hold to maturity. Uncertainty about post-auction gains leads risk-averse dealers to demand a risk premium. Dealers' demand elasticity decreases with demand risk and heterogeneity in holding costs relative to long-term investors. Inelastic demand at the auction positively predicts post-auction returns. When all bidders, including dealers and long-term investors, exhibit inelastic demand, returns remain predictable over longer horizons. Unique data on Swiss Treasury auctions with bidder identities validate the model's empirical predictions, showing how the investor base shapes the risk–return profile of safe assets and their post-auction dynamics.

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1 Introduction

Sovereign debt is widely issued through auctions, including by countries whose debt is regarded as a safe asset.[2] Safety of nominal payoffs and minimal information asymmetries[3] make safe government debt appealing to a diverse set of investors, who typically have heterogeneous valuations of the assets (OECD, 2019). This demand heterogeneity is evident in bidding behavior in the primary market and shapes both auction outcomes and secondary market dynamics. Yet, understanding how such heterogeneity impacts safe asset valuations and government financing costs poses a challenge to standard representative-agent asset pricing models. Motivated by this, we address two fundamental questions, both theoretically and empirically. How does demand heterogeneity influence the pricing of safe assets? In what ways do differences in investment horizons shape bidding strategies and post-auction price dynamics?

Our contribution is to study the demand for safe assets in a tractable heterogeneous agent framework and test implications for bidding behavior and auction outcomes. We build on the uniform-price double auction model (Vives, 2011). The key innovation lies in our analysis of safe government debt, which is free from the fundamental uncertainty or information asymmetries about liquidation values commonly assumed in the literature (Kyle, 1989; Vayanos, 1999). Our main methodological contribution is modeling demand heterogeneity for safe assets through differences in investment horizons. We consider two types of investors. First, *long-term investors* buy the asset at the auction and hold it to maturity. In line with the preferred-habitat view (Vayanos & Vila, 2021), we interpret long-term investors as regional banks, insurance companies, and pension funds, which are typically less active in secondary markets. Second, short-term investors purchase the asset with the intention of distributing at least a portion of it in the secondary market. We identify short-term investors as *dealer banks*, implicitly acting as primary dealers

[2]More than 80% of OECD countries primarily issue debt through auctions (OECD, 2016).

[3]See Dang, Gorton, Holmström, and Ordoñez (2017), Gorton (2017), and Gorton and Ordoñez (2022).

and market makers, whose option to resell exposes them to aggregate demand risk or inventory risk (Boyarchenko, Lucca, & Veldkamp, 2021; Fleming, Nguyen, & Rosenberg, 2024). The buy-and-hold behavior of long-term investors insulates them from secondary market price fluctuations and attenuates their incentives to learn from prices. These investors operate with private values. In contrast, dealer banks' intent to resell implies they operate with a common value driven by future demand uncertainty.

Our model has three periods. First, dealer banks and long-term investors bid in an auction for safe government bonds. Second, dealer banks trade in the secondary market with the investors that did not participate in the auction, while long-term investors abstain from trading. Finally, the bond pays off a deterministic amount, and the game ends. All agents incur quadratic holding costs each period in which they hold the asset. They draw marginal cost intercepts from a common distribution with an unknown mean, referred to as the average cost, which is observed privately by each agent. The price in the secondary market reflects the average holding cost across all investors, so that the private cost intercept is a noisy signal of the post-auction capital gains. Uncertainty in post-auction gains drives risk-averse dealer banks to demand a risk premium, a key distinction from Du and Zhu (2017), where traders are risk-neutral. In our setup, the distribution of post-auction returns conditional on prices and private information are *endogenously* linked to demand risk, cost dispersion, and the ratio of dealer banks to total participants. Distinct from the models of Rostek and Yoon (2021) and Allen and Wittwer (2023), where the volatility of asset returns is given, our results show that the subjective volatility of post-auction returns, and thus subjective risk premia, vary across investor types and depend on the relative number of dealer banks and long-term investors bidding at the auction.

In our model, dealer banks participate in the secondary market while long-term investors do not, so that we associate heterogeneity in *investment horizons* to heterogeneity in expected holding periods. We characterize a Bayes-Nash equilibrium in demand schedules to demonstrate how such heterogeneity influences bidding behavior and post-auction return dynamics. A key novelty of our approach is the analysis of an *asymmetric* equilibrium, where demand schedules are symmetric within types but differ across types. We demonstrate that an equilibrium with downward-sloping demand curves always exists and is never symmetric. Dealer banks, because of anticipated future resales, benefit from learning about average costs from auction prices, while long-term investors, who are not exposed to fluctuations in the secondary market price, lack such incentives. Our model nests pure private values and pure common value as special cases. Pure private values arise when only long-term investors participate. By contrast, a pure common value arises when only dealer banks participate. Under private values, bidding strategies are unaffected by demand uncertainty, cost dispersion, or risk premia. In intermediate cases, two predictions emerge: (i) demand schedules steepen as either demand uncertainty or cost dispersion increases, with a more pronounced effect for dealer banks; (ii) equilibrium prices include compensation for aggregate demand risk, tied explicitly to demand uncertainty and cost dispersion. Lower demand elasticity during auctions therefore positively predicts post-auction returns. When only dealer banks' demand is less elastic, post-auction return predictability is short-lived until dealer banks offload their inventories in the secondary market. However, when long-term investors also exhibit inelastic demand, post-auction returns remain predictable for longer periods, up to one month. This prediction aligns with the literature on auction cycles and preferred-habitat models, in which mean-reverting supply shocks drive short-horizon return predictability, with effects more pronounced when dealer banks' demand elasticity is lower (Greenwood & Vayanos, 2014). When long-term investors also exhibit less elastic demand, this reflects broader aggregate inelasticity that extends beyond the auction. As a result, the secondary market's ability to absorb dealers' inventories diminishes, making the unwinding process slower and prolonging return predictability over longer horizons.

Our second major contribution to the literature is empirical. We validate our model using a unique and novel dataset of hand-collected Swiss government bond auction data. The Swiss setting is particularly well-suited to our research questions for at least three reasons. First, Swiss Treasuries are widely recognized as safe assets.[4] Second, Switzerland does not formally have a primary dealer system, meaning that auctions are *open* to a wide range of participants. This set includes large banks *de facto* acting as primary dealers as well as long-term oriented investors such as regional banks, pension funds, and insurance companies. A key innovation of our dataset is that we directly observe the *identities* of individual bidders. Thus, we can distinguish dealer banks performing market-making activities from more long-term oriented investors such as pension funds, insurance companies, and smaller regional banks. Accordingly, we bring the model to the data by interpreting large, systemic banks as dealer banks and classifying all other bidders as long-term investors.[5] Our ability to measure demand elasticities at the bidder level is a significant improvement over prior studies, which typically rely on aggregate measures (Albuquerque, Cardoso-Costa, & Faias, 2024) or use only allotment and price data (Boyarchenko et al., 2021). Third, our model and empirical findings have relevance beyond Switzerland: many of the features we study—such as the heterogeneity between dealers and long-term investors, and the interplay between primary and secondary markets—are also present in other sovereign and high-grade bond markets. Our dataset spans more than forty years of Treasury auctions, covering bonds with maturities from two to fifty years. This extensive time series allows us to analyze bidding behavior across diverse economic conditions and regulatory regimes, including the Basel III reform. All these features provide internal and external validity for our conclusions on how auction-participant composition affects price formation and liquidity dynamics.

Five key findings emerge from our paper. First, we document substantial cross-sectional heterogeneity in the level and the slope of demand schedules. Dealer banks systematically submit steeper demand curves relative to long-term investors. Across all bidders, de-

[4]Swiss sovereign debt has never faced downgrades or negative outlooks. S&P rated U.S. debt AA+ in August 2011 and gave Germany a negative outlook in December 2011. Japan and UK are currently rated A+ and AA. Additionally, the combination of a low debt-to-GDP ratio and prudent debt management policies minimizes concerns about rollover risk and auction failures.

[5]We apply the official designation of systemically important banks in Switzerland established by the Swiss National Bank (SNB).

mand elasticities decline with bond maturity, consistent with a duration exposure channel (Allen, Kastl, & Wittwer, 2024; Greenwood & Vayanos, 2014). Second, as in our theory, dealer banks are more sensitive to demand risk than long-term investors. Dealer banks' demand schedules become steeper than those of long-term investors when bond return volatility rises before the auction. Through the lens of our model, this provides evidence of a common value in Treasury bond valuations driven by future resale in the secondary market. Third, our empirical analysis supports the hypothesis that dealer banks' demand elasticity decreases relative to other long-term investors when cross-sectional bid dispersion is higher. Fourth, we use a difference-in-differences design to analyze bidding behavior before and after the implementation of Basel III capital requirements, which primarily affect dealer banks through their market-making activities (BIS, 2017). Comparing dealer banks (*treatment*) to long-term investors (*control*), we find that Basel III regulatory costs lead to steeper demand schedules for dealer banks relative to the control group. Surprisingly, we also observe that dealer banks bid at a significantly lower discount to the secondary market after the reform. Fifth, we study the predictive power of demand elasticity for post-auction returns. Consistent with our theoretical predictions, we find that lower dealer banks' elasticity predicts higher bond returns up to two days after the auction. When long-term investors also display less elastic demand—signaling broader aggregate inelasticity—returns remain predictable for up to one month, consistent with a slower unwinding of dealers' inventories.

1.1 Related Literature

First, we contribute to the literature on safe assets by studying the determinants and implications of demand heterogeneity for safe government debt across the primary and secondary markets.[6] Much of the literature focuses on the supply of safe assets, their scarcity (see, e.g., Caballero & Farhi, 2017; Caballero, Farhi, & Gourinchas, 2016), substi-

[6]The shortage of safe assets and the macroeconomic and financial stability implications are studied by Caballero and Krishnamurthy (2009), Caballero, Farhi, and Gourinchas (2017), and Caballero and Farhi (2017).

tutability (Krishnamurthy & Vissing-Jorgensen, 2012), and overall effects of their supply (Benigno & Nisticò, 2017; Infante, 2020). We document significant heterogeneity in safe asset demand. Our main contribution is to theorize and provide consistent evidence that heterogeneity in investment horizons introduces a demand risk premium. As a result, our paper links the concept of safe assets to heterogeneity in demand and the investor composition in the primary market. Another strand of the literature predicts cross-sectional dispersion in (quasi-)safe assets and convenience yields.[7] Barro, Fernández-Villaverde, Levintal, and Mollerus (2022) theorize heterogeneous risk-averse agents with rare disasters. Our paper makes a novel contribution by theoretically modeling and empirically analyzing private and common components in safe asset valuations, which are revealed in the primary market through strategic interactions among bidders.

Second, we contribute to the extensive literature on bidding behavior in Treasury auctions. The earlier literature on Treasury auctions explores the theoretical predictions of the share auction model of Wilson (1977) and Back and Zender (2001).[8] We depart from this literature by taking the auction mechanism as given and studying the implications of demand heterogeneity on bidding behavior and post-auction returns. The debate on the best way to sell government debt is very old (Friedman, 1991). Counterfactual exercises to assess which auction format would maximize government revenue have been the subject of many studies, often concluding that switching between discriminatory and uniform price auctions entails little efficiency gains (Hortaçsu & McAdams, 2010). Although our model is silent on optimal auction design, we emphasize that governments should also take into account the composition of the investor base. Furthermore, our unique sample

[7] See the discussions on the variations in the perceived safety and liquidity premiums associated with different assets in Krishnamurthy & Vissing-Jorgensen, 2012; Stein, 2012; Caballero, Farhi, & Gourinchas, 2016; Nagel, 2016; He, Krishnamurthy, & Milbradt, 2019.

[8] See Hamao and Jegadeesh (1998) for Japan, Nyborg, Rydqvist, and Sundaresan (2002) for Sweden, Keloharju, Nyborg, and Rydqvist (2005) for Finland, Armantier and SbaÏ (2006) and Février, Préget, and Visser (2002) for France, Goldreich (2007) and Hortaçsu, Kastl, and Zhang (2018) for the US, Hortaçsu and Kastl (2012) and Allen and Wittwer (2023) for Canada, Hortaçsu and McAdams (2010) for Turkey, Beetsma, Giuliodori, Hanson, and de Jong (2020) for euro countries, Umlauf (1993) for Mexico, and Kastl (2011) for the Czech Republic.

covers more than four decades of auctions for bonds with maturities ranging from 2 to 50 years, providing plenty of variation in economic conditions and asset characteristics.[9] Our assumption about investment horizons implies that dealer banks operate with a common value, whereas long-term investors operate with pure private values. Structural models of multi-unit auctions generally assume private values for computational tractability (Hortaçsu & McAdams, 2010; Hortaçsu et al., 2018; Richert, 2024). Hortaçsu and Kastl (2012) test for common values in Canadian auctions for 3-month and 12-month Treasury bills by looking at whether primary dealers update their bids after observing customer orders, but find little evidence in support of common value components. We complement these results by inspecting Treasury auctions of longer-term bonds in a setting where the primary market is open to the general public. We show that when bidders have different investment horizons, there is significant heterogeneity in how bidding strategies respond to demand uncertainty and secondary market liquidity, suggesting the presence of a common value for securities with longer maturity.

A recent asset pricing literature explores the price impact of anticipated supply shocks around Treasury auctions. For the US, Lou, Yan, and Zhang (2013) show that yields drift up in the days before the auction and revert in the days after the auction. Beetsma, Giuliodori, De Jong, and Widijanto (2016) and Albuquerque et al. (2024) also document similar auction cycles in Italy and Portugal, respectively. Albuquerque et al. (2024) show that return predictability is driven by auctions where the aggregate elasticity of demand is low. Our contribution to this literature is unveiling which investors determine the magnitude and the length of auction cycles. We measure demand elasticities at the bidder level and show that the price impact of Treasury auctions is more persistent when both long-term investors and dealer banks submit steeper demand curves. Our findings support the view that demand curves for safe government bonds are downward sloping (Gabaix & Koijen, 2023; Vayanos & Vila, 2021). We show that heterogeneity in

[9] In comparison, the closest data in terms of comprehensiveness is Allen, Hortacsu, Richert, and Wittwer (2024) and Allen and Wittwer (2023) who observe Canadian auctions from 1999 to 2022.

investment horizons can generate inelastic demand, and how that is reflected in auction bids. Our framework implies a trade-off between paying a demand risk premium (only dealer banks) and having a less liquid secondary market (only long-term investors). The reduction in demand risk premia when long-term investors participate in the auction is akin to the interpretation of insurance companies and pension funds as asset insulators (Chodorow-Reich, Ghent, & Haddad, 2020). Our assumption on buy-and-hold behavior, and the mechanism through which it may impact the final allocation, finds empirical support in Musto, Nini, and Schwarz (2018), where assets held by buy-and-hold agents eventually become more illiquid.

Third, our theoretical model extends the literature on uniform-price double auctions by studying asymmetric equilibria with heterogeneous agents and deterministic payoffs. To characterize equilibria with downward sloping demand schedules, we build on the linear-quadratic setting of Vives (2011). As in Vives (2011), and in contrast to Kyle (1989) and Klemperer and Meyer (1989), equilibrium existence does not rely on aggregate demand shocks or noise trading. Different from Vives (2011) and Rostek and Weretka (2012), however, we simultaneously model private and common valuation components in a way that makes the average correlation in values vary across bidder types. Common values endogenously emerge through future resale in the secondary market, and the investment horizon determines incentives to learn from prices. Our empirical analysis reveals that bidding strategies are significantly heterogeneous across investor types and respond differently to changes in risk. The existence of an equilibrium with asymmetric strategies, combined with an asset free of fundamental risk, distinguishes our model from Vayanos (1999), Rostek and Weretka (2012), Du and Zhu (2017), and Rostek and Yoon (2021). Rostek and Weretka (2012) study a similar environment in the linear-quadratic setting, allowing a rich pattern of correlation in the signals in a setting with quadratic payoffs and uncertainty about marginal costs. Du and Zhu (2017) present a model of sequential double auctions with quadratic flow costs where common value shocks arise through signals about a stochastic terminal payoff. In our setting, agents are risk averse, and bidders use private signals to update their estimates of future resale prices. In the framework of Rostek and Yoon (2021), asset returns are exogenously specified and the conditional distribution of asset returns is unrelated to signal dispersion and prior uncertainty. Duffie, Malamud, and Manso (2009) and Chen and Duffie (2021) emphasize welfare implications but take expected returns as given and explore symmetric equilibria. In Kyle, Obizhaeva, and Wang (2017), agents are overconfident and each of them perceives their signal to be more informative than the other agents, but the equilibrium still remains symmetric.

1.2 Organization

The rest of the paper is structured as follows. Section 2 presents the institutional setting and describes the data. Section 3 explains the model. Section 4 presents the empirical results. Section 5 concludes and discusses policy implications.

2 Swiss Treasury Auctions

This section describes the institutional background and presents descriptive statistics for our novel bid data. We emphasize the institutional background relevant to our analysis, and refer to Ranaldo and Rossi (2016) for further details.

2.1 Institutional Background

Switzerland has been one of the first OECD countries to issue government debt exclusively through auctions for all medium- and long-term maturities. The Swiss National Bank (SNB) has conducted sealed-bid uniform-price auctions for Swiss government bonds on behalf of the Treasury since 1980. Auction participants submit demand schedules, which consist of multiple price-quantity pairs that specify the amounts they are willing to buy (*bid quantity*) at each price (*bid price*). Bidders can also submit non-competitive quantity bids, which are filled with certainty.[10] Bidders can simultaneously submit competitive

[10]Noncompetitive bidding rules changed several times, see Annex I in Ranaldo and Rossi (2016).

and non-competitive bids, and can always abstain from bidding. The SNB does not impose any restrictions on participation, bid steps, and individual awards on competitive bids. At the auction close, the Treasury compares aggregate demand and aggregate supply, net of non-competitive bids, to determine the market clearing price, which is the lowest accepted bid. Bids below the market clearing price are rejected, while bids above it are fully allocated at that price. Bids at the market clearing price may be prorated.

A key feature of Swiss bond issues is that the auctions have always been open to the general public rather than being restricted to a limited group of primary dealers.[11] This feature makes the Swiss setting well-suited to our analysis of heterogeneity in safe asset demand for two reasons. First, open participation attracts a broad spectrum of investors with different horizons, although large banks *de facto* act as primary dealers. The SNB groups all bidders into six categories, namely cantonal banks, big (systemic) banks, foreign investors, other banks (including private banks, trade banks, exchange banks, small credit banks), regional banks (including savings banks and Raiffeisen banks), and a residual category that includes insurance companies, pension funds, and individuals. Since we directly observe the identities of the bidders, we can separate large and systemic banks from all the other participants and measure bond demand at the bidder level. In both the theory and the empirical section, following the definition applied by the Swiss financial authority,[12] we will refer to large and systemic banks as *dealer banks*, and to all other investors such as regional banks, insurance companies and pension funds, as *long-term investors*. Second, the absence of an official primary dealers system reduces artificial demand for Treasury debt driven by contractual obligations of a primary dealer system.[13] Without contractual constraints, all bidders are treated equally and retain full flexibility

[11] The Treasury auctions literature often studies settings where only primary dealers bid in the auction, e.g. Allen, Kastl, and Wittwer (2024) for Canada, Albuquerque et al. (2024) for Portugal, Kang and Puller (2008) for South Korea, Nyborg et al. (2002) for Sweden and Keloharju et al. (2005) for Finland.

[12] For the various decrees issued by the SNB concerning systemic importance, see `https://www.snb.ch/en/publications/communication/press-releases/2012/pre_20121220`.

[13] US auctions are also open to all investors, but primary dealers face constraints on participation and maximal awards, see Hortaçsu et al. (2018) and Boyarchenko et al. (2021). Payne and Szöke (2024) show how financial regulation creating captive demand for Treasuries can distort yields on government debt.

in their bidding strategies, creating a more transparent and competitive auction environment.

A measurement challenge arises because, after the switch to electronic bidding in 2001, most non-bank financial institutions lost direct access to the auction platform. While large non-bank investors can still participate directly, smaller institutions often route their bids through dealer banks. In such cases, we cannot distinguish dealer banks' bids placed for their own accounts from those submitted on behalf of clients. We therefore impute such indirect bids to the corresponding dealer banks, which provides an upper bound on their exposure to demand risk, since part of these bids are likely client-driven. As a result, dealers' observed bidding behavior may resemble that of long-term investors, leading our estimates to understate—rather than overstate—the true heterogeneity in bidding strategies. Discussions with practitioners confirm that indirect bidders typically delegate a non-negligible share of strategic decisions to direct bidders rather than submitting price–quantity pairs themselves.

The auction process begins with an announcement by the Treasury. The time between announcement and auction has gradually declined from several days to just one day since 1998. The bidding window opens at 9:30 AM and closes at 11:00 AM. Although the settlement date occurs several days after the auction, the securities begin trading immediately after the auction closes. The Treasury established an advance notice period to help participants prepare for the auctions. The auction announcement includes the coupon, the maturity, and, starting in August 1993, any amount it may want to reserve for subsequent sales in the secondary market, referred to as the Treasury's own tranche cancellation. The disclosure of the issue size has become progressively less precise over time. Initially, the Treasury announced an approximate borrowing target until October 1991, after which it began providing a maximum borrowing amount until November 1999. Since January 2000, no information on the emission size has been disclosed prior to an auction. After the auction, the Treasury releases summary statistics, including the total volume of received and accepted bids, the market clearing price and yield, the sum of non-competitive bids, payment date, (possible) fungibility with a previous issue, and the own tranche.

2.2 Data Description

Table 1 describes the sample of uniform-price auctions for Swiss government bonds and reports summary statistics for the main auction-level and macro-financial variables used in the empirical analysis.

	N	Mean	SD	Min	Median	Max
Auction variables						
Maturity	530	15.01	9.08	2.00	11.96	50.00
Issue size	530	356'879	237'243	56'700	284'375	1'553'470
Bid volume	530	607'540	461'792	99'100	475'487	4'676'315
Cover ratio	530	1.77	0.69	1.00	1.59	8.63
Bid steps	530	68.03	51.77	12.00	50.00	306.00
Participants	530	16.41	11.25	5.00	12.00	73.00
Auxiliary variables						
Volatility	330	0.42	0.29	0.05	0.34	2.00
Yield spread	359	0.02	0.03	-0.05	0.02	0.19
Inflation	344	1.09	1.47	-1.44	0.73	6.57
KOF Barometer	317	-0.01	1.05	-5.69	0.05	3.55
SARON	250	0.33	1.09	-0.75	0.02	3.39
Slope	327	0.74	0.65	-1.36	0.71	2.09

Table 1: Sample summary statistics. Maturity is the difference in years between settlement date and maturity date. Issue size (thousands CHF) is the total quantity issued in each auction, which is equal to the sum of the allocated quantities less the own tranche. Bid volume is the total volume of bids. Cover ratio is the ratio between bid volume and issue size. Volatility is the standard deviation of bond returns in the month prior to the auction. Yield spread is the difference between the auction market clearing yield and the secondary market yield. Slope is the difference between the 10-year and the 2-year yield. The auction sample is from 1980 to present. The secondary market sample is from 2000 to present.

Our data cover the period from 1980 to 2023 and contain bidder-level demand schedules for 530 auctions. The total issue size is on average CHF 356.9 million (approximately

USD 450 million at the current exchange rate). The average bid volume is CHF 607.5 million, which far exceeds the average issue size. The average cover ratio (bid volume to issue size) is 1.77, indicating excess demand for Swiss Treasury bonds. However, since the Treasury does not announce the issue size in advance and can adjust it based on observed demand, the minimum cover ratio is effectively one. There is significant variation over time in auction participation, ranging from a minimum of five to a maximum of 73 participants. The average number of participants is 16.5, which is comparable to other economies (Hortaçsu & Kastl, 2012; Kastl, 2011). The average maturity is 15 years, ranging from a minimum of 2 years up to a maximum of 50 years.

2.3 Auxiliary Variables

We obtain secondary market prices for all outstanding Swiss government bonds from Bloomberg, which provides comprehensive coverage. The secondary market sample starts in 2000, since prior to that prices are sparse and contain significant gaps. For bond re-openings, we measure return volatility as the standard deviation of daily returns in the month prior to each auction closing day, provided there are at least 15 observations. The secondary market yield spread, henceforth *yield spread*, is the difference between the auction market clearing yield and the prevailing secondary market yield at the auction close. We measure secondary market liquidity as the relative bid-ask spread (RBAS), given by the ratio of the bid-ask spread to the midprice. Most of the other auxiliary variables are from the SNB data portal. We retrieve monthly CPI inflation data from December 1982 to the present. Daily Treasury yields and interest rate data include overnight (SARON), one-week (SAR1W), two-week (SAR2W), and one-month (SAR1M) rates from June 1999 onward, as well as 10-year and 2-year yields from January 1988 onward. We compute the slope of the term structure as the difference between the 10-year and the 2-year yield. We finally use the KOF Economic Barometer as a proxy of the business cycle.

The bottom panel of Table 1 presents summary statistics of the auxiliary variables that we use in the main analysis in Section 4. A positive yield spread indicates that auctions are underpriced. On average, buying at the auction is cheaper than in the secondary market. The yield spread is 2 basis points, up to a maximum of 19 basis points. These numbers are comparable in magnitude to earlier findings in Cammack (1991) for US three-month T-bill auctions. Throughout our sample, there is significant variation in economic and financial conditions. The average overnight rate (SARON) is 0.33%. While the average overnight rate is slightly positive, our sample includes periods when interest rates fell into negative territory, reaching as low as −75 basis points. The average slope of the term structure is 74 basis points. The monthly inflation rate ranges from −1.44% to 6.57%.

3 Theoretical Framework

We develop a model of uniform-price auctions in a linear–quadratic framework to analyze how heterogeneity in investment horizons shapes bidding strategies and auction outcomes. The model highlights how risk-averse dealers, who intermediate between primary and secondary markets, differ from long-term investors who hold to maturity. It provides clear testable implications that guide our empirical analysis. All proofs are presented in the Internet Appendix.

3.1 Environment

Assets and Timing There are three periods, $t = 0, 1, 2$. The financial market consists of a two period bond that pays off a unit of the consumption good in period 2 with certainty. There are no other risky assets. The exogenous risk-free rate is set to zero and it is the numeraire. Let p_t denote the bond price at time t, and Q_t its outstanding supply.

Agents and Preferences The economy is populated by a continuum of agents. Each agent has CARA utility over terminal wealth W_{i2} given by

$$-\exp(-\gamma W_{i2})$$

where γ denotes the coefficient of risk aversion. At time $t = 0$, the government issues Q_a units of the bond through a uniform price auction. At $t = 1$, agents trade the two period bond in the secondary market. The bond matures at $t = 2$ and the game ends.

We assume that only a finite (exogenous) number $N = n + m$ of bidders participates in the auction. Of those N, there are $j = 1, \ldots, n$ dealer banks and $k = 1, \ldots, m$ long-term investors. The difference between the two types is their expected holding period, which we refer to as *investment horizon*. Dealer banks participate in the secondary market, whereas long-term investors buy and hold until maturity. The heterogeneity in investment horizons is sufficient to break symmetry of the linear equilibrium, and the slope of the demand schedule will be different across types. The framework nests the special cases of pure common values ($m = 0$) and pure private values ($n = 0$).

The $t = 1$ budget constraint for agents that participate in the secondary market, that is the n dealer banks plus the general public who does not bid in the auction, is

$$W_{i2} = W_{i1} + (1 - p_1)q_{i1} - \lambda_i q_{i1} - \frac{\kappa}{2} q_{i1}^2$$

where q_{i1} denotes bond quantities and p_1 is the equilibrium price. Because the secondary market is competitive, no agent has market power. This assumption implies that we do not have to keep track of beliefs about the auction allocation and information leakages in the primary market to determine the equilibrium in the secondary market.

We introduce uncertainty in the demand for safe assets by assuming that agents pay a quadratic cost $\Lambda(q_{it}) = \lambda_i q_{it} + \frac{1}{2}\kappa q_{it}^2$ for each period in which they hold the bond. We specify the cost function such that the intercept of the marginal cost λ_i varies across investors, but the slope of the marginal costs is constant and publicly known (Vives, 2011). A positive value of λ_i can be interpreted as a regulatory requirement or balance sheet constraints. A negative value λ_i can be interpreted as a non-pecuniary benefit from holding the asset in the spirit of Krishnamurthy and Vissing-Jorgensen (2012). Since the bond payoff is deterministic, the quadratic term ($\kappa > 0$) ensures that bond demand is bounded.

Agents that only participate in the secondary market (the competitive fringe) are endowed with exogenous wealth W_{i1} that they obtain from sources outside of the model (e.g. labor income). The n dealer banks who participate in the secondary market are endowed with wealth W_{i0} at $t = 0$ and buy bonds in the auction such that

$$W_{j1} = W_{j0} + (p_1 - p_0)q_{j0} - \lambda_j q_{j0} - \frac{\kappa}{2} q_{j0}^2$$

where q_{j0} is the quantity of bonds purchased at the auction and p_0 is the equilibrium price in the primary market. The m long-term investors who participate in the auction cannot retrade in the secondary market, so that their budget constraint is

$$W_{k2} = W_{k0} + (1 - p_0)q_{k0} - 2\left(\lambda_k q_{k0} + \frac{\kappa}{2} q_{k0}^2\right)$$

We associate long-term investors with regional banks, insurance companies, and pension funds that buy in the auction and hold to maturity with minimal retrading in the secondary market. For simplicity, we interpret the auction as a new emission, so that the initial endowment of the asset is zero. Without loss of generality, we normalize initial wealth to zero, $W_{k0} = W_{j0} = 0$.

Information Structure The intercept of the marginal cost λ_i varies across agents. Agent i obtains a draw of λ_i such that $\lambda_i = \lambda + \varepsilon_i$ prior to bidding in the auction, where λ is an unknown parameter. Agent i privately observes λ_i and never reveals it to the public. We assume that $\lambda \sim \mathcal{N}(\bar{\lambda}, \sigma_\lambda^2)$ and that $\varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, where $\mathbb{C}\text{ov}(\varepsilon_i, \varepsilon_j) = 0$ for $i \neq j$. The prior variance σ_λ^2 is interpreted as aggregate demand uncertainty, whereas the variance σ_ε^2 is interpreted as dispersion in holding costs across agents. The key distinction from Vives (2011) is that the signals λ_i are payoff-relevant, so that an equilibrium does not collapse in the pure common value case. This is because agents' strategies will still depend on λ_i even in situations in which the price is a sufficient statistics of the aggregate information in the market. Unlike Kyle (1989), we do not explicitly rely on noise traders or random supply. Further, the asset payoff is deterministic and there is no uncertainty about asset fundamentals. In contrast, aggregate uncertainty at $t = 0$, arises endogenously through the resale market as a function of how many dealer banks relative to long-term investors bid in the auction. All the agents in the economy agree about the terminal payoff of the asset, and there is no ex-ante information asymmetry. In Kyle (1989) and subsequent literature, informed traders observe a private signal about the a stochastic liquidation value, so that information sets are different across informed and uninformed investors. We use the convention that $\int_0^1 \varepsilon_i di = 0$ so that $\int_0^1 \lambda_i di = \lambda$.

Primary Market We model the auction as a multi-unit uniform price auction in the quadratic-normal setting (Vives, 2011). Auction participants compete in demand schedules. Their strategy is a price-contingent downward sloping demand schedule $\{q_{j0}(p)\}_{j=1}^{n}$, $\{q_{k0}(p)\}_{k=1}^{m}$. The auction rules are as in the canonical uniform price mechanism. The solution concept we adopt is a Bayesian-Nash equilibrium in demand schedules. The assumption that the number of bidders is finite and common knowledge is motivated by the fact that auctions are dominated by dealer banks. Further, although there is no formally established primary dealer system in Switzerland, the number of participants in the auctions tend to be much smaller than the number of investors trading in the secondary market. Figure 7 in the Internet Appendix B.1 plots the number of participants and the fraction of each issuance absorbed by the top three bidders. The number of bidders peaks in the early 1990s and has since then been declining. The top three bidders absorb around 75% of each issuance on average.

Market Clearing From the perspective of dealer banks, supply at $t = 1$ is uncertain. Purchases of long-term investors $\sum_{k=1}^{m} q_{k0}$ effectively reduce the residual outstanding supply, so that dealer banks must form expectations about how much will be available for trading in the secondary market. To avoid this additional layer of complications, we assume that the government reopens the market and issues additional $Q_1 = \sum_{k=1}^{m} q_{k0}$ of the same bond at $t = 1$. This is consistent with the idea that the Treasury relies on reopenings to improve secondary market liquidity. Furthermore, the Treasury retains a sizable fraction of each issuance that reaches the secondary market only at a later stage. Figure 7 in the Internet Appendix decomposes allocations across competitive bids, non-competitive bids, and own tranches. The Treasury retains part of the issue size for liquidity management reasons. Most of the issues are absorbed by competitive bids, but we observe an increasing share obtained by non-competitive bidders in the most recent years. Accordingly, the market clearing conditions in the secondary market is

$$Q_a - \sum_{k=1}^{m} q_{k0} + Q_1 = Q_a = \int_i q_{i1} di$$

Finally, the market clearing condition in the primary market is $\sum_{j=1}^{n} q_{j0} + \sum_{k=1}^{m} q_{k0} = Q_a$. The market clearing price p_0 equalizes aggregate demand and supply. If there is no such price or if multiple prices exist, then no trade takes place. Strictly downward-sloping demand schedules are sufficient to rule out trivial equilibria (Rostek & Weretka, 2012).

3.2 Equilibrium in the Secondary Market

We solve the model backwards, starting from $t = 1$. The secondary market is competitive such that nobody is large enough to influence the price. Proposition 1 characterizes the equilibrium price of the bond and the quantity demanded by each agent. The proof, which is in the Internet Appendix, solves for equilibrium prices and quantities by looking for a symmetric price-taking equilibrium in demand functions. What is important to our theory is that sets of investors in the primary and the secondary market are different.

Proposition 1 (Secondary market equilibrium)**.** *The equilibrium in the secondary market fully reveals the average cost λ. The market clearing price is*

$$p_1^* = 1 - \lambda - \kappa Q_a \tag{1}$$

Further, equilibrium demand is

$$q_{1i}^* = \frac{\lambda}{\kappa} - \frac{\lambda_i}{\kappa} + Q_a \tag{2}$$

The price p_1^* declines with the average intercept λ and the slope κ. Agents with a below-average marginal cost intercept λ_i purchase a quantity in excess of the per-capita supply Q_a, and vice-versa. The quadratic term in the cost function ensures that the solution for asset demand is bounded. The assumption of a continuum of agents is convenient because it implies that the equilibrium bond price p_1^* in Proposition 1 is fully revealing. Indeed, in the aggregate, the idiosyncratic noise ε_i vanishes, and agents learn the average intercept λ from the market clearing price. As opposed to Kyle (1989), agents submit demand schedules that depend on λ_i even when the price eventually reveals λ. The reason is that the private signal λ_i is payoff-relevant, and so will generate heterogeneity in agents' demand even with in the full-information case.

Remark on Auction Outcomes In auctions with resale, information disclosure by the auctioneer has implications on the final allocation of the asset, see e.g. Dworczak (2020). The outcome of the auction game reveals information about agents' types and asset holdings, which impact trading in the resale market through private information or market power. The assumption of a perfectly competitive secondary market that fully reveals λ implies that any post-auction differences in beliefs about λ are irrelevant. Further, although they are the only sellers in the secondary market, dealers do not exert market power. This modelling strategy is common in games where auction participants interact with each other in an aftermarket (Haile, 2001, 2003).

3.3 Equilibrium in the Primary Market

Taking p_1^* and q_{1i}^* as given, we next characterize a linear equilibrium in demand schedules. A strategy is a mapping from the signal space to the space of non-increasing continuous functions as in Vives (2011). This assumption is made for tractability, although bidders usually submit discrete step functions rather than continuous demand schedules (Hortaçsu and Kastl (2012); Kastl (2011)). The construction of the equilibrium is standard. First, we conjecture that agents play linear strategies and characterize the random (inverse) residual supply curve that each bidder faces. Second, given the conjectured strategies, we rewrite terminal consumption as a quadratic function of the common value λ. Third, we derive best responses and solve for the unknown coefficients.

In the model, the intercept of marginal costs λ_i plays two important roles. First, it is a noisy signal about future capital gains. Retrading generates a common value component due to the fact that future prices linearly depend on the same unknown parameter λ for all dealer banks. The common value impacts equilibrium strategies and also how bidding behavior responds to changes in uncertainty. In fact, dealer banks will have an incentive to learn about λ from the price p_0. Second, it introduces a linear penalty for holding the bond that is heterogeneous across agents. As a result, the signal enters directly into the payoff function, and an equilibrium exists even in the case of pure common values.

Inverse Residual Supply Heterogeneity in investment horizons prevents the equilibrium from being symmetric. However, within each type, each agent will submit the same demand schedule. We construct a Bayes-Nash equilibrium in demand schedules by conjecturing that dealer banks (indexed by D) and long-term investors (indexed by L) submit demand schedules of the form

$$q_j = b_D - a_D p - c_D \lambda_j \quad : \quad j \in \mathcal{N} = \{1, \dots, n\}$$
$$q_k = b_L - a_L p - c_L \lambda_k \quad : \quad k \in \mathcal{M} = \{1, \dots, m\}$$

where we omit the time subscript to simplify notation. Market clearing requires

$$\sum_{j=1}^{n} q_j + \sum_{k=1}^{m} q_k = Q_a$$

From the perspective of dealer j, the (inverse) residual supply is

$$p = d_D q_j + I_{j,D}$$

where $d_D \doteq [(n-1)a_D + ma_L]^{-1}$ and $I_{j,D} \doteq d_D \{(n-1)b_D + mb_L - h_{j,D} - Q_a\}$ are the (endogenous) slope and intercept of the inverse (residual) supply curve. Therefore, for dealer j, the price p is informationally equivalent to the total signal $h_{j,D} = c_D \sum_{j' \neq j} \lambda_{j'} + c_L \sum_{k=1}^{m} \lambda_k$. By submitting a price-contingent schedule, each dealer bank essentially conditions on the random intercept of the inverse residual supply function $I_{j,D}$. The endogenous coefficient d_D determines the price impact of each dealer bank.

A similar argument reveals that the residual supply faced by long-term investors is $p = d_L q_k + I_{k,L}$, where the slope is $d_L \doteq [na_D + (m-1)a_L]^{-1}$ and the total signal is $h_{j,L} = c_D \sum_{j=1}^{n} \lambda_j + c_L \sum_{k' \neq k}^{m} \lambda_{k'}$, so that the intercept is $I_{j,L} \doteq d_M \{nb_D + (m-1)b_L - h_{j,L} - Q_a\}$. From the perspective of a long-term investor, p is informationally equivalent to $h_{j,L} \neq h_{j,D}$. Hence, each type of agents faces a different (inverse) residual supply curve.

Dealers' Problem We rewrite dealer banks' objective substituting in the equilibrium p_1^* and q_{j1}^* in the secondary market from Proposition 1. Given the strategies of the other $n-1$ dealers and the m long-term investors, the terminal wealth of dealer j is

$$W_{j2} = (p_1^* - p_0)q_j - \lambda_j q_j - \frac{\kappa}{2} q_j^2 + (1 - p_1^*)q_{j1}^* - \lambda_j q_{j1}^* - \frac{\kappa}{2}(q_{j1}^*)^2$$

The structure is reminiscent of Vayanos and Wang (2011), but trading at time $t = 0$ occurs through a uniform price auction. The terminal payoff is a quadratic function of the unknown average cost λ, that is $W_{j2} = \pi_0(q_j) + \lambda \pi_1(q_j) + \frac{\lambda^2}{2\kappa}$ where the coefficients $\pi_0(q_j)$ and $\pi_1(q_j)$ are given in the Appendix. The best response of agent j therefore solves

$$\max_{q_j} -\mathbb{E}_0^D \left[e^{-\gamma \left\{ \pi_0(q_j) + \lambda \pi_1(q_j) + \frac{\lambda^2}{2\kappa} \pi_2 \right\}} \middle| \lambda_j, p_0 \right] \tag{3}$$

The next Lemma shows that the objective (3) is equivalent to a quadratic function of q_{ja}.

Lemma 1 (Dealers' objective)**.** *Given strategy profiles* $q_{j'} = b - a_D p_0 - c_D \lambda_{j'}$ *for* $j' \neq j$ *and* $q_k = b - a_L p_0 - c_L \lambda_k$*, dealers* j*'s best response solves*

$$\max_{q_j} \pi_0(q_j) + \mu_\lambda \pi_1(q_j) - \frac{\hat{\gamma}}{2}\left(\pi_1(q_j) + \mu_\lambda \kappa^{-1}\right)^2 - p_0 q_j \tag{4}$$

where $\mu_\lambda \doteq \mathbb{E}_0^D[\lambda|\lambda_j, p_0]$ *is dealer* j*'s posterior mean* λ *conditional on* λ_j *and the price* p*. Given* $\Sigma_\lambda \doteq \mathbb{V}ar_0^D[\lambda|\lambda_j, p_0]$*, the effective risk aversion coefficient* $\hat{\gamma} > 0$ *is defined as*

$$\hat{\gamma} \doteq \frac{\gamma}{\Sigma_\lambda^{-1} + \gamma\kappa^{-1}}$$

The penalty $\hat{\gamma}$ *increases with the dispersion in marginal costs* σ_ε^2 *and declines with the number of bidders* $n + m$*. As* $n + m \to \infty$*, the penalty approaches zero* $\hat{\gamma} \to 0$*.*

The objective (4) shows that dealer banks, and dealer banks only, are subject to a penalty from bond holdings for three reasons. First, dealer banks must pay a quadratic holding cost, since $\kappa > 0$. Second, dealer banks refrain from trading due to price impact d_D. The third penalty endogenously arises through the interaction of risk aversion and imperfect information about the average marginal cost λ. When λ is known, the bond price p_1^* is deterministic, and the curvature in the objective comes solely from the quadratic cost κ and price impact. When λ is stochastic, however, the capital gain between the auction and the secondary market is also stochastic, and risk-averse agents demand an additional compensation, which we interpret as inventory risk in the spirit of Fleming et al. (2024). As a result, uncertainty about aggregate demand and signal dispersion impact bond demand through the effective risk aversion $\hat{\gamma}$. This third penalty arises endogenously through the resale motive, and not because of uncertainty about the asset fundamentals. In fact, the penalty is higher when the dispersion in marginal costs σ_ε is large, when the number of participants is low, and when the prior variance σ_λ^2 is high. A higher number of bidders lowers the posterior variance $\mathbb{V}\text{ar}(\lambda|h_j, \lambda_j) = \Sigma_\lambda$, as the market aggregates more information about λ, and hence about future capital gains.

Long-term Investors' Problem Taking equilibrium strategies as given, long-term investor k chooses a demand schedule to maximize

$$\max_{q_k} -\mathbb{E}_0^L \left[e^{-\gamma\left\{q_k(1-p)-2\lambda_k q_k-\kappa(q_k)^2\right\}} | \lambda_k, p \right]$$

Given that long-term investors do not access the secondary market, they pay the holding costs for purchases q_k twice, once for each period. However, their consumption is deterministic and they face no uncertainty. In fact, long-term investors' terminal value does not depend on the uncertain parameter λ. The problem simplifies to

$$\max_{q_k} q_k(1-p) - 2\lambda_k q_k - \kappa\left(q_k\right)^2 \tag{5}$$

As opposed to dealers, long-term investors refrain from trading only because of price impact and the quadratic holding cost κ, but not because of inventory risk associated with the stochastic capital gain. Furthermore, since their terminal wealth does not depend on λ, long-term investors have no incentive to learn from the equilibrium price p.

Best Responses and Equilibrium Strategies The solutions to problem (4) and (5) determine the best response of each agent and, therefore, the equilibrium in the auction game. The next Proposition characterizes necessary conditions on the coefficients to define a Bayes-Nash equilibrium in demand schedules.

Proposition 2 (Equilibrium of the auction game)**.** *In a linear Bayes-Nash equilibrium, in demand schedules, each agent type submits the demand schedules*

$$\begin{aligned} q_{j0} &= b_D - a_D p_0 - c_D \lambda_j \quad &: \quad j = 1, \ldots, n \\ q_{k0} &= b_L - a_L p_0 - c_L \lambda_k \quad &: \quad j = 1, \ldots, m \end{aligned}$$

The slopes $\boldsymbol{a} = (a_D, a_L)$ *and the loadings on the private cost* $\boldsymbol{c} = (c_D, c_L)$ *solve the system*

$$a_D = (\kappa + \hat{\gamma}(\boldsymbol{c}) + d_D(\boldsymbol{a}))^{-1} \left\{1 - \mu_\lambda^p(\boldsymbol{a}, \boldsymbol{c})(\hat{\gamma}(\boldsymbol{c})\kappa^{-1} - 1)\right\} \tag{6}$$

$$c_D = (\kappa + \hat{\gamma}(\boldsymbol{c})) + d_D(\boldsymbol{a}))^{-1} (\hat{\gamma}(\boldsymbol{c})\kappa^{-1} + 1 - \mu_\lambda^\lambda(\boldsymbol{c})(\hat{\gamma}(\boldsymbol{c})\kappa^{-1} - 1)) \tag{7}$$

$$a_L = (2\kappa + d_L(\boldsymbol{a}))^{-1} \tag{8}$$

$$c_L = 2(2\kappa + d_L(\boldsymbol{a}))^{-1} \tag{9}$$

where $d_D(\boldsymbol{a})$ and $d_L(\boldsymbol{a})$ are the slope of dealer banks' and long-term investors' residual (inverse) supply. The penalty $\hat{\gamma}(\boldsymbol{c})$ and the loadings $\mu_\lambda^p(\boldsymbol{c})$, $\mu_\lambda^\lambda(\boldsymbol{c})$ are given in Lemma 1.

Proposition 2 shows that, if an equilibrium exists, then the coefficients on price p and holding cost must satisfy equations (6) through (9). We refer to a_D and a_L as the slope of the demand curve, and we say that demand curves are steeper when either a_D and a_L are small. The coefficients $\boldsymbol{c} = (c_D, c_L)$ are the demand loadings on the intercept of marginal holding costs, whereas the coefficients $\boldsymbol{b} = (b_D, b_L)$ denote the demand intercepts.

Given equilibrium strategies, the equilibrium price in the primary market p_0 is

$$p_0^* = \frac{1}{na_D + ma_L} \left\{ nb_D + mb_L - c_D \sum_j \lambda_j - c_L \sum_k \lambda_k \right\}$$

The revenue of the government is $R_0 \doteq p_0^* Q_a$ and the capital gain from the auction to the secondary market is $p_1^* - p_0^* = 1 - \lambda - \kappa Q_a - p_0^*$.

3.4 Special Cases

We characterize the equilibrium demand schedules for two special cases that can be solved in closed form. The first case is the private value (PV) case in which only long-term investors bid in the auction. The second case is the interdependent values environment, which we refer to as common value (CV), in which only dealer banks bid in the auction.

Pure Private Values We characterize the (unique) Bayes-Nash equilibrium in demand functions when only long-term investors participate to the auction.

Proposition 3 (Private values). *With only long-term investors ($n = 0$), the equilibrium is symmetric. Each bidder submits a linear schedule $q_{k0} = a_L^{PV} - b_L^{PV} p_0 - c_L^{PV} \lambda_k$, where*

$$a_L^{PV} = \frac{m-2}{m-1}\frac{1}{2\kappa}$$
$$c_L^{PV} = \frac{m-2}{m-1}\frac{1}{\kappa}$$

Furthermore, $\mu_\lambda^\lambda = 0$.

The equilibrium strategies in Proposition 3 do not depend on risk aversion, demand uncertainty, and cost dispersion. The coefficient on price a_L^{PV} only depends on the slope of marginal costs only κ and the total number of participants m. As the number of long-term investors grows large, the equilibrium converges to the perfectly competitive case.

Long-term investors buy at the auction and hold the asset to maturity. As a result, the post-auction capital gain is not payoff relevant. The private holding cost λ_k is a perfect signal of long-term investors' own payoffs. Therefore, long-term investors' consumption is deterministic, since movements in post-auction prices do not impact their consumption. In addition, since their payoff is independent of λ, long-term investors can always learn the average signal from the market prices, but they have no incentive to do so.

Pure Common Values Proposition 4 characterizes the equilibrium when only dealer banks participate in the auction. Unlike in Kyle (1989), the fundamental value of the asset is known, and the signal λ_j is directly payoff-relevant.

Proposition 4 (Common values). *With only dealer banks ($m = 0$), the equilibrium is symmetric. Each bidder submits a linear schedule $q_{j0} = b_D^{CV} - a_D^{CV} p_0 - c_D^{CV} \lambda_j$, where*

$$a_D^{CV} = \frac{(n-2)(\hat{\gamma}+\kappa) + n\tau_\lambda(\hat{\gamma}-\kappa)}{(n-1)(\hat{\gamma}+\kappa)\left[(\hat{\gamma}+\kappa) - n\tau_\lambda(\hat{\gamma}-\kappa)\right]}$$
$$c_D^{CV} = \frac{(n-2)(\hat{\gamma}+\kappa) + n\tau_\lambda(\hat{\gamma}-\kappa)}{(n-1)(\hat{\gamma}+\kappa)\kappa}$$

where $\tau_\lambda = \frac{\sigma_\lambda^2}{\sigma_\varepsilon^2 + n\sigma_\lambda^2}$. *Furthermore,* $\mu_\lambda^\lambda(\boldsymbol{c}) = 0$.

As in the private value case, both a_D^{CV} and c_D^{CV} vary with the number of bidders and with the slope of marginal holding costs. On the other hand, bidding strategies are now sensitive to demand uncertainty σ_λ^2 and cost dispersion σ_ε^2. As it is standard in the literature, an increase in the number of participants leads to flatter demand curves primarily because more bidders share the aggregate risk, but also because price impact declines (Keloharju et al., 2005; Kyle, 1989). First, an increase in the prior uncertainty about aggregate demand makes the post-auction capital gain riskier, and risk-averse bidders incorporate a demand risk-premium through the penalty $\hat{\gamma}$. Second, dealers have an incentive to learn about the common value component λ, since λ is payoff relevant. Dealer banks use prices to learn about the future price of the asset and to reduce demand uncertainty. To see why these are two distinct forces, note that a_D^{CV} and c_D^{CV} are different than the private value case even when dealers are risk-neutral, that is $\gamma = 0$. The posterior mean loading on the private signal $\mu_\lambda^\lambda(\boldsymbol{c})$ is zero as in the pure private value case of Proposition 3. This is because the price p_0 is a sufficient statistics of the aggregate information in the market.

The equilibrium in Proposition 4 is in contrast to Kyle (1989) and Vives (2011). The equilibrium with common value does not collapse even without uncertainty or noise traders. The common value component arises endogenously through future resale. This is also in contrast to Biais, Martimort, and Rochet (2000), where agents are risk-neutral and common values come from information asymmetries about a stochastic liquidation value. In our setting, there is no information asymmetry about the asset payoff.

3.5 General Case

We establish existence of a Bayes-Nash equilibrium for the general case in which both long-term investors and dealers participate in the auction. Proposition 5 also proves that there is always an equilibrium in which all bidders submit downward sloping demand schedules, implying existence and uniqueness of the market clearing price p_0.

Proposition 5 (Equilibrium existence)**.** *Let $\boldsymbol{c} = (c_L, c_D)$, $n > 1$, $m > 1$. There exists a Bayes-Nash equilibrium with downward sloping demand schedules*

$$a_D(\boldsymbol{c}) = c_L \frac{2 - m + \kappa(m-1)c_L}{2n(1 - c_L\kappa)} > 0$$
$$a_L(\boldsymbol{c}) = \frac{1}{2}c_L > 0$$

The coefficients $\boldsymbol{c}^* = (c_L^*, c_D^*)$ solve the system $f(\boldsymbol{c}) = (f_1(\boldsymbol{c}), f_2(\boldsymbol{c})) = \boldsymbol{c}$ defined by

$$\boldsymbol{c} = \left(\frac{1 - \mu_\lambda^p(\boldsymbol{c})(\hat{\gamma}(\boldsymbol{c})\kappa^{-1} - 1)}{\kappa + \hat{\gamma}(\boldsymbol{c}) + d_D(\boldsymbol{c})} \cdot \frac{2n(1 - c_L\kappa)}{2 - m + \kappa(m-1)c_L} \quad , \quad \frac{\hat{\gamma}(\boldsymbol{c})\kappa^{-1} + 1 - \mu_\lambda^\lambda(\boldsymbol{c})(\hat{\gamma}(\boldsymbol{c})\kappa^{-1} - 1)}{\kappa + \hat{\gamma}(\boldsymbol{c}) + d_D(\boldsymbol{c})} \right)$$

where $d_D(\boldsymbol{c}) = [(n-1)a_D(\boldsymbol{c}) + m a_L(\boldsymbol{c})]^{-1}$ and

$$\mu_\lambda^\lambda(\boldsymbol{c}) = \frac{m\sigma_\lambda^2 c_L(c_L - c_D)}{[(n-1)c_D + mc_L]^2\sigma_\lambda^2 + \left[c_D^2(n-1) + c_L^2 m\right](\sigma_\varepsilon^2 + \sigma_\lambda^2)}$$
$$\mu_\lambda^p(\boldsymbol{c}) = -\frac{\sigma_\lambda^2((n-1)c_D + mc_L)\frac{c_L}{2}\frac{2-\kappa c_L}{1-\kappa c_L}}{[(n-1)c_D + mc_L]^2\sigma_\lambda^2 + \left[c_D^2(n-1) + c_L^2 m\right](\sigma_\varepsilon^2 + \sigma_\lambda^2)}$$
$$\Sigma_\lambda(\boldsymbol{c}) = \frac{\left[c_D^2(n-1) + c_L^2 m\right]\sigma_\varepsilon^2\sigma_\lambda^2}{[(n-1)c_D + mc_L]^2\sigma_\lambda^2 + \left[c_D^2(n-1) + c_L^2 m\right](\sigma_\varepsilon^2 + \sigma_\lambda^2)}$$

Further, the coefficients $c_L \in \left(\frac{1}{\kappa}\frac{m-2}{m-1}, \frac{1}{\kappa}\right)$ and $c_D > 0$ are strictly positive.

In any equilibrium with downward sloping demand curves, c_L and c_D are strictly positive. Furthermore, c_L lies between the pure private value case of Proposition 4 and the perfectly competitive case. The next proposition shows that there does not exist an equilibrium in which strategies are symmetric across investor types.

Proposition 6 (Asymmetry)**.** *Suppose $m > 0$ and $n > 0$. Then, the equilibrium strategies are not symmetric across types. Thus, $\mu_\lambda^\lambda(\boldsymbol{c}) \neq 0$.*

Intuitively, equations (8) and (9) imply that $c_L = 2a_L$, whereas the ratio between a_D and c_D is typically different from two. On the one hand, dealer banks find it optimal to learn about λ in the auction. As a result, the equilibrium strategies of dealer banks depend directly on the posterior mean μ_λ. On the other hand, long-term investors are indifferent about what they learn from prices, since λ is not payoff-relevant and their terminal wealth is deterministic. Given that long-term investors face no risk, their strategies do not directly respond to changes in demand uncertainty σ_λ^2 and bid dispersion σ_ε^2. The denominator of equations (6) and (7) is $\kappa + \hat{\gamma} + d_D$, which means that dealer banks restrict trading because of holding costs, risk aversion, and price impact. In contrast, the denominator of equations (8) and (9) is $\kappa + d_L$, which implies that long-term investors restrict trading only because of price impact and holding costs, but not because of risk. Importantly, this does not imply that the equilibrium strategies of long-term investors are independent of demand uncertainty and cost dispersion. The reason this is not the case is that changes in σ_λ^2 and σ_ε^2 do affect the equilibrium strategies of dealer banks, impacting the slope of the residual demand that long-term investors face. As a result, even if the bond is completely safe from the perspective of long-term investors, a_L and c_L still vary with demand uncertainty.

We now derive a sufficient condition on bidders' composition such that dealer banks are more sensitive in absolute terms to demand uncertainty relative to long-term investors

Proposition 7 (Sensitivity to demand risk)**.** *If* $(m-1)(m-2) > n$, *then*

$$\left|\frac{\partial a_D}{\partial \sigma_\lambda^2}\right| > \left|\frac{\partial a_L}{\partial \sigma_\lambda^2}\right|$$

Proposition 7 demonstrates that an increase in demand uncertainty impacts the slope of the demand schedules of both investor types. While we are not able to provide a sharper analytical characterization of the sign of these derivatives, the numerical results below indicate that $\frac{\partial a_D}{\partial \sigma_\lambda^2} < \frac{\partial a_L}{\partial \sigma_\lambda^2} < 0$. An increase in demand uncertainty implies that both types submit steeper demand schedules. However, the effect is stronger for dealer banks.

Numerical Results We present numerical solutions for the case in which dealer banks and long-term investors participate in the auction. We solve for equilibrium strategies in two steps. First, equations (6) through (9) in Proposition 2 form a non-linear system of four equations in four unknowns, which we solve numerically given parameters κ, γ,

σ_λ, σ_ε, $\bar{\lambda}$ and Q_a. Second, given a solution to equations (6)–(9), we compute $b_L = a_L$. Substituting a_D, a_L, c_D, c_L and b_L into the non-linear equation that characterizes b_D yields another nonlinear equation, which we also solve numerically. Figure 1 plots the price loadings $\boldsymbol{a} = (a_D, a_L)$ of dealer banks and long-term investors against the ratio of dealer banks to total participants. When a_D increases, we say that bidders submit flatter demand curves. When there are no dealer banks, the equilibrium converges to the pure private value case of Proposition 3. In the pure private value case, demand curves are the flattest. This is because long-term investors are not affected by demand risk σ_λ, and only restrict trading because of the holding cost κ and price impact. At the other extreme, when the fraction of dealer banks approaches one, the equilibrium approaches to the common value case, where demand curves are the steepest. A high proportion of dealer banks intensifies adverse selection, and dealer banks refrain from trading also because of the risky capital gain. For intermediate cases in which the ratio of dealer banks to total participants is between zero and one, long-term investors submit flatter demand curves relative to dealer banks. The gap between the slope of the demand curves shrinks as the ratio of dealer banks to total participants approaches zero.

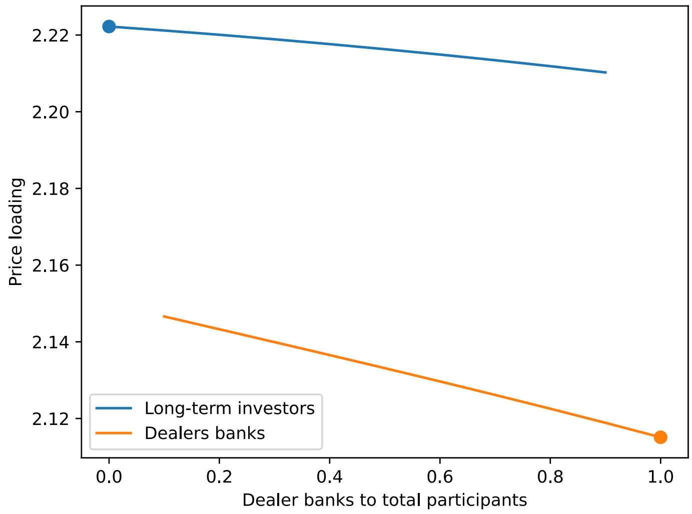

Figure 1: Convergence to special cases. The figure plots coefficients a_D and a_L as participant composition shifts from zero dealer banks to only dealer banks. The markers indicate the pure private value case (orange) and the pure common value case (blue), with total participants fixed at $N = m + n = 10$. The model parameters are $\gamma = 3$, $\kappa = 0.2$, $\sigma_\varepsilon = 0.6$ and $\sigma_\lambda = 1$.

Figure 2a plots the price loading $\boldsymbol{a} = (a_D, a_L)$ for dealer banks and long-term investors. When uncertainty about average costs is higher, both types submit steeper demand curves. Our calibration suggests that $\frac{\partial a_D}{\partial \sigma_\lambda} < 0$ and $\frac{\partial a_L}{\partial \sigma_\lambda} < 0$. Further, the effect is stronger for dealer banks than for long-term investors, so that $\frac{\partial a_D}{\partial \sigma_\lambda} < \frac{\partial a_L}{\partial \sigma_\lambda} < 0$ as in Proposition 7. The relative magnitudes of the price loadings across bidder types depend on the level of demand uncertainty. When prior uncertainty is large, dealer banks have very noisy estimates of future prices, so that the post-auction capital gain is riskier. Because of this, the risk-averse dealer banks act more cautiously and submit steeper demand curves. In contrast, long-term investors adjust their strategies only to the extent that an increase in σ_λ influences the price impact of their trades. This effect vanishes in the pure private value case, in which strategies are independent of demand uncertainty.

(a) Loading on price. (b) Loading on private signal.

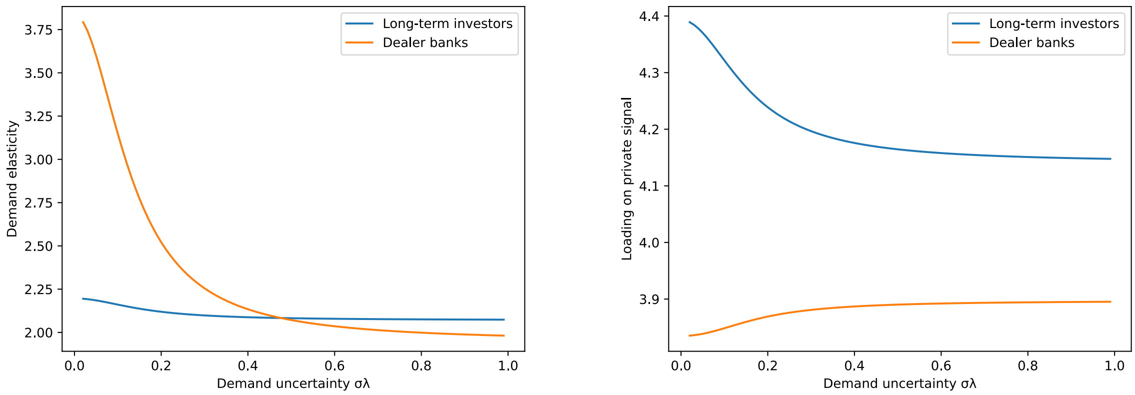

Figure 2: The left panel plots the price loading $\boldsymbol{a} = (a_D, a_L)$ for dealer banks and long-term investors. The right panel plots the private signal loading $\boldsymbol{c} = (c_D, c_L)$ for dealer banks and long-term investors. The model parameters are $\gamma = 3$, $\kappa = 0.2$, $\sigma_\varepsilon = 0.6$, and $\sigma_\lambda \in (0.2, 1)$. The investor composition is $m = 4$ long-term investors and $n = 3$ dealer banks. The average holding cost is $\lambda = 0.25$, and the prior mean is $\bar{\lambda} = 0.05$. Bond supply at the auction is $Q_a = 1$.

Conversely, Figure 2b reveals that the impact of higher demand uncertainty on the signal loading may be asymmetric across types. In the calibration with $\gamma = 3$, long-term investors trade more aggressively on their own private signal than dealer banks, so that $c_L > c_D$ for all $\sigma_\lambda \in (0, 1)$. Higher demand uncertainty leads dealer banks to trade even more aggressively on their own signal, whereas long-term investors trade less aggressively. This is because the heterogeneity in investment horizons generates different incentives to learn from prices across investor types. Long-term investors refrain from trading too aggressively on their private information because doing so will reduce capital gain uncertainty and increase dealer banks' willingness to pay.

Asymmetric responses of signal loadings $\boldsymbol{c}$ to σ_λ is not a universal feature across all parameter configurations. We find that when the coefficient of risk aversion is small, e.g. $\gamma = 1$, an increase in demand uncertainty impacts the signal loading of long-term investors and dealer banks in the same direction. When risk aversion is low, the reduction in the demand risk premium is very small, and long-term investors trade more aggressively. The asymmetry emerges for a large enough coefficient of risk aversion because learning about the capital gain becomes particularly valuable when dealer banks' risk aversion is moderately large. Long-term investors find it beneficial to trade against uninformed dealer banks and keep demand risk premia high to lower the auction price. This mechanism only emerges when long-term investors and dealer banks simultaneously participate in the auction. As shown Propositions 3 and 4 for the pure private and pure common value cases, the impact of an increase in σ_λ always has the same sign for all bidders. Our main takeaway is that heterogeneity in investment horizons can potentially affect the way in which the primary and the secondary markets aggregate information.

Informational Advantages and Risk Aversion A common feature of competitive rational expectations equilibria (Admati, 1985; Diamond & Verrecchia, 1991) is that some traders have an informational advantage due to more precise private signals. Heterogeneity in signal precision also leads to asymmetric equilibria in which bidding strategies depend on traders' information sets. Competitive equilibria typically imply that traders with an information advantage submit flatter demand curves relative to uninformed traders (Vives, 2008). The same holds in models of imperfect competition where traders do not take prices as given (Kyle, 1989), although price impact complicates an explicit characterization of the slope of the demand schedules except in special cases. Because primary dealers generally have informational advantages (Boyarchenko et al., 2021; Hortaçsu & Kastl, 2012), modeling heterogeneity that way would imply flatter dealer banks' demand schedules. Consistent with the empirical findings in Section 4, our model instead implies that dealer banks' may submit *steeper* demand curves ($a_L > a_D$) relative to long-term investors when demand uncertainty is sufficiently large. Our analysis highlights important interactions between investment horizons and dealer banks' risk-bearing capacity. Investment horizons determine the extent to which the risk-bearing capacity of financial intermediaries impact prices at the auction. A decline in the risk-bearing capacity impacts equilibrium strategies only if dealer banks participate to the auction.

Post-auction Capital Gains The post-auction capital gain is $R_{0|1} \doteq p_1^* - p_0^* = 1 - \lambda - \kappa Q_a - p_0^*$. From the perspective of dealer bank j, the subjective distribution of the post-auction capital gain conditional on the private signal λ_j and p_0 is

$$R_{0|1} \,|\, p_0, \lambda_j \sim \mathcal{N}(1 - \mu_\lambda - \kappa Q_a - p_0^*, \Sigma_\lambda)$$

where μ_λ and Σ_λ are given in Proposition 5.

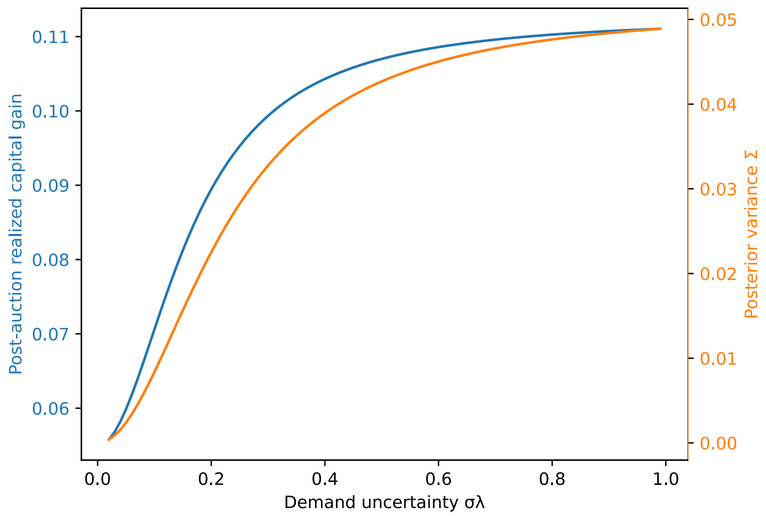

Figure 3: Realized post-auction capital gain and posterior variance Σ_λ. The blue line plots the *realized* post-auction capital gain $p_1^* - p_0^*$ against demand uncertainty. The orange line plots the posterior variance for dealer banks Σ_λ against demand uncertainty. The model parameters are $\gamma = 3$, $\kappa = 0.2$, $\sigma_\varepsilon = 0.6$, and $\sigma_\lambda \in (0.2, 1)$. The investor composition is $m = 4$ long-term investors and $n = 3$ dealer banks. The average holding cost is $\lambda = 0.25$, and the prior mean is $\bar{\lambda} = 0.05$. Bond supply at the auction is $Q_a = 1$.

Figure 3 plots the *realized* capital gain against demand uncertainty σ_λ. Risk-averse dealer banks require an additional compensation for their exposure to aggregate risk between the auction and the secondary market. The aggregate risk premium is a function of the total supply allocated to dealer banks $Q_{a,D} = \sum_{j=1}^{n} q_{j0}$ and of aggregate demand uncertainty σ_λ^2. Accordingly, the blue line shows that, in our calibration, the realized capital gain monotonically increases in demand uncertainty σ_λ. On the one hand, an increase in σ_λ leads to steeper demand curves. On the other hand, risk-averse dealer banks charge an additional risk premium to hold the bond that is positively related to the conditional variance of the capital gain Σ_λ. The orange line in Figure 3 shows that higher aggregate demand risk translates into higher posterior variance.

3.6 Predictions

Guided by our theory, we now formulate four empirical predictions on bidding behavior and post-auction price dynamics that we test in Section 4. The first two predictions follow directly from Propositions 5 and 7 and relate to the behavior of the slope of demand schedules across investor types in response to an increase in uncertainty.

Prediction 1 (Proposition 5)**.** *Both long-term investors and dealer banks submit downward sloping demand schedules. Dealer banks' demand schedules are steeper.*

Prediction 2 (Proposition 7)**.** *Both long-term investors and dealer banks submit steeper demand curves as demand uncertainty increases. Dealer banks exhibit greater sensitivity to demand uncertainty and holding cost dispersion relative to long-term investors.*

Prediction 3 (Return Predictability)**.** *Inelastic demand from dealer banks at the auction positively predicts post-auction returns. When all investors exhibit inelastic demand at the auction, returns become predictable over longer horizons.*

Informed by our numerical solution, we turn to post-auction return predictability. Dealer banks are more cautious when demand uncertainty is high and submit steeper demand schedules. This demand rigidity captures a risk premium that dealer banks require until they can resell their inventories in the secondary market. The more rigid dealer banks' demand is, the higher the associated demand risk premium. Empirically, this suggests that inelastic demand from dealer banks at the auction predicts positively predicts post-auction excess bond returns. This prediction finds support in Albuquerque et al. (2024). Post-auction price dynamics depend on who will absorb inventory in the secondary market and how elastic their demand is. When dealer banks (market makers) display inelastic demand but other investors remain elastic, dealers can quickly distribute their holdings, so any return effects are short-lived. By contrast, when *both* dealer banks and other auction participants exhibit inelastic demand at the auction, this is an informative signal that aggregate secondary-market demand is also inelastic. Dealers then unwind more slowly and carry inventory longer, which extends the horizon over which excess returns are predictable. We observe bidder identities and we can separate dealers from long-term investors to test composition-based implications tied to heterogeneous expected holding periods.

Prediction 4 (Secondary Market Liquidity)**.** *Dealer banks submit steeper demand curves when they anticipate the secondary market to be more illiquid, whereas the bidding strategies of long-term investors remain essentially unaffected.*

Our theory assumes a competitive secondary market, so that there are neither trading frictions nor transaction costs at $t = 1$. Therefore, the framework cannot provide explicit predictions about the impact of secondary market liquidity on bidding behavior and, vice versa, how the auction allocation affects secondary market liquidity. Nevertheless, we propose extending the empirical analysis with an additional prediction based on the idea that expected liquidity is primarily a concern for investors who expect to redistribute part of their purchases in the secondary market. Accordingly, we conjecture that agents' expectations of greater secondary market liquidity should alleviate demand rigidity, particularly for dealer banks with shorter expected holding periods and market-making obligations (Amihud & Mendelson, 1986). Our hypothesis is that a less liquid secondary market likely impairs market-making activities, adversely affecting dealer banks' profits from resale. On the other hand, we expect long-term investors with longer expected holding periods to be less affected by secondary market liquidity, and even sort into cheaper securities that are highly illiquid (Musto et al., 2018). Although this final prediction is partly outside the model, it expands the scope of our analysis and provides an additional test of our assumption on heterogeneity in investment horizons.

4 Demand Heterogeneity and Investment Horizons

We explore demand heterogeneity for Swiss Treasury bonds and empirically validate our theoretical model by testing Predictions 1 through 4. First, we document heterogeneity in bidding behavior and explore its determinants over time. We then show that dealer banks' demand steepens relative to long-term investors when demand uncertainty is higher and when the secondary market is more illiquid.

4.1 Bidder Demand Schedules

Our analysis of demand heterogeneity emphasizes cross-sectional differences in bidding strategies. We construct two measures of bidding heterogeneity: one for the level and one for the slope of demand schedules. Let j, i and k index auctions, bidders, and bid steps, respectively. We calculate the quantity-weighted yield *discount* for each bidder as $\text{Discount}_{ij} = \sum_{k=1}^{K} w_{ijk} B_{ijk} - y_j$ where $w_{ijk} = \frac{Q_{ijk}}{\sum_{k=1}^{K} Q_{ijk}}$. For security reopenings, discount_{ij} is the difference between the average bid yield of bidder i compared to the secondary market yield y_j of the same bond at the end of the auction closing day. A positive value means that bidder i is bidding, on average, less than the secondary market price. Using the discount as a normalized measure of bid level is standard in the literature, as it captures bidders' strategic bid shading (Keloharju et al., 2005; Nyborg et al., 2002). The discount is different from the yield spread in Table 1, which is the difference between the auction market clearing price b_j and the secondary market yield y_j.

Second, we collect price-quantity pairs $(B_{ijk}, \mathcal{Q}_{ijk})$ such that $\mathcal{Q}_{ijk}$ equals the sum of the quantity bid at bid price B_{ijk} or above. We include non-competitive bids by adding the non-competitive bid quantity $\mathcal{Q}_{ijk}^{nc}$ to all quantity bids $\mathcal{Q}_{ijk}$. Non-competitive bids are always fully allocated. As a result, these bids do not have an associated price, but they shift demand schedules upwards at each bid step. We then estimate the elasticity of demand β_{ij} (TE, total elasticity) by regressing the log bid quantity $q_{ijk} = \log \mathcal{Q}_{ijk}$ on a constant and the log bid price $b_{ijk} = \log B_{ijk}$. We interpret the coefficient β_{ij} as the percentage reduction in bid quantity in response to a one percent increase in bid price. We use the elasticity of demand rather than the absolute slope for better cross-sectional comparisons, as elasticities are scale-invariant and offer a more consistent measure across bidders with significantly different bidding volumes (Albuquerque et al., 2024). We only consider demand schedules with five or more bid steps. A higher value of β_{ij} means that demand is more elastic and that demand curves are flatter. As alternative measures, we also estimate the elasticity of demand by dropping the highest and the lowest bids ($\hat{\beta}_{ij}$, intermediate elasticity IE) and by considering winning bids only ($\tilde{\beta}_{ij}$, winning elasticity WE). For all three measures, we report the logarithm of minus the coefficient estimate.

Table 2 reports summary statistics on bidding behavior. Across all 530 auctions, we observe 8'699 unique demand schedules. On average, bidders submit four bid steps and a median of three. The average demand schedule accounts for 6.09% of the total bidding volume. Similarly, each bidder obtains, on average, 6.09% of the total supply. In many cases, however, the allocation is highly concentrated among few bidders, with the top bidders receiving a sizable share of the issue as shown in Figure 7. The mean of the *log* total elasticity is 5.08 (implying an average elasticity of $\exp(5.08) \approx 161$ in levels), and the intermediate (IE) and winning (WE) measures are of comparable magnitude. The average magnitude of our estimates is comparable to those of Albuquerque et al. (2024) for Portuguese Treasury auctions. In Table 18 in Appendix B.5, we contrast our investor-level measure with the marginal elasticity measure of Albuquerque et al. (2024). The correlation between our total elasticity measure and the marginal elasticity is 0.51.

	N	Mean	SD	Min	Median	Max
Bid steps	8'699	4.15	4.11	1.00	3.00	38.00
Bid quantity	8'699	37'015	97'165	1.00	10'000	4'040'380
Bid share	8'699	6.09	10.56	0.00	1.59	92.71
Allocated quantity	8'699	21'743	53'244	0.00	4'859	1'026'580
Allocated share	8'699	6.09	11.62	0.00	1.19	98.56
TE β_{ij}	2'279	5.08	0.99	0.56	5.18	7.50
IE $\hat{\beta}_{ij}$	2'279	5.19	1.00	−4.34	5.29	8.01
WE $\tilde{\beta}_{ij}$	1'601	5.26	1.14	0.36	5.35	7.85
Discount$_{ij}$	3'482	0.02	0.12	−1.45	0.02	3.94

Table 2: Summary of bidding behavior. Bid steps is the number of price-quantity pairs submitted by each bidder. Bid quantity is the total bid volume. Bid share is the fraction of total bid volume tendered by each bidder. Allocated quantity is the awarded volume per bidder. Allocated share is share of issue allocated to each bidder. Total elasticity (TE) is the demand elasticity using all bids. Intermediate elasticity (IE) excludes the highest and the lowest bids. Winning elasticity (WE) uses only winning bids. Discount is the difference between the quantity-weighted bid yield and the secondary market yield. The sample is from 1980 to present.

The range of demand elasticities is substantial, reflecting significant heterogeneity across bidders. The standard deviation of total elasticity is approximately one, and the elasticity of demand ranges from 0.56 to 7.50 (in logs). As shown in Table 8 in the Internet Appendix B.2, the demand elasticity is negatively associated with volatility, bid dispersion, illiquidity, and maturity, whereas it is positively associated with the number of participants and total supply. The positive relationship with supply suggests that the government may increase issuance of the margin when observing flatter demand curves. Auction participants bid higher yields than in the secondary market, so that the yield discount is on average positive. There is, however, substantial cross-sectional dispersion in yield discounts, ranging from a minimum of −1.45% to a maximum of 3.94%. Some bidders regularly submit bids above prevailing secondary market prices..

Figure 4 demonstrates heterogeneity in bidding behavior by plotting time-series averages of total elasticity and bidder yield discounts. The left panel shows that there is significant dispersion in the level of demand. Approximately two-thirds of the bidders submit bids at higher yields (i.e., lower prices) than those observed in the secondary market. In contrast, the remaining bidders are more aggressive, often bidding prices above those in the secondary market. The right panel displays the average time-series demand elasticity. The elasticity of the demand schedules (in logs) exhibits significant cross-sectional variation. The two most elastic bidders have log demand elasticities of 6.74 and 6.64, whereas the least elastic bidder has a log elasticity of 4.48. In levels, this disparity translates into a remarkable difference of 757.32. As in our theoretical framework for large enough σ_λ, dealer banks are typically less elastic, on average, than long-term investors. All dealer banks, except one, have a demand elasticity of no more than 5.22. Conversely, most long-term investors submit significantly flatter demand curves.

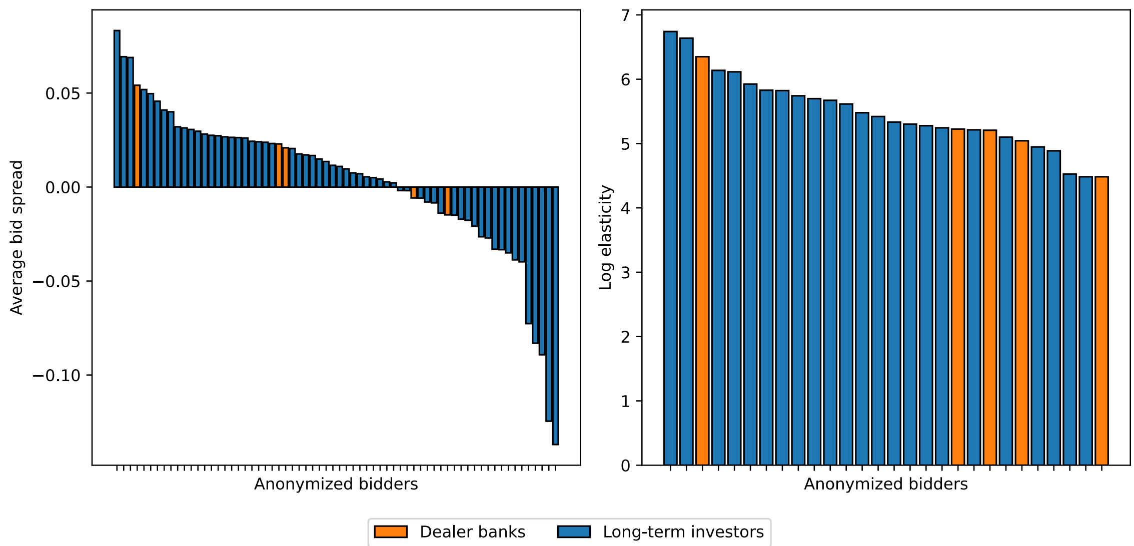

Figure 4: Time-series averages of yield discount and demand elasticity. The left panel displays average yield discounts for all bidders. The right panel shows the total demand elasticity (TE). Elasticities are estimated using all bid steps from bidders with at least five submissions. We report the log of minus the estimated elasticity. The sample is from 1980 to the present.

Long-duration bonds are more sensitive to interest rate movements, so that we expect yield discounts and demand elasticities to vary with bond maturity. While the relation between yield discounts and bond maturity is ex-ante ambiguous, demand elasticities typically decline as bond maturity increases. Table 3 reports yield discounts and demand elasticities by maturity interval, separately for dealer banks and long-term investors.

	Yield discount				Log demand elasticity			
Maturity	$[2, 10)$	$[10, 15)$	$[15, 20)$	$[20, 50]$	$[2, 10)$	$[10, 15)$	$[15, 20)$	$[20, 50]$
Dealer banks	0.009	0.002	0.029	0.008	5.293	5.055	4.757	4.272
Long-term investors	0.025	0.013	0.034	0.025	5.627	5.495	4.860	4.511
Cantonal banks	0.017	0.019	0.053	0.035	5.533	5.505	4.671	4.565
Regional banks	0.072	0.042	0.069	0.048	5.865	5.454	4.603	4.177
Foreign-controlled	0.021	0.017	0.035	0.027	5.767	5.624	4.808	4.442
Non-finance companies	0.035	0.011	0.047	0.064	–	4.883	4.851	4.440
Others	0.025	-0.003	-0.016	-0.011	5.621	5.340	5.735	4.651

Table 3: Average yield discount and demand elasticity by maturity. Elasticities are estimated using all bid steps from bidders with at least five submissions. We report the log of minus the estimated elasticity. We group long-term investors into cantonal banks, regional banks, foreign-controlled entities, non-finance companies, and others. The sample is from 1980 to the present.

Two clear patterns emerge across all maturity intervals. First, dealer banks bid lower secondary market discounts as compared to long-term investors, so that dealer banks' underpricing is less severe. Decomposing long-term investors across the five bidder categories, we observe that long-term investors' underpricing is a robust pattern across all categories with the exception of other bidders. Auction underpricing relative to dealer banks is particularly severe for regional banks and non-finance companies. Second, as predicted by the theory, dealer banks submit steeper demand schedules compared to long-term investors. We interpret this pattern through the lens of aggregate demand risk: both bidder types shade their bids to account for price impact and holding costs, but dealer banks also shade their bids due to risk aversion, reducing their elasticity even further. Another consistent finding is that demand elasticity decreases with bond maturity across all investor groups, aligning with Greenwood and Vayanos (2014). In addition, there is substantial heterogeneity across different groups of long-term investors.

4.2 Sensitivity to Aggregate Demand Risk

We test Predictions 1 and 2 by comparing how dealer banks and long-term investors respond to an increase in demand uncertainty. We measure demand uncertainty as the volatility of daily bond returns, $\sigma_{j-21,j}$, in the month prior to the auction, provided that there are at least fifteen observations. Second, we proxy holding cost dispersion using the cross-sectional standard deviation $\sigma_{b,j}$ of quantity-weighted bid yields within each auction.

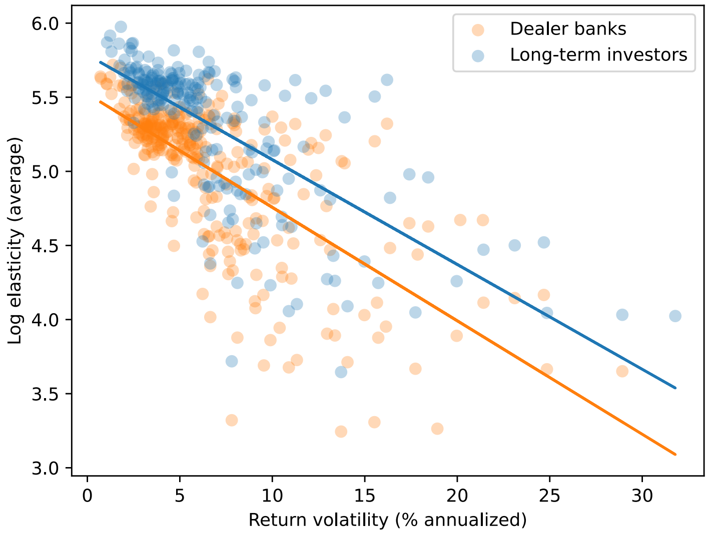

Figure 5: Bond return volatility and adjusted demand elasticity. The orange dots indicate dealer banks. The blue dots indicate long-term investors. Return volatility is the standard deviation of daily bond returns in the month prior to the auction, provided that there are at least 15 observations. Log elasticity is the average total elasticity β_{ij}. We adjust demand elasticity for maturity by projecting β_{ij} onto a constant and bond maturity, and computing the fitted values. The solid lines represent linear fits of adjusted elasticity onto return volatility. The sample covers reopenings from 2000 to present.

Figure 5 plots annualized return volatility in the month prior to the auction date against average elasticity of demand separately for dealer banks and long-term investors, adjusted for bond maturity. Dealer banks typically submit steeper demand curves as compared to long-term investors. Further, there is a negative relation between return volatility and demand elasticity for both investor types. In periods of high volatility, the elasticity of demand declines. However, as shown by the solid lines, the effect is stronger for dealer banks. An increase in volatility leads to a steepening of dealer banks' demand curves relative to long-term investors.

Return Volatility We estimate the linear regression model

$$\beta_{ij} = b_0 + b_1 \cdot \sigma_{x,j} + b_2 \cdot \sigma_{x,j} \times \mathbb{1}\{\text{DB}\}_i + b_3 \cdot x_j + \varepsilon_{ij} \tag{10}$$

where β_{ij} is total demand elasticity, and $\sigma_{x,j}$ is is either return volatility $\sigma_{j-21,j}$ or bid dispersion $\sigma_{b,j}$. The indicator $\mathbb{1}\{\text{DB}\}_i$ equals one if bidder i is a dealer bank. The vector of controls x_j includes the number of participants, bond maturity, the relative bid-ask spread, and a set of macroeconomic indicators. Because the issue amount is an equilibrium outcome at the auction, we do not control for the issue size. We also include inflation, the short-term rate, a business cycle indicator, and the slope of the yield curve. We do not control for bidder yield discounts, which is an endogenous outcome of the auction. The coefficients of interest are b_1 and b_2, where b_2 captures the response of dealer banks relative to long-term investors to higher volatility or bid dispersion. Predictions 1 and 2 imply that b_1 and b_2 should both be negative. Estimates for are in Table 4.

The first column shows that the demand elasticity declines in response to an increase in volatility. Return volatility explains roughly one quarter of the variation. The second column demonstrates that the effect is stronger for dealer banks, and the coefficient estimate is economically and statistically significant. A one-percentage-point increase in daily return volatility is associated with a demand elasticity (in logs) that is 0.64 lower for dealer banks compared to long-term investors. As in Table 3, the elasticity of demand declines with maturity. A higher number of participants leads to flatter demand curves as the auction becomes more competitive. In Table 9 in the Internet Appendix B.2, we obtain quantitatively similar results using the intermediate elasticity (IE) and the winning elasticity (WE). Internet Appendix B.2 confirms that our results are not driven by outlier auctions around the sudden removal of the EUR/CHF floor or during the Covid period.

	Log demand elasticity			
	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}
$\sigma_{j-21,j}$	-1.58^{***}	-1.23^{***}	-0.48^{**}	-0.34^{*}
	(0.15)	(0.15)	(0.19)	(0.19)
$\sigma_{j-21,j} \times \mathbb{1}\{\text{DB}\}_i$		-0.58^{***}	-0.56^{***}	-0.57^{***}
		(0.13)	(0.12)	(0.12)
Maturity			-0.03^{***}	-0.02^{**}
			(0.01)	(0.01)
Participants			0.02^{**}	0.02^{**}
			(0.01)	(0.01)
RBAS$_j$				-0.24^{***}
				(0.08)
Constant	5.59^{***}	5.62^{***}	5.61^{***}	5.60^{***}
	(0.08)	(0.08)	(0.14)	(0.14)
Macro	✓	✓	✓	✓
Adj. R^2	0.25	0.27	0.30	0.30
N	993	993	993	993

Table 4: Estimates of regression (10). The dependent variable is the total elasticity (TE) of demand (in logs) at the bidder level. $\sigma_{j-21,j}$ is the volatility of daily bond returns in the month prior to the auction. $\mathbb{1}\{\text{DB}\}$ is an indicator equal to one if bidder i is a dealer bank. Maturity refers to time to maturity at the auction date. Participants is the number of bidders. RBAS$_j$ is the relative bid-ask spread in the secondary market at the auction close. Macro controls include inflation, short-term rate (SARON), slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to present and only includes reopenings. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

Cost Dispersion We repeat the same exercise with the standard deviation of bid yields, $\sigma_{b,j}$. This is our preferred proxy of holding costs dispersion σ_ε. Table 5 reports the results with bid dispersion and illustrates a similar pattern to that in Table 4.

The elasticity of demand declines with bid dispersion, but the overall effect is not statistically significant. However, the effect is negative and statistically significant for dealer banks, as shown in the second column. Coefficient estimates are qualitatively similar after controlling for maturity, the number of participants, relative bid-ask spread, and return volatility. As a first robustness check, we consider three alternative measures of bid dispersion, namely the cross-sectional standard deviation of equally-weighted bid yields, the interquartile range of quantity-weighted bid yields, and the interquartile range of equally-weighted bid yields. We report coefficient estimates using these three measures in columns two through four of Table 12 in Appendix B.2.

	Log demand elasticity			
	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}
$\sigma_{b,j}$	-0.23	0.62	0.44	0.55
	(0.50)	(0.41)	(0.36)	(0.38)
$\sigma_{b,j} \times \mathbb{1}\{\text{DB}\}_i$		-1.96^{**}	-1.91^{**}	-1.85^{**}
		(0.93)	(0.81)	(0.84)
Maturity			-0.04^{***}	-0.02^{**}
			(0.00)	(0.01)
Participants			0.02^{**}	0.02^{***}
			(0.01)	(0.01)
$\sigma_{j-21,j}$				-0.68^{***}
				(0.19)
RBAS_j				-0.24^{***}
				(0.08)
Constant	4.94^{***}	4.96^{***}	5.61^{***}	5.60^{***}
	(0.06)	(0.07)	(0.13)	(0.14)
Adj. R^2	0.12	0.13	0.27	0.30
N	1087	1087	1087	993
p-sum		0.08	0.04	0.07

Table 5: Coefficient estimates of regression (10). The dependent variable is the total elasticity (TE) of demand (in logs) at the bidder level. $\sigma_{b,j}$ is the cross-sectional standard deviation of quantity-weighted bid yields, whereas $\mathbb{1}\{\text{DB}\}_i$ is an indicator equal to one if bidder i is a dealer bank, and zero otherwise. Maturity refers to time to maturity at the auction date. Participants is the number of bidders. $\sigma_{j-21,j}$ denotes the volatility of the bond in the month prior to the auction. RBAS_j is the relative bid-ask spread at the auction date. Macro controls include inflation, the short-term rate (SARON), the slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to present and only considers security reopenings. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively. p-sum is the p-value from testing the null hypothesis that $b_1 + b_2 \geq 0$.

For comparison, the first column on Table 12 is identical to the fourth column of Table 5. Across all different measures and specifications, the coefficient on the interaction between bid dispersion and the dealer bank indicator remains negative and statistically significant, as predicted by our theory. We also separately test whether the total effect $b_1 + b_2$ is negative and statistically significant, and we reject the null hypothesis that $b_1 + b_2 \geq 0$. Overall, an increase in bid dispersion is associated with dealer banks submitting steeper demand schedules relative to all other investors. The magnitude of the coefficient is larger when we consider the interquartile range because of the different units.

A challenge in measuring holding cost dispersion is that bidders' holding costs are unobservable. While the cross-sectional volatility in bid yields $\sigma_{b,j}$ is related to σ_ε, the dispersion in bid yields is an endogenous outcome that reflects bidders' strategies. In particular, the slope of their demand schedules and the number of bid steps influence this dispersion measure. As a result, the link between the demand slope and the observed cross-sectional dispersion in bid yields is partly mechanical. Because the alternative proxies in the Internet Appendix B.2 also face the same limitation, we construct a measure of cross-sectional dispersion that does not rely on the standard deviation of bid yields. We describe our approach in detail the Internet Appendix, where we also report our estimates. Table 13 in Appendix B.3 reports estimates of specification (10), but measuring holding cost dispersion using $\hat{\sigma}_{\varepsilon,j}$. Table 13 corroborates our findings that dealer banks steepen their demand curves relative to long-term investors when dispersion in holding costs is higher. The estimates of the interaction term are negative and statistically significant in all three columns. The total effect $b_1 + b_2$ of higher bid dispersion on dealer banks is also negative and statistically significant across most specifications. In summary, Table 4, Table 5, Table 12, and Table 13 strongly suggest that bidding strategies respond to changes in aggregate uncertainty that we proxy by either bond return volatility or bid dispersion. The effect is stronger for dealer banks, which are significantly more sensitive to uncertainty relative to long-term investors.

4.3 Holding Costs and Bidding Behavior

We next investigate how changes in the regulatory environment influence bidding behavior in the primary market. Basel III regulations impose higher capital requirements and introduce additional buffers for large systemic banks, especially those engaged in market-making activities (Duffie, 2016). These regulatory measures directly impact the dealer banks in our sample. As a result, we hypothesize that dealer banks will submit steeper demand curves than other investors, such as pension funds, insurance companies, and regional banks, who are not subject to comparable regulatory constraints. To this purpose, we implement a difference-in-differences (DiD) design around the gradual implementation of the Basel III regulatory framework, which we interpret as an increase in the slope of marginal holding costs κ for dealers only. Although Basel III was endorsed in 2013, its capital requirements were gradually phased in starting January 2015, which we use as the cutoff for our DiD design. To increase statistical power we consider a symmetric five-year window around January 1, 2015. In the Internet Appendix B.3, we perform the same analysis using three- and four-year windows, and estimates are qualitatively and quantitatively similar. The pre-implementation period runs from January 2010 to January 2015, and the post-implementation from January 2015 to January 2020. The DiD design is

$$z_{ij} = b_0 + b_1 \mathbb{1}\{\text{Basel III}\}_j + b_2 \mathbb{1}\{\text{DB}\}_i + b_3 \mathbb{1}\{\text{Basel III}\}_j \cdot \mathbb{1}\{\text{DB}\}_i + b_4 x_j + \varepsilon_{ij} \tag{11}$$

The indicator $\mathbb{1}\{\text{Basel III}\}_j$ equals one if auction j occurred post 2015 when Basel III requirements were being phased in. Similarly, $\mathbb{1}\{\text{DB}\}_i$ is an indicator equal to one if bidder i is a dealer bank. Our theory predicts a negative coefficient. Liquidity and capital requirements make systemic banks less elastic relative to other bidders who are not subject to Basel III. We consider two outcome variables z_{ij}, that is the total elasticity of demand (TE β_{ij}) and the yield discount (discount_{ij}). The controls x_j includes bond maturity and the number of participants. Through the lens of Proposition 2, we expect an increase in dealer banks' holding cost to cause a steepening of their demand curves relative to long-term investors that are not subject to the regulation. Accordingly, this maps into a negative b_3 when the dependent variable is the elasticity of demand.

	Log elasticity		Yield discount	
	TE β_{ij}	TE β_{ij}	Discount_{ij}	Discount_{ij}
$\mathbb{1}\{\text{Basel III}\}_j$	−0.11	−0.03	0.02	0.02
	(0.14)	(0.12)	(0.01)	(0.01)
$\mathbb{1}\{\text{DB}\}_i$	−0.21**	−0.26***	0.01	0.01
	(0.10)	(0.09)	(0.01)	(0.01)
$\mathbb{1}\{\text{Basel III}\}_j \times \mathbb{1}\{\text{DB}\}_i$	−0.57***	−0.41***	−0.03**	−0.03**
	(0.19)	(0.16)	(0.01)	(0.02)
Maturity		−0.05***		−0.00
		(0.00)		(0.00)
Participants		−0.03*		−0.00
		(0.02)		(0.00)
Constant	5.35***	6.56***	0.01	0.02
	(0.08)	(0.26)	(0.01)	(0.04)
Adj. R^2	0.10	0.31	0.00	0.00
N	562	562	1375	1375

Table 6: Coefficient estimates of the difference in differences specification (11). In the first and second column, the dependent variable is the total elasticity of demand (in logs). In the third and in the fourth column, the dependent variable is the quantity-weighted yield discount. $\mathbb{1}\{\text{Basel III}\}_j$ is an indicator equal to one if the auction occurs after January 2015. $\mathbb{1}\{\text{DB}\}_i$ is an indicator equal to one if bidder i is a dealer bank. The sample period is from January 2010 to December 2019 and spans a five-year window around the introduction of the Basel III regulations. Robust standard errors are reported in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

Table 6 reports coefficient estimates using the log total demand elasticity and the yield discount as the dependent variable. As in Figure 4, the first and the second columns show that dealer banks submit, on average, steeper demand schedules relative to other auction participants. The first column shows that, in the post-Basel III period, the gap between dealer banks' and long-term investors' demand elasticity has increased. The coefficient estimate of −0.57 is highly statistically and economically significant. The introduction of the Basel III framework is associated with a reduction of 0.57 (in log units) in dealers' elasticity of demand relative to other investors. The magnitude and the statistical significance remain stable after controlling for maturity, number of participants, and issue size. Robustness checks in the Internet Appendix B.3 exclude auctions around the sudden EUR/CHF floor removal on January 15, 2015 and recover similar estimates.

The third and the fourth columns reveal that large banks have been offering lower yields (higher prices) than in the secondary market after the introduction of the new capital requirements. The fourth column implies that dealer banks bid at significantly lower discounts of 3 basis points compared to the prevailing secondary market prices. However, the DiD specification explains little of the variation in bidder level yield discounts. Taken together, our results indicate that regulatory requirements cause dealer banks' demand schedules to become steeper.

4.4 Relation to Secondary Market Outcomes

In this section, we further examine how bidding strategies influence outcomes in the secondary market and, vice versa, how secondary market conditions influence bidding behavior. To this purpose, we first study how demand elasticities respond to secondary market liquidity. Second, we explore the connection between bidding behavior and post-auction return predictability.

Market Liquidity Our assumptions of investment horizons and resale imply that dealer banks with a shorter expected holding period behave more cautiously when the secondary market is expected to be illiquid. In contrast, long-term investors with longer holding periods are less affected by liquidity conditions (Amihud & Mendelson, 1986). To test our conjecture that dealer banks' demand schedules become less elastic in response to higher illiquidity, we estimate the following linear regression model

$$\beta_{ij} = b_0 + b_1 \cdot \text{RBAS}_j + b_2 \cdot \text{RBAS}_j \times \mathbb{1}\{\text{DB}\}_i + b_3 \cdot x_j + \varepsilon_{ij} \tag{12}$$

We measure secondary market liquidity using the relative bid-ask spread RBAS_j at the auction close. Due to the strong autocorrelation in bid-ask spreads, the current bid-ask spread well captures expectations about future liquidity in the secondary market.

Consistent with Prediction 4, the last three columns in Table 17 in the Internet Appendix reveal that a higher relative bid-ask spread leads to a steepening of dealer banks' demand curves only, whereas there is no effect on the demand elasticity of long-term investors. The estimates on the interaction term are economically and statistically significant across all specifications. The significance of the unconditional effect b_1 vanishes once we control for bond maturity and the number of participants. Both the sign and the significance of these estimates are consistent with our interpretation on heterogeneity in investment horizons. Furthermore, the effect remains statistically significant after controlling for return volatility, suggesting that market liquidity impacts bidding behavior over and above aggregate risk. Long-term investors with a longer holding period are not affected by secondary market liquidity as they do not plan to resell the security right after the auction. On the other hand, dealer banks are more exposed to changes in liquidity conditions around the auction through their market making activities. We obtain the same results when we consider the average bid-ask spread in the month prior to the auction.

Return Predictability Lastly, we validate our mechanism by studying the relation between bidding behavior and post-auction return predictability. We test Prediction 3 by estimating predictive regressions of post-auction excess return on demand elasticities. For each auction j, we construct one-day, two-day, one-week and one-month post-auction excess bond returns $rx_{j,j+h}$, for $h \in \{1, 2, 5, 21\}$. We compute returns relative to market clearing price at the auction given that this is the price at which auction participants purchased the securities. We convert returns into excess returns by subtracting the horizon-matched risk free rate. For $h \in \{1, 2\}$ we use the SARON, whereas for $h = 5$ and $h = 21$ we use the SAR1W and SAR1M rates, respectively. Accordingly, we project bond excess return on the average demand elasticity $\bar{\beta}_j = \frac{1}{I}\sum_{i=1}^{I} \beta_{ij}$

$$rx_{j,j+h} = b_0 + b_1 \cdot \bar{\beta}_j + b_2 \cdot x_j + \varepsilon_j \tag{13}$$

where x_j includes bond maturity, the number of participants, the issue size, and the relative bid-ask spread. The intuition is that dealer banks require a risk premium to hold the securities between the auction and the secondary market because the post-auction capital gain is stochastic. In our theory, this risk premium increases with demand uncertainty and the aggregate quantity purchased by these agents at the auction. Because demand elasticities decline with aggregate uncertainty, a less elastic average demand positively predicts post-auction returns. We further separate dealer banks and long-term investors to assess whether the horizon of return predictability depends on which group bids less elastic demand schedules. Intuitively, the demand risk premium vanishes once dealer banks can distribute their inventories in the secondary market. This adjustment is less likely when all bidders, including long-term investors, display inelastic demand at the auction, signaling aggregate inelasticity that also extends to the secondary market. In such an environment, the secondary market's capacity to absorb dealers' inventories is reduced, delaying their unwinding. Consequently, less elastic demand limited to dealer banks should predict returns only at short horizons, whereas inelastic demand across all investors implies return predictability over longer horizons. To this purpose, we estimate

$$rx_{j,j+h} = b_0 + b_1 \cdot \bar{\beta}_j^{\text{LT}} + b_2 \cdot \bar{\beta}_j^{\text{DB}} + b_3 \cdot x_j + \varepsilon_j \tag{14}$$

The vector of controls x_j includes maturity, number of bidders, and the relative bid-ask spread. Our analysis differs from Albuquerque et al. (2024) for two reasons. First, we measure demand elasticities at the investor level. Thus, we can include the average demand elasticity separately for dealer banks and long-term investors and explore which investors drive auction cycles in the Swiss primary market. In contrast, Albuquerque et al. (2024) include a measure of aggregate elasticity called marginal elasticity (ME) in the predictive regressions. Second, we control for auction and bond characteristics. In the baseline analysis, we do not include the marginal elasticity because there are many auctions in which there are very few bid steps below the market clearing price.

The top panel of Table 7 reports coefficient estimates of regression (13). We find short-term return predictability until one week after the auction. For very short horizons, the regression R^2 statistics are relatively sizable. The first column documents that the average demand elasticity explains up to 12% of the one-day post-auction excess bond returns. However, although coefficients estimates have the expected sign and are statistically significant, their magnitudes do not follow any clear pattern. The bottom panel of Table 7 reveals a different picture once we distinguish between long-term investors and dealer banks. Lower demand elasticity of dealer banks positively predicts post-auction excess bond returns only up to two days after the auction. However, estimates for horizons longer than one week are statistically insignificant. In contrast, the elasticity of demand of long-term investors predicts post-auction bond returns up to one month after the auction. Further, the coefficient on $\bar{\beta}_j^{\text{LT}}$ increases monotonically with the horizon.

	Aggregate elasticity				Dealer banks vs. long-term investors			
	$rx_{j,j+1}$	$rx_{j,j+2}$	$rx_{j,j+5}$	$rx_{j,j+21}$	$rx_{j,j+1}$	$rx_{j,j+2}$	$rx_{j,j+5}$	$rx_{j,j+21}$
$\bar{\beta}_j$	-0.20^{***}	-0.17^{**}	-0.28^{**}	-0.28				
	(0.07)	(0.08)	(0.14)	(0.28)				
$\bar{\beta}_j^{\text{LT}}$					-0.19^{**}	-0.27^{***}	-0.41^{***}	-0.70^{***}
					(0.09)	(0.09)	(0.11)	(0.27)
$\bar{\beta}_j^{\text{DB}}$					-0.22^{**}	-0.14	-0.09	0.35
					(0.09)	(0.11)	(0.14)	(0.28)
Constant	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.12	0.03	0.00	0.04	0.14	0.06	0.03	0.05
N	342	342	338	314	226	226	223	205

Table 7: Estimates of regressions (13) and (14). The top panel regresses h-day ahead excess returns onto the average total elasticity (TE) across bidders, which is computed as $\bar{\beta}_j = \frac{1}{I}\sum_{i=1}^{I}\beta_{ij}$. The bottom panel regresses h-day ahead excess returns onto the average demand elasticity of dealer banks $\bar{\beta}_j^{\text{DB}}$ and long-term investors $\bar{\beta}_j^{\text{LT}}$ separately. Excess returns are computed based on the auction price. Controls include maturity, number of bidders, and the relative bid-ask spread. The sample runs from 2000 to the present. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively

To contrast our results with the existing literature, Table 19 in Internet Appendix B.5

extends the baseline analysis using first an aggregate measure of elasticity, and then jointly including ME and our investor-level elasticity measures. In line with Albuquerque et al. (2024), the marginal elasticity negatively predicts bond returns. However, once we control for bond maturity, number of participants, and market liquidity, the coefficient estimates lose statistical significance. Table 20 further explores the predictive regression (14), now including the marginal elasticity measure. This exercise yields a clear message: identifying which investors exhibit inelastic demand provides incremental predictive power for bond excess returns at auction. When demand elasticity cannot be measured at the investor-level, aggregate proxies like the marginal elasticity can still be informative. However, in our sample, statistical significance depends on whether auction- and bond-level controls are included. We also show that controlling for pre-auction drift and volatility outcomes in Table 21 does not affect our conclusions. Finally, for comparison with Albuquerque et al. (2024), we repeat the same exercise using abnormal log-returns relative to a broad government bond index. We report estimates in Table 22, which demonstrates that the same pattern emerges with an alternative measure of post-auction returns.

4.5 External Validity and Evidence from Other Markets

Our model of safe asset demand shows how heterogeneous investment horizons shape investors' valuations and bidding strategies. While we test its predictions using investor-level data from Swiss Treasury auctions—where bidder identities are observable—the framework is more general. It applies to any market in which investors differ in their ability or willingness to resell before maturity. In this section, we relate the model's implications to evidence from other asset classes and discuss how it can be adapted to account for additional empirical patterns.

4.5.1 Sovereign Bond Auctions

Our model can, in principle, be tested using auction data from other safe asset issuers, such as the United States or EU member states. A necessary condition is that auctions are open to a broad set of investors, allowing researchers to distinguish demand by investor type. Unfortunately, investor-level data are rarely available in these settings. As a result, the literature typically offers only indirect evidence on how investment horizons affect bidding behavior and auction outcomes (e.g., Boyarchenko et al. (2021)). Still, auction cycle patterns—where yields rise before issuance and fall afterward—have been documented in the US (Lou et al., 2013), Portugal (Albuquerque et al., 2024), and other EU countries (Beetsma et al., 2016), especially when dealers' risk-bearing capacity is low. However, these studies generally focus on aggregate outcomes without distinguishing investor types.

A common interpretation is that dealer banks require price concessions to bear under-diversification risk until they offload bonds in the secondary market (Grossman & Miller, 1988). Our theory shares this idea and connects to a broader literature on slow-moving capital and intermediaries' limited risk-bearing capacity (Duffie, 2010). Yet, our model adds new insights. First, it shows that asset valuation depends not just on risk aversion, but on its interaction with investment horizons: risk-bearing capacity matters primarily when investors plan to resell before maturity (see Proposition 3). Second, dealer risk aversion affects not only the risk premium but also the bidding strategies of long-term investors, by changing the slope of the residual supply they face. Long-term investors thus benefit from auction discounts without being exposed to demand risk. By contrast, our model is silent on how dealer behavior—such as pre-auction hedging—affects secondary market prices before issuance (Fleming et al., 2024; Lou et al., 2013; Sigaux, 2024).

4.5.2 Corporate Bond Issuance

Our framework helps interpret patterns in the corporate bond primary market, where demand uncertainty is a key feature. Underpricing at issuance is well-documented (e.g., Wang (2021)), and Bessembinder, Jacobsen, Maxwell, and Venkataraman (2022) show that underwriters often overallocate to manage order flow uncertainty. In line with the auction cycle literature, Siani (2025) finds evidence of price pressure around issuance. As in safe asset auctions, corporate bond investors can be categorized into long-term buy-and-hold investors and short-term "flippers." The share of short-term investors tends to rise in bad times, when issuance premia are also higher. Because underwriters are implicitly expected to stabilize secondary market prices, the investor composition matters. Our model suggests that such periods—when dealer banks' risk aversion increases—lead to larger price concessions and a greater allocation to long-term investors.

Corporate bonds differ from sovereign ones by relying on over-the-counter trading, which invites two extensions to our theory: search costs and market power (Breckenfelder, Collin-Dufresne, & Corradin, 2025). Our model assumes a competitive secondary market and continuous trading opportunities. Introducing search frictions would affect dealer valuations. The effect, however, is ambiguous—reduced ability to resell makes dealers resemble long-term investors. Market power, in contrast, could increase dealers' willingness to bid if they can extract rents from secondary buyers. However, our assumption of symmetric information about fundamentals is less suitable in this context.

4.5.3 Municipal Bonds

A growing literature documents both price dispersion and underpricing in municipal bond issuance (Green, Hollifield, & Schürhoff, 2007). In this market, underwriters typically acquire bonds and resell them to end investors in the secondary market (Garrett, Ordin, Roberts, & Suárez Serrato, 2022). While resale opportunities influence pricing, valuation heterogeneity also stems from differences in investors' tax advantages (see Cestau, Hollifield, Li, and Schürhoff (2019) for a review). Our model can be extended to account for heterogeneous tax regimes by allowing a subset of secondary market investors to draw holding costs from a distribution with a lower mean. This extension preserves the key insight that secondary market demand is uncertain. Auction bidders cannot fully observe other participants' tax status or anticipate who intends to trade the bond after issuance.

5 Conclusion

This paper demonstrates, both theoretically and empirically, that heterogeneity in investment horizons plays a critical role in determining bidding behavior and post-auction price dynamics of safe assets. Using a novel dataset with detailed bidder identities, we show that short-term oriented dealers are more sensitive to demand uncertainty: uncertainty about post-auction resale values drives risk-averse dealers to demand a risk premium, shade their bids, and display less elastic demand, resulting in steeper demand curves and asset return predictability lasting only a few days. In contrast, when all investors—including dealer banks and long-term investors—exhibit inelastic demand at the auction, this reflects aggregate inelasticity also in the secondary market, making it harder for dealers to unwind their inventories and extending return predictability to longer horizons, up to one month. These findings emphasize how changes in the investor base can impact the risk–return profile of safe assets and their post-auction dynamics.

Our paper provides at least three important implications for both policymakers and academics. First, our theoretical findings offer new insights into how investors price safe assets and how differences in investment horizons influence bidding behavior in the primary market. Second, we propose a novel approach to Treasury auction design, emphasizing the critical role of bidder composition. Our findings reveal that both *how* an asset is sold and *to whom* it is sold significantly impact its return distribution. Unlike much of the existing literature, which focuses on auction rules and post-auction disclosure of results, we highlight the heterogeneity among auction participants and their investment horizons (dealers versus long-term investors). Finally, our results hint at a trade-off between secondary market liquidity (supported by dealers) and post-auction price volatility (driven by their short-term trading horizons and inventory offloading). This trade-off allows us to derive the costs and benefits of a primary dealer system. On the cost side, primary dealership induces a risk premium that must be borne by the government. On the benefit side, a well-established primary dealer system ensures a more liquid secondary market.

Our policy recommendation to Debt Management Offices is to integrate secondary market dynamics into the auction design process, rather than treating auctions in isolation. Lastly, our paper revisits the concept of a safe asset by linking it to demand risk and investment horizons, extending the traditional view that focuses on fundamental risk or information asymmetry (Dang et al., 2017). This broader perspective highlights the role of investor heterogeneity as a key determinant of asset prices, showing that market structure can influence prices and, ultimately, the final allocation, even in settings without fundamental risk or information asymmetry.

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Internet Appendix

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A Mathematical Results

A.1 Proofs

A.1.1 Proof of Proposition 1

Proof. We construct a linear symmetric equilibrium by conjecturing that demand is

$$q_{i1} = a - bp_1 - c\lambda_i$$

Market clearing requires

$$\int_i (a - bp_1 - c\lambda_i)di = a - bp_1 - c\lambda = Q_a$$

so that the equilibrium price reveals λ, so that $\mathbb{E}[\lambda|\lambda_i, p] = \lambda$. Agent i's objective is

$$-\max_{q_{i1}} \mathbb{E}_1 \left[\exp(-\gamma W_{i2})\right]$$

subject to the one-period budget constraint

$$W_{i2} = W_{i1} + (1 - p_1)q_{i1} - \lambda_i q_{i1} - \frac{\kappa}{2}q_{i1}^2$$

Given $\mathbb{E}[\lambda|\lambda_i, p] = \lambda$, the problem is rewritten as

$$\max_{q_{i1}} W_{i1} + (1 - p_1)q_{i1} - \lambda_i q_{i1} - \frac{\kappa}{2}q_{i1}^2$$

The first-order condition is

$$(1 - p_1) - \lambda_i - \kappa q_{i1} = 0 \Longrightarrow q_{i1} = a - bp_1 - c\lambda_i = \frac{1 - p_1 - \lambda_i}{\kappa}$$

Matching coefficients gives

$$c = \frac{1}{\kappa} \quad : \quad a = \frac{1}{\kappa} \quad : \quad b = \frac{1}{\kappa}$$

which verifies the initial conjecture. Market clearing requires

$$\frac{1 - p_1 - \int_i \lambda_i di}{\kappa} = \frac{1 - p_1 - \lambda}{\kappa} = Q_a \Longrightarrow p_1 = 1 - \lambda - \kappa Q_a$$

Plugging p_1^* into the demand function gives the desired result and completes the proof. ■

A.1.2 Proof of Lemma 1

Proof. From Proposition 1, the equilibrium in the secondary market is $p_1^* = 1 - \lambda - \kappa Q_a$ and $q_{j1}^* = \frac{\lambda}{\kappa} - \frac{\lambda_j}{\kappa} + Q_a$. Plugging these expressions into the dealer bank j's budget constraint gives

$$\begin{aligned} W_{j2} &= (p_1^* - p)q_j - \lambda_j q_j - \frac{\kappa}{2}q_j^2 + (1 - p_1^*)q_{j1}^* - \lambda_j q_{j1}^* - \frac{\kappa}{2}(q_{j1}^*)^2 \\ &= (1 - \lambda - \kappa Q_a - p)q_j - \lambda_j q_j - \frac{\kappa}{2}q_j^2 + \frac{\lambda^2}{2\kappa} + \frac{\lambda_j^2}{2\kappa} - \frac{\lambda\lambda_j}{\kappa} + Q_a(\lambda - \lambda_j) + \frac{\kappa}{2}Q_a^2 \\ &= (1 - \kappa Q_a - p)q_j - \lambda_j q_j - \frac{\kappa}{2}q_j^2 + \frac{\lambda_j^2}{2\kappa} - Q_a\lambda_j + \lambda\left(Q_a - q_j - \frac{\lambda_j}{\kappa}\right) + \frac{\lambda^2}{2\kappa} + \frac{\kappa}{2}Q_a^2 \end{aligned}$$

Let

$$\begin{aligned} \pi_0(q_j) &\doteq (1 - \kappa Q_a - \lambda_j)q_j - \frac{\kappa}{2}q_j^2 \\ \pi_1(q_j) &\doteq \left(Q_a - q_j - \lambda_j\kappa^{-1}\right) \end{aligned}$$

so that

$$W_{j2} = \frac{\lambda_j^2}{2\kappa} - Q_a\lambda_j + \frac{\kappa}{2}Q_a^2 + \pi_0(q_j) + \pi_1(q_j)\lambda + \frac{\lambda^2}{2\kappa} - pq_j$$

is a quadratic function of λ. As a result, the objective is rewritten as

$$-\mathbb{E}_0^D\left[-e^{-\gamma W_{i2}}|p,\lambda_j\right] = -\mathbb{E}_0^D\left[-e^{-\gamma\left(\pi_0(q_j)+\pi_1(q_j)\lambda+\frac{\lambda^2}{2\kappa}-pq_j\right)}\middle|p,\lambda_j\right]e^{-\gamma\left(\frac{\lambda_j^2}{2\kappa}-Q_a\lambda_j+\frac{\kappa}{2}Q_a^2\right)}$$

Further, let $\mu_\lambda = \mathbb{E}_0^D[\lambda|\lambda_j,p]$ and $\Sigma_\lambda = \mathbb{V}\mathrm{ar}_0^D[\lambda|\lambda_j,p]$ denote dealer bank j's subjective posterior mean and variance of λ. We can rewrite λ as $\lambda = \mu_\lambda + \eta$, where $\eta \sim \mathcal{N}(0,\Sigma_\lambda)$ so that

$$W_{j2} = \frac{\lambda_j^2}{2\kappa} - Q_a\lambda_j + \frac{\kappa}{2}Q_a^2 + \frac{\mu_\lambda^2}{2\kappa} + \pi_0(q_j) + \mu_\lambda\pi_1(q_j) + \eta\left(\pi_1(q_j)+\mu_\lambda\kappa^{-1}\right) + \eta^2\frac{1}{2\kappa} - pq_j$$

where the term $\frac{\lambda_j^2}{2\kappa} - Q_a\lambda_j + \frac{\kappa}{2}Q_a^2 + \frac{\mu_\lambda^2}{2\kappa}$ does not depend on q_j and only enters as multiplicative constants. The objective is an expectation of a quadratic form of normal variables, so that

$$\mathbb{E}_0^D\left[-e^{-\gamma W_{i2}}|p,\lambda_j\right] = \frac{1}{\sqrt{\det\Sigma_\lambda\det\left(\Sigma_\lambda^{-1}+\gamma\kappa^{-1}\right)}}e^{-\gamma\pi_0(q_j)-\gamma pq_j+\frac{\gamma^2}{2}\frac{\left(\pi_1(q_j)+\mu_\lambda\kappa^{-1}\right)^2}{\Sigma_\lambda^{-1}+\gamma\kappa^{-1}}}e^{-\gamma\left(\frac{\lambda_j^2}{2\kappa}-Q_a\lambda_j+\frac{\kappa}{2}Q_a^2+\frac{\mu_\lambda^2}{2\kappa}\right)}$$

It follows that dealer banks' problem is equivalent to

$$\max_{q_j}\pi_0(q_j) + \mu_\lambda\pi_1(q_j) - \frac{\hat{\gamma}}{2}\left(\pi_1(q_j)+\mu_\lambda\kappa^{-1}\right)^2 - pq_j$$

where we define dealer banks' effective risk aversion as

$$\hat{\gamma} \doteq \frac{\gamma}{\Sigma_\lambda^{-1}+\gamma\kappa^{-1}}$$

In the final step of the proof, we characterize the posterior distribution of λ conditional on the auction price p and λ_j. The price p is informationally equivalent to the total signal $h_{j,D}$. Hence, the joint distribution of the signals and the parameter λ is normal and given by

$$\theta_j \doteq \begin{pmatrix} \lambda \\ \lambda_j \\ h_{j,D} \end{pmatrix} \sim \mathcal{N}\left(\mathbb{E}_0^D[\theta_j], \mathbb{V}\mathrm{ar}_0^D(\theta_j)\right)$$

The mean and the covariance matrix of the signals are given by

$$\mathbb{E}_0^D[\theta_j] = \begin{pmatrix} \bar{\lambda} \\ \bar{\lambda} \\ \bar{\lambda}\bar{c} \end{pmatrix} \quad : \quad \mathbb{V}\mathrm{ar}_0^D(\theta_j) = \begin{pmatrix} \sigma_\lambda^2 & \sigma_\lambda^2 & \bar{c}\sigma_\lambda^2 \\ \sigma_\lambda^2 & \sigma_\lambda^2 + \sigma_\varepsilon^2 & \bar{c}\sigma_\lambda^2 \\ \bar{c}\sigma_\lambda^2 & \bar{c}\sigma_\lambda^2 & \bar{c}^2\sigma_\lambda^2 + \sigma_\varepsilon^2[c_D^2(n-1) + c_M^2 m] \end{pmatrix}$$

where we define

$$\bar{c} \doteq [(n-1)c_D + mc_L]$$

The projection theorem implies

$$\mu_\lambda \doteq \mathbb{E}_0^D[\lambda | h_{j,D}, \lambda_j] = \mu_\lambda + \Sigma_{\lambda s}\Sigma_{ss}^{-1}(s - \mu_s)$$

where s is short-hand notation for the second and third element of θ_j, that is λ_j and $h_{j,D}$. Some algebra yields

$$\mu_\lambda = \bar{\lambda} + \frac{1}{\bar{c}^2\sigma_\lambda^2 + [c_D^2(n-1) + c_L^2 m]\left(\sigma_\varepsilon^2 + \sigma_\lambda^2\right)} \begin{pmatrix} \sigma_\lambda^2\left[c_D^2(n-1) + c_L^2 m\right] & \bar{c}\sigma_\lambda^2 \end{pmatrix} \begin{pmatrix} \lambda_j - \bar{\lambda} \\ h_{j,D} - \bar{\lambda}\bar{c} \end{pmatrix}$$

Using the definition $h_{j,D} = nb_D - na_D p + mb_L - ma_L p - c_D\lambda_j - Q_a$ gives

$$\begin{aligned} \mu_\lambda = \bar{\lambda}&\frac{\sigma_\varepsilon^2[c_D^2(n-1) + c_L^2 m]}{\bar{c}^2\sigma_\lambda^2 + [c_D^2(n-1) + c_L^2 m]\left(\sigma_\varepsilon^2 + \sigma_\lambda^2\right)} + \lambda_j \frac{m\sigma_\lambda^2 c_L(c_L - c_D)}{\bar{c}^2\sigma_\lambda^2 + [c_D^2(n-1) + c_L^2 m]\left(\sigma_\varepsilon^2 + \sigma_\lambda^2\right)} \\ &- \frac{\bar{c}\sigma_\lambda^2[na_D + ma_L]}{\bar{c}^2\sigma_\lambda^2 + [c_D^2(n-1) + c_L^2 m]\left(\sigma_\varepsilon^2 + \sigma_\lambda^2\right)} p + \frac{\bar{c}\sigma_\lambda^2(nb_D + mb_L - Q_a)}{\bar{c}^2\sigma_\lambda^2 + [c_D^2(n-1) + c_L^2 m]\left(\sigma_\varepsilon^2 + \sigma_\lambda^2\right)} \\ = &\ \bar{\lambda}\bar{\mu}_\lambda + \lambda_j\mu_\lambda^\lambda + \mu_\lambda^p p \end{aligned}$$

where

$$\bar{\mu}_\lambda \doteq \frac{\bar{\lambda}\sigma_\varepsilon^2[c_D^2(n-1)+c_L^2 m]}{\bar{c}^2\sigma_\lambda^2+[c_D^2(n-1)+c_L^2 m]\,(\sigma_\varepsilon^2+\sigma_\lambda^2)}+\frac{\bar{c}\sigma_\lambda^2(nb_D+mb_L-Q_a)}{\bar{c}^2\sigma_\lambda^2+[c_D^2(n-1)+c_L^2 m]\,(\sigma_\varepsilon^2+\sigma_\lambda^2)}$$

and μ_λ^λ and μ_λ^p are the posterior loadings on the private signal and the price. Finally, the posterior variance is

$$\Sigma_\lambda \doteq \mathbb{V}\mathrm{ar}_0^D\left(\lambda|\lambda_j,p\right)=\Sigma_{\lambda,\lambda}-\Sigma_{\lambda,s}\Sigma_{s,s}^{-1}\Sigma_{s\lambda}=\frac{[c_D^2(n-1)+c_L^2 m]\,\sigma_\varepsilon^2\sigma_\lambda^2}{\bar{c}^2\sigma_\lambda^2+[c_D^2(n-1)+c_L^2 m]\,(\sigma_\varepsilon^2+\sigma_\lambda^2)}$$

It immediately follows that, as the number of bidders grows large,

$$\lim_{n\to\infty}\Sigma_\lambda=0 \quad : \quad \lim_{m\to\infty}\Sigma_\lambda=0$$

which is the desired result and completes the proof. In the special case that $m=0$, that is the pure common value, μ_λ and Σ_λ simplify to

$$\mu_\lambda=\bar{\lambda}\frac{\sigma_\varepsilon^2}{n\sigma_\lambda^2+\sigma_\varepsilon^2}-\frac{\sigma_\lambda^2 na_D}{c_D[n\sigma_\lambda^2+\sigma_\varepsilon^2]}p+\frac{\sigma_\lambda^2(nb_D-Q_a)}{c_D[n\sigma_\lambda^2+\sigma_\varepsilon^2]}=\bar{\lambda}\tau_\varepsilon-\frac{na_D}{c_D}\tau_\lambda p+\tau_\lambda\frac{(nb_D-Q_A)}{c_D}$$

and

$$\Sigma_\lambda \doteq \mathbb{V}\mathrm{ar}_0^D\left(\lambda|\lambda_j,p\right)=\Sigma_{\lambda,\lambda}-\Sigma_{\lambda,s}\Sigma_{s,s}^{-1}\Sigma_{s\lambda}=\frac{\sigma_\varepsilon^2\sigma_\lambda^2}{\sigma_\varepsilon^2+n\sigma_\lambda^2}$$

■

A.1.3 Proof of Proposition 2

Proof. Taking other bidders' strategies as given, the dealer banks maximize the objective

$$\max_{q_j}\pi_0(q_j)+\mu_\lambda\pi_1(q_j)-\frac{\hat{\gamma}}{2}\left(\pi_1(q_j)+\mu_\lambda\kappa^{-1}\right)^2-pq_j$$

where $p = I_{j,D} + d_D q_j$ The first-order condition for q_j is

$$\pi_0'(q_j) + \mu_\lambda \pi_1'(q_j) - I_{j,D} - 2q_j d_D = \hat{\gamma}\left(\pi_1(q_j) + \mu_\lambda \kappa^{-1}\right)\pi_1'(q_j)$$

From Lemma 1, it follows that

$$\begin{aligned}\pi_0'(q_j) &= 1 - \kappa Q_a - \lambda_j - \kappa q_j \\ \pi_1'(q_j) &= -1\end{aligned}$$

As a result, the first-order condition is rewritten as

$$1 - \kappa Q_a - \lambda_j - \kappa q_j - \mu_\lambda - p - q_j d_D = \hat{\gamma}\left(q_j + \lambda_j \kappa^{-1} - \mu_\lambda \kappa^{-1} - Q_a\right)$$

where we substitute $I_{j,D} = p - d_D q_j$. Solving for q_j gives

$$b_D - a_D p - c_D \lambda_j = q_j = \frac{1 - p + (\hat{\gamma} - \kappa)Q_a - \lambda_j(1 + \hat{\gamma}\kappa^{-1}) + \mu_\lambda(\hat{\gamma}\kappa^{-1} - 1)}{\kappa + d_D + \hat{\gamma}}$$

Matching coefficients on p and λ_j gives

$$\begin{aligned}c_D &= (\kappa + \hat{\gamma} + d_D)^{-1}\left\{(1 + \hat{\gamma}\kappa^{-1}) - \mu_\lambda^\lambda(\hat{\gamma}\kappa^{-1} - 1)\right\} \\ a_D &= (\kappa + \hat{\gamma} + d_D)^{-1}\left\{1 - \mu_\lambda^p(\hat{\gamma}\kappa^{-1} - 1)\right\}\end{aligned}$$

which gives equations (6) and (7). The demand intercept b_D solves

$$b_D = (\kappa + \hat{\gamma} + d_D)^{-1}\left\{1 + (\hat{\gamma} - \kappa)Q_a + \bar{\mu}_\lambda(\hat{\gamma}\kappa^{-1} - 1)\right\}$$

Taking other bidders' strategies as given, long-term investor k maximizes

$$\max_{q_k} q_k(1 - p) - 2\lambda_k q_k - \kappa\left(q_k\right)^2$$

where $p = I_{k,L} + d_L q_k$. The first-order condition is

$$1 - I_{k,L} - 2q_k d_D - 2\lambda_k - 2\kappa q_k = 0$$

Using $I_{k,L} = p - d_L q_k$ and solving for q_k gives

$$b_L - a_L p - c_L \lambda_k = q_k = \frac{1 - p - 2\lambda_k}{d_L + 2\kappa}$$

Matching coefficients on p and λ_k gives

$$a_L = (d_L + 2\kappa)^{-1}$$
$$c_L = 2(d_L + 2\kappa)^{-1}$$

The demand intercepts b_L is

$$b_L = (d_L + 2\kappa)^{-1} = a_L$$

This is the desired result and it completes the proof. ■

A.1.4 Proof of Proposition 3

Proof. If $n = 0$, the slope of the inverse residual supply is $d_L = a_L^{-1}(m-1)^{-1}$. It follows that

$$a_L = (a_L^{-1}(n-1)^{-1} + 2\kappa)^{-1}$$

Solving for a_L gives

$$a_L^{\text{PV}} = \frac{m-2}{m-1}\frac{1}{2\kappa}$$

Since $c_L = 2a_L$, it immediately follows that $c_L^{\text{PV}} = \frac{m-2}{m-1}\frac{1}{\kappa}$, concluding the proof. As $m \to \infty$, the private value case approaches the competitive case. ■

A.1.5 Proof of Proposition 4

Proof. Setting $m = 0$, it immediately follows that $d_D = a_D^{-1}(n-1)^{-1}$ and that

$$\mu_\lambda^\lambda = 0$$

Therefore, the system of equations simplifies to

$$c_D = \frac{1 + \hat{\gamma}\kappa^{-1}}{\kappa + \hat{\gamma} + d_D}$$
$$a_D = \frac{1 + \frac{n a_D}{c_D}\tau_\lambda(\hat{\gamma}\kappa^{-1} - 1)}{\kappa + \hat{\gamma} + d_D}$$

where we substitute $\mu_\lambda^p = -\frac{n a_D}{c_D}\tau_\lambda$. Hence

$$a_D = (\kappa + \hat{\gamma} + d_D)^{-1}\left\{1 + n a_D \tau_\lambda(\kappa + \hat{\gamma} + d_D)\frac{\hat{\gamma} - \kappa}{\hat{\gamma} + \kappa}\right\}$$

Rearranging and using the definition of d_D gives

$$\frac{a_D(n-1)(\kappa + \hat{\gamma}) + 1}{n-1} = \left[1 - n\tau_\lambda\frac{\hat{\gamma} - \kappa}{\hat{\gamma} + \kappa}\right]^{-1}$$

Solving for a gives

$$a_D = \left\{(n-1)\left[1 - n\tau_\lambda\frac{\hat{\gamma} - \kappa}{\hat{\gamma} + \kappa}\right]^{-1} - 1\right\}\frac{1}{(n-1)(\kappa + \hat{\gamma})} = \frac{(n-2)(\hat{\gamma} + \kappa) + n\tau_\lambda(\hat{\gamma} - \kappa)}{(n-1)(\hat{\gamma} + \kappa)\left[(\hat{\gamma} + \kappa) - n\tau_\lambda(\hat{\gamma} - \kappa)\right]}$$

Finally, c_D is given by

$$c_D = \frac{\hat{\gamma}\kappa^{-1} + 1}{\kappa + \hat{\gamma} + (n-1)^{-1}a_D^{-1}}\frac{\hat{\gamma}\kappa^{-1} + 1}{\kappa + \hat{\gamma} + \frac{(\hat{\gamma}+\kappa)[(\hat{\gamma}+\kappa) - n\tau_\lambda(\hat{\gamma}-\kappa)]}{(n-2)(\hat{\gamma}+\kappa) + n\tau_\lambda(\hat{\gamma}-\kappa)}} = \frac{(n-2)(\hat{\gamma} + \kappa) + n\tau_\lambda(\hat{\gamma} - \kappa)}{(n-1)(\hat{\gamma} + \kappa)\kappa}$$

In summary

$$a_D^{\text{CV}} = \frac{(n-2)(\hat{\gamma} + \kappa) + n\tau_\lambda(\hat{\gamma} - \kappa)}{(n-1)(\hat{\gamma} + \kappa)\left[(\hat{\gamma} + \kappa) - n\tau_\lambda(\hat{\gamma} - \kappa)\right]}$$

$$c_D^{\text{CV}} = \frac{(n-2)(\hat{\gamma}+\kappa) + n\tau_\lambda(\hat{\gamma}-\kappa)}{(n-1)(\hat{\gamma}+\kappa)\kappa}$$

which is the desired result and completes the proof. ■

A.1.6 Proof of Proposition 5

Proof. Downward sloping demand schedules, that is $a_D > 0$ and $a_L > 0$, require that $c_L \in \mathcal{C}_L \doteq \left(\frac{1}{\kappa}\frac{m-2}{m-1}, \frac{1}{\kappa}\right)$. Further, $c_D > 0$. To see why, suppose instead that $c_D \leqslant 0$. Given $a_D > 0$ and $a_L > 0$, it follows that $\kappa + \hat{\gamma}(\boldsymbol{c}) + d_D(\boldsymbol{c}) > 0$. Hence, $c_D = f_2(\boldsymbol{c}) \leqslant 0$ is negative only if

$$\mu_\lambda^\lambda(\boldsymbol{c})(\hat{\gamma}(\boldsymbol{c})\kappa^{-1} - 1) \geqslant \hat{\gamma}(\boldsymbol{c})\kappa^{-1} + 1 \iff \mu_\lambda^\lambda(\boldsymbol{c}) \leqslant \frac{\hat{\gamma}(\boldsymbol{c})\kappa^{-1}+1}{\hat{\gamma}(\boldsymbol{c})\kappa^{-1}-1} = -\left(\frac{2\gamma\Sigma_\lambda(\boldsymbol{c})}{\kappa} + 1\right) \leqslant -1$$

Substituting the definition of $\mu_\lambda^\lambda(\boldsymbol{c})$ and rearranging, $\mu_\lambda^\lambda(\boldsymbol{c}) \leqslant -1$ implies that

$$m\sigma_\lambda^2 c_L c_D \geqslant [(n-1)c_D + mc_L]^2\sigma_\lambda^2 + \left[c_D^2(n-1) + c_L^2 m\right](\sigma_\varepsilon^2 + \sigma_\lambda^2) + m\sigma_\lambda^2 c_L^2$$

All terms on the right-hand side are strictly positive, so the inequality cannot hold for $c_D \leqslant 0$. Further, since $n > 1$, there is no $\boldsymbol{c} \in \mathbb{R}^2$ such that $\mu_\lambda^\lambda(\boldsymbol{c}) \leqslant -1$. Hence $f_2(\boldsymbol{c}) > 0$ for all $\boldsymbol{c} \in \mathbb{R}^2$.

I next derive bounds for $c_D = f_2(\boldsymbol{c})$. First, $f_2(\boldsymbol{c}) > 0$ for all $\boldsymbol{c} \in \mathbb{R}^2$, so that $m_D = 0$ is a lower bound. Given that $f_2(c_L, c_D)$ is continuous in c_D, $f_2(c_L, 0) > 0$ and since $\lim_{c_D\to\infty} f_2(c_L, c_D) < \infty$ is finite for all $c_L \in \mathcal{C}_L$, the intermediate value theorem implies that there is $\overline{c}_D(c_L) < \infty$ such that $\overline{c}_D(c_L) = f_2(c_L, \overline{c}_D(c_L))$ for all $c_L \in \mathcal{C}_L$. Hence, there is an upper bound $M_D < \infty$ such that $f(c_L, c_D) \leqslant M_D$. Thus, the set $\mathcal{F}_D = [0, M_D]$ satisfies $0 < f_2(\boldsymbol{c}) \leqslant M_D$ for all $\boldsymbol{c} \in \mathcal{C}_L \times \mathcal{F}_D$.

Second, consider $f_1(\boldsymbol{c})$, $c_D \in \mathcal{F}_D$ and $c_L \in \mathcal{C}_L = \left(\frac{1}{\kappa}\frac{m-2}{m-1}, \frac{1}{\kappa}\right)$. The function $f_1(\boldsymbol{c})$ is continuous over $\mathcal{C}_L \times \mathcal{F}_D$. As c_L approaches the left endpoint $\frac{1}{\kappa}\frac{m-2}{m-1}$, $f_1(\boldsymbol{c}) \to \infty$ for all

$c_D \in \mathcal{F}_D$. The limit of $f_1(\boldsymbol{c})$ as c_L approaches the right endpoint $\frac{1}{\kappa}$ is

$$\lim_{c_L \to \frac{1}{\kappa}} f_1(c_L, c_D) = \frac{n \cdot \sigma_\lambda^2((n-1)c_D + m\kappa^{-1}) \cdot (\hat{\gamma}(\kappa^{-1}, c_D)\kappa^{-1} - 1)}{(\kappa + \hat{\gamma}(\kappa^{-1}, c_D))\left[((n-1)c_D + m\kappa^{-1})^2\sigma_\lambda^2 + (c_D^2(n-1) + m\kappa^{-2})\left(\sigma_\varepsilon^2 + \sigma_\lambda^2\right)\right]} \cdot \frac{1}{\kappa}$$

which is finite. The denominator is strictly positive, whereas the numerator is strictly negative given that $(\hat{\gamma}(\kappa^{-1}, c_D)\kappa^{-1} - 1) < 0$. Hence $\lim_{c_L \to \frac{1}{\kappa}} f_1(c_L, c_D) < 0$. By the intermediate value theorem, there exists c_L^* for each $c_D \in \mathcal{F}_D$ with the property that $c_L^* = f_1(c_L^*, c_D)$ such that $c_L^* \in \mathcal{C}_L$. Define the function $g(c_L^*, c_D) \doteq f_1(c_L^*, c_D) - c_L^*$, and note that $g(c_L^*, c_D) = 0$. By the implicit function theorem, there exists a continuously differentiable function $c_L^* = h(c_D)$ in an open set $U \subset \mathbb{R}$, $c_D \in U$. Because the conditions for the implicit function theorem are satisfied for all $c_D \in \mathcal{F}_D$, h is continuous over $\mathcal{F}_D$.

Substituting $c_L^* = h(c_D)$ into $f_2(\boldsymbol{c})$ gives

$$c_D = f_2(h(c_D), c_D) = \frac{\hat{\gamma}(h(c_D), c_D)\kappa^{-1} + 1 - \mu_\lambda^\lambda(h(c_D), c_D)(\hat{\gamma}(h(c_D), c_D)\kappa^{-1} - 1)}{\kappa + \hat{\gamma}(h(c_D), c_D) + d_D(h(c_D), c_D)}$$

The range of $h(c_D)$ is $\mathcal{C}_L$, so that $f_2(h(c_D), c_D)$ is continuous and maps the compact and convex set $\mathcal{F}_D$ into itself. Brouwer's fixed point theorem applies, and there exists a fixed point $\boldsymbol{c}^* = (c_L^*, c_D^*)$, $f(\boldsymbol{c}^*) = \boldsymbol{c}^*$, such that $a_D > 0$ and $a_L > 0$. Both (c_L^*, c_D^*) are strictly positive. ■

A.1.7 Proof of Proposition 6

Proof. By way of contradiction, suppose that there is a symmetric equilibrium with $a = a_D = a_L$ and $c = c_D = c_L$. The number of bidders is $N = m + n$. It follows that $\mu_\lambda(\lambda_j) = 0$ and that

$$\mu_\lambda(p) = -\frac{Na\sigma_\lambda^2}{c\left[N\sigma_\lambda^2 + \sigma_\varepsilon^2\right]} = -\frac{Na}{c}\tau_\lambda$$

Since the slope is $d_D = d_A = d = (N-1)^{-1}a^{-1}$, it immediately follows that

$$\begin{aligned} a &= \left(\kappa + \hat{\gamma} + (N-1)^{-1}a^{-1}\right)^{-1}\left\{1 + \frac{Na}{c}\tau_\lambda(\hat{\gamma}\kappa^{-1} - 1)\right\} \\ c &= \left(\kappa + \hat{\gamma} + (N-1)^{-1}a^{-1}\right)^{-1}(\hat{\gamma}\kappa^{-1} + 1) \\ a &= ((N-1)^{-1}a^{-1} + 2\kappa)^{-1} \\ c &= 2((N-1)^{-1}a^{-1} + 2\kappa)^{-1} \end{aligned}$$

The third and the fourth line imply that $a = 2c$. However, it must then be the case that

$$1 + 2N\tau_\lambda(\hat{\gamma}\kappa^{-1} - 1) = 2\left(\hat{\gamma}\kappa^{-1} + 1\right)$$

Rearranging, we see that

$$(N\tau_\lambda - 1)2\frac{\hat{\gamma}}{\kappa} - 1 - 2N\tau_\lambda = 0$$

However, since $N\tau_\lambda - 1 = -\tau_\varepsilon < 0$, $\hat{\gamma} > 0$, $\kappa > 0$ and $N > 0$, all terms on the right hand side are negative. It follows that the equation cannot hold, which is a contradiction. ∎

A.1.8 Proof of Proposition 7

Proof. Consider the interval $c_L \in \left(\frac{1}{\kappa}\frac{m-2}{m-1}, \frac{1}{\kappa}\right)$ in which demand schedules are downward sloping for both types. Differentiating a_D with respect to c_L gives

$$\frac{\partial a_D}{\partial c_L} = \frac{1}{2n}\frac{1-(m-1)(1-\kappa c_L)^2}{(1-\kappa c_L)^2}\frac{\partial a_D}{\partial c_L} = \frac{1}{2}\cdot\frac{1}{n}\left\{\frac{1}{(1-\kappa c_L)^2} - (m-1)\right\}$$

Since $\frac{\partial a_L}{\partial c_L} = \frac{1}{2}$, it is sufficient to show that

$$\frac{1}{n}\left\{\frac{1}{(1-\kappa c_L)^2} - (m-1)\right\} > 1$$

Define the function $f(x)$

$$f(x) \doteq \frac{1}{n}\left\{\frac{1}{(1-\kappa x)^2} - (m-1)\right\}$$

in the interval $x \in \mathcal{X} \doteq \left[\frac{1}{\kappa}\frac{m-2}{m-1}, \frac{1}{\kappa}\right)$. First, note that $f'(x) > 0$ for $x \in \mathcal{X}$. Since $x > 0$ and $n > 0$

$$f'(x) = \frac{1}{n}\frac{2\kappa}{(1-\kappa x)^3} \quad \longrightarrow \quad f'(x) > 0 \quad \text{if} \quad x < \frac{1}{\kappa}$$

Hence, $f(x)$ is minimal for $x_0 = \frac{1}{\kappa}\frac{m-2}{m-1}$. Dealer banks are more sensitive if $f(x_0) > 1$, or

$$f(x_0) = \frac{1}{n}(m-1)(m-2) > 1 \iff (m-1)(m-2) > n$$

which completes the proof. ■

A.2 Theory Supplements

Normal Random Variables and CARA Utility

Let

$$\mu = \begin{bmatrix} \mu_\theta \\ \mu_s \end{bmatrix} \quad : \quad \Sigma = \begin{bmatrix} \Sigma_{\theta,\theta} & \Sigma_{\theta,s} \\ \Sigma_{s,\theta} & \Sigma_{s,s} \end{bmatrix}$$

The conditional density of θ given s is normal with conditional mean

$$\mathbb{E}[\theta|s] = \mu_\theta + \Sigma_{\theta,s}\Sigma_{s,s}^{-1}(s - \mu_s)$$

and variance-covariance matrix

$$\mathbb{V}\text{ar}(\theta|s) = \Sigma_{\theta,\theta} - \Sigma_{\theta,s}\Sigma_{s,s}^{-1}\Sigma_{s,\theta}$$

In a two-dimensional case, since $\mu_s = \bar{\theta}$, the conditional expectation can be written as

$$\mathbb{E}[\theta|s] = \frac{\mathbb{C}\text{ov}(\theta,s)}{\mathbb{V}\text{ar}(s)}s + \left(1 - \frac{\mathbb{C}\text{ov}(\theta,s)}{\mathbb{V}\text{ar}(s)}\right)\bar{\theta} = \xi s + (1-\xi)\bar{\theta}$$

which is the standard Bayesian updating rule with normal priors and normal likelihood. The expression can be generalized to accommodate for common and private values.

Another useful result is the expectation of a quadratic form of normal random variables. Let $\omega = c + b'z + z'Az$ and $z \sim \mathcal{N}(0, \Sigma)$. Then

$$-\mathbb{E}[e^{-\rho\omega}] = (\det\Sigma)^{-\frac{1}{2}}\left(\det\left(\Sigma^{-1} + 2\rho A\right)\right)^{-\frac{1}{2}} e^{-\rho\left[c - \frac{1}{2}\rho b'\left(\Sigma^{-1}+2\rho A\right)^{-1}b\right]}$$

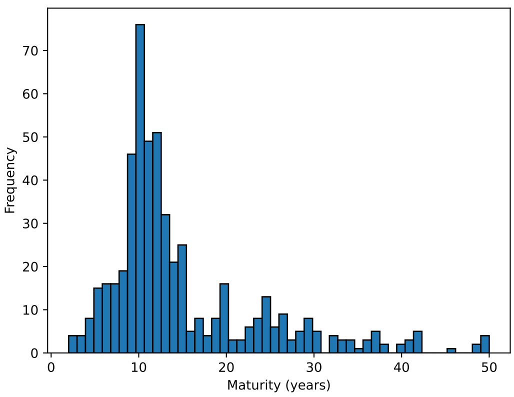
A proof can be found in Danthine and Moresi (1993).

B Additional Results

B.1 Sample Description

Bond Maturity and Issue Size over Time

(a) Histogram of bond maturities.



(b) Bond emissions over time.

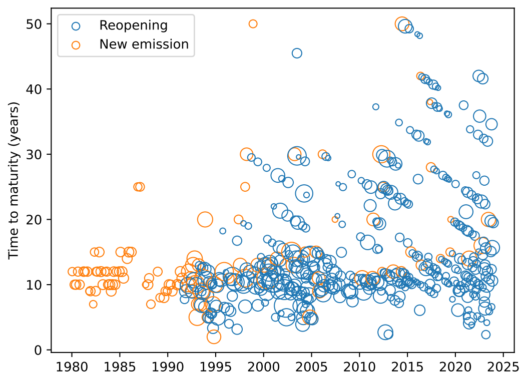


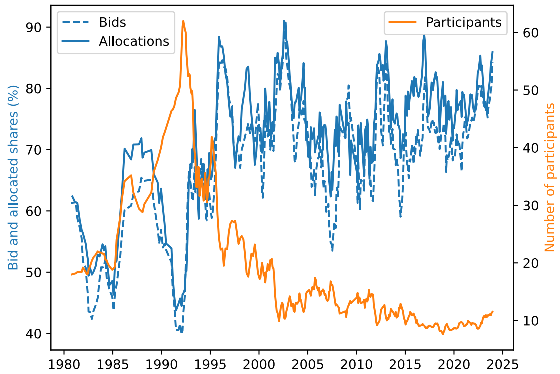
Figure 6: The left panel plots a histogram of bond maturities. The right panel plots bond issuance over time, separating new issues (orange circles) from reopenings (blue circles). Marker size is proportional to the issue size. The sample covers 530 auctions from 1980 to present.

The left panel of Figure 6 plots the distribution of bond maturities. Nearly half of the 530 auctions involve medium-term bonds with a maturity between 10 and 20 years. However, our sample also includes a considerable number of issues of bonds with maturities exceeding 30 years. Auctions with fractional maturities typically correspond to security reopenings.

The scatter plot in the right panel of Figure 6 plots issue size and maturity for new emissions and security reopenings over time. The market size is proportional to the issue size. Most auctions after 2000 are reopenings of existing CUSIPs, with identical coupon rate and maturity date. During this period, the Treasury relied on reopenings to manage liquidity in the secondary market. new bond issues became less frequent, larger in size, and have longer maturities. Until 1990, the Swiss government only issued two bonds with maturity longer than 20 years. In contrast, after 1995, the maturity of newly issued securities regularly exceeds 25 years.

Market Concentration and Competitive Bidding

(a) Market concentration



(b) Non-competitive bids and own tranches.

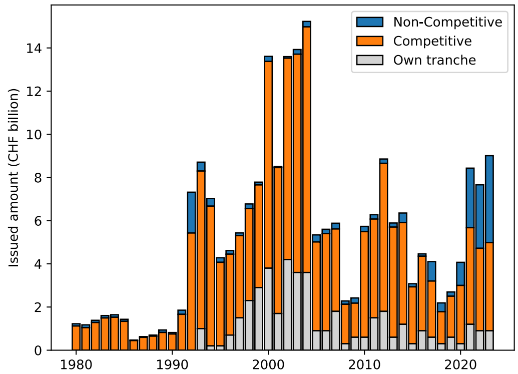


Figure 7: Market concentration and issuance composition. The left panel shows the time series of market concentration (left axis) and the number of bidders (right axis). Market concentration is the share of total bid volume or issuance absorbed by the top three bidders. The right panel breaks down issuances by competitive bids, non-competitive bids, and own tranches. The sample is from 1980 to present.

B.2 Determinants of demand heterogeneity

Correlation between demand elasticity and auxiliary variables

	Log demand elasticity					
	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}
$\sigma_{j-21,j}$	-1.78^{***}					-0.92^{***}
	(0.13)					(0.16)
$\sigma_{b,j}$		-0.31				-0.08
		(0.52)				(0.42)
RBAS$_j$			-0.68^{***}			-0.30^{***}
			(0.04)			(0.07)
Maturity				-0.05^{***}		-0.01
				(0.00)		(0.01)
Participants					0.07^{***}	0.03^{***}
					(0.01)	(0.01)
Constant	5.88^{***}	5.15^{***}	5.59^{***}	5.93^{***}	4.19^{***}	5.52^{***}
	(0.06)	(0.04)	(0.04)	(0.06)	(0.09)	(0.12)
Adj. R^2	0.22	-0.00	0.22	0.20	0.09	0.28
N	993	1087	1087	1188	1188	993

Table 8: Determinants of demand elasticity. TE is the total elasticity of demand using all bids. $\sigma_{j-21,j}$ denotes the volatility of the bond in the month prior to the auction. RBAS$_j$ is the relative bid-ask spread at the auction date. Maturity refers to time to maturity at the auction date. Participants is the number of bidders. Log issue size is the logarithm of supply. The sample is from 2000 to present. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

Alternative measures of demand elasticity

	Log demand elasticity		
	TE β_{ij}	IE β_{ij}	WE β_{ij}
$\sigma_{j-21,j}$	-0.48^{**}	-0.78^{***}	-0.50^{*}
	(0.19)	(0.19)	(0.29)
$\sigma_{j-21,j} \times \mathbb{1}\{\text{DB}\}_i$	-0.56^{***}	-0.35^{***}	-0.53^{***}
	(0.12)	(0.12)	(0.19)
Maturity	-0.03^{***}	-0.03^{***}	-0.03^{***}
	(0.01)	(0.01)	(0.01)
Participants	0.02^{**}	0.00	0.03^{*}
	(0.01)	(0.01)	(0.01)
Constant	5.61^{***}	5.93^{***}	5.74^{***}
	(0.14)	(0.13)	(0.22)
Macro	✓	✓	✓
Adj. R^2	0.30	0.38	0.21
N	993	993	660

Table 9: Coefficient estimates of regression (10). $\sigma_{j-21,j}$ denotes the volatility of the bond in the month prior to the auction, whereas $\mathbb{1}\{\text{DB}\}$ is a binary variable equal to one if bidder i is a dealer bank. Maturity refers to time to maturity at the auction date. Participants is the number of bidders. Log issue size is the logarithm of supply. Macro controls include inflation, the short term rate (SARON), the slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to present and only considers security reopenings. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively. We include alternative measures of the steepness of demand curves. TE is the total elasticity of demand using all bids. IE is the demand elasticity obtained by dropping the highest and the lower bids. WE is the demand elasticity computed using winning bids.

Robustness checks: dropping auctions around EURCHF floor removal

	Log demand elasticity		
	TE β_{ij}	TE β_{ij}	TE β_{ij}
$\sigma_{j-21,j}$	-1.58^{***}	-1.24^{***}	-0.55^{***}
	(0.15)	(0.16)	(0.20)
$\sigma_{j-21,j} \times \mathbb{1}\{\text{DB}\}_i$		-0.60^{***}	-0.58^{***}
		(0.13)	(0.13)
Maturity			-0.02^{***}
			(0.01)
Participants			0.02^{**}
			(0.01)
Constant	5.59^{***}	5.63^{***}	5.59^{***}
	(0.09)	(0.08)	(0.14)
Macro	✓	✓	✓
R-squared Adj.	0.25	0.27	0.29
N	975	975	975

Table 10: Coefficient estimates of regression (10). The dependent variable is the total elasticity (TE) of demand (in logs) at the bidder level. $\sigma_{j-21,j}$ denotes the volatility of the bond in the month prior to the auction, whereas $\mathbb{1}\{\text{DB}\}$ is an indicator equal to one if bidder i is a dealer bank. Maturity refers to time to maturity at the auction date. Participants is the number of bidders. Macro controls include inflation, the short term rate (SARON), the slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to present and only considers security reopenings. We drop auctions around the EURCHF cap removal on January 15, 2015. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

Robustness checks: dropping auctions around the Covid-19 shock.

	Log demand elasticity		
	TE β_{ij}	TE β_{ij}	TE β_{ij}
$\sigma_{j-21,j}$	-1.61^{***}	-1.26^{***}	-0.53^{***}
	(0.16)	(0.16)	(0.20)
$\sigma_{j-21,j} \times \mathbb{1}\{\text{DB}\}_i$		-0.59^{***}	-0.59^{***}
		(0.13)	(0.13)
Maturity			-0.03^{***}
			(0.01)
Participants			0.02^{**}
			(0.01)
Constant	5.58^{***}	5.61^{***}	5.61^{***}
	(0.10)	(0.09)	(0.15)
Macro	✓	✓	✓
Adj. R^2	0.26	0.28	0.30
N	959	959	959

Table 11: Coefficient estimates of regression (10). The dependent variable is the total elasticity (TE) of demand (in logs) at the bidder level. $\sigma_{j-21,j}$ denotes the volatility of the bond in the month prior to the auction, whereas $\mathbb{1}\{\text{DB}\}$ is an indicator equal to one if bidder i is a dealer bank. Maturity refers to time to maturity at the auction date. Participants is the number of bidders. Macro controls include inflation, the short term rate (SARON), the slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to present and only considers security reopenings. We drop auctions between March 2020 and September 2020. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

Alternative measures of bid dispersion

	Log demand elasticity			
	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}
$\sigma_{b,j}$	0.55			
	(0.38)			
$\sigma_{b,j} \times \mathbb{1}\{\text{DB}\}_i$	-1.85^{**}			
	(0.84)			
$\hat{\sigma}_{b,j}$		0.60^{*}		
		(0.36)		
$\hat{\sigma}_{b,j} \times \mathbb{1}\{\text{DB}\}_i$		-1.68^{**}		
		(0.72)		
$\bar{\sigma}_{b,j}$			-0.53	
			(1.90)	
$\bar{\sigma}_{b,j} \times \mathbb{1}\{\text{DB}\}_i$			-6.83^{***}	
			(1.52)	
$\tilde{\sigma}_{b,j}$				0.34
				(1.96)
$\tilde{\sigma}_{b,j} \times \mathbb{1}\{\text{DB}\}_i$				-7.02^{***}
				(1.60)
Constant	5.60^{***}	5.59^{***}	5.72^{***}	5.69^{***}
	(0.14)	(0.14)	(0.14)	(0.14)
Controls	✓	✓	✓	✓
Macro	✓	✓	✓	✓
Adj. R^2	0.30	0.30	0.31	0.31
N	993	993	993	993
p-sum	0.07	0.07	0.00	0.00

Table 12: Estimates of regression (10) using alternative proxies of cross-sectional cost dispersion. First, $\sigma_{b,j}$ is the standard deviation of quantity-weighted bid yields. Second, $\hat{\sigma}_{b,j}$ is the standard deviation of equally-weighted bid yields. Third, $\bar{\sigma}_{b,j}$ is the interquartile range of quantity-weighted bid yields. Fourth, $\tilde{\sigma}_{b,j}$ is the interquartile range of quantity-weighted bid yields. Controls include maturity, number of bidders, quantity-weighted yield spread, return volatility in the previous month, and the relative bid-ask spread. Macro controls include inflation, the short-term rate (SARON), the slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to present and only considers security reopenings. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.p-sum is the p-value from testing the null hypothesis that $b_1 + b_2 \geq 0$.

Cost dispersion as volatility of residuals

For each auction j, given price-quantity pairs $(B_{ijk}, \mathcal{Q}_{ijk})$ for bidder i, we estimate

$$q_{ijk} = \delta_0 + \mathbb{1}\{\text{DB}\}_i + \delta_1 b_{ijk} + \delta_2 \mathbb{1}\{\text{DB}\}_i \times b_{ijk} + \gamma_i + \varepsilon_{ijk} \tag{15}$$

where γ_i is a set of bidder fixed effects and $\mathbb{1}\{\text{DB}\}_i$ is an indicator equal to one if bidder i is a dealer bank. Again, we add non-competitive bid quantities to $\mathcal{Q}^{nc}_{ijk}$ to each bid step. The proxy for σ_ε is the standard deviation of the regression residuals $\hat{\sigma}_{\varepsilon,j} = \sqrt{\mathbb{V}\text{ar}(\varepsilon_{ijk})}$.

	Log demand elasticity			
	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}
$\hat{\sigma}_{\varepsilon,j}$	-0.02	0.03	0.04*	0.03
	(0.02)	(0.03)	(0.03)	(0.03)
$\hat{\sigma}_{\varepsilon,j} \times \mathbb{1}\{\text{DB}\}_i$		-0.08***	-0.08***	-0.07**
		(0.03)	(0.03)	(0.03)
Maturity			-0.05***	-0.02**
			(0.00)	(0.01)
Participants			0.01	0.02**
			(0.01)	(0.01)
$\sigma_{j-21,j}$				-0.70***
				(0.20)
RBAS_j				-0.24**
				(0.09)
Constant	4.84***	4.84***	5.65***	5.60***
	(0.06)	(0.06)	(0.14)	(0.15)
Adj. R^2	0.11	0.11	0.27	0.28
N	1152	1152	1152	963
p-sum		0.04	0.07	0.05

Table 13: Coefficient estimates of regression (10). The dependent variable is the total elasticity (TE) of demand (in logs) at the bidder level. $\hat{\sigma}_{\varepsilon,j}$ is the standard deviation of regression (15) whereas $\mathbb{1}\{\text{DB}\}_i$ is a binary variable equal to one if bidder i is a dealer bank, and zero otherwise. Maturity refers to time to maturity at the auction date. Participants is the number of bidders. $\sigma_{j-21,j}$ denotes the volatility of the bond in the month prior to the auction. RBAS_j is the relative bid-ask spread at the auction date. Macro controls include inflation, the short-term rate (SARON), the slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to present and only considers security reopenings. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively. p-sum is the p-value from testing the null hypothesis that $b_1 + b_2 \geq 0$.

B.3 Difference in Differences (DiD) Design

Robustness checks: three-year window

	Log elasticity		Yield discount	
	TE β_{ij}	TE β_{ij}	Discount_{ij}	Discount_{ij}
$\mathbb{1}\{\text{Basel III}\}_j$	-0.11	0.01	0.01	0.01
	(0.16)	(0.13)	(0.02)	(0.02)
$\mathbb{1}\{\text{DB}\}_i$	-0.22	-0.28^{**}	0.00	-0.00
	(0.14)	(0.11)	(0.02)	(0.02)
$\mathbb{1}\{\text{Basel III}\}_j \times \mathbb{1}\{\text{DB}\}_i$	-0.71^{***}	-0.50^{**}	-0.04^{*}	-0.04^{*}
	(0.24)	(0.20)	(0.02)	(0.02)
Maturity		-0.05^{***}		-0.00
		(0.01)		(0.00)
Participants		-0.02		-0.00
		(0.03)		(0.00)
Constant	5.37^{***}	6.52^{***}	0.02	0.06
	(0.10)	(0.35)	(0.02)	(0.04)
Adj. R^2	0.12	0.36	0.00	0.00
N	350	350	881	881

Table 14: Coefficient estimates of the difference in differences specification (11). In the first and second column, the dependent variable is the total elasticity of demand (in logs). In the third and in the fourth column, the dependent variable is the quantity-weighted yield spread. $\mathbb{1}\{\text{Basel III}\}_j$ is a binary variable equal to if the auction occurs after January 2015. $\mathbb{1}\{\text{DB}\}_i$ is a binary variable equal to one if bidder i is a dealer bank. The sample period is from January 2012 to December 2017 and spans a three-year window around the introduction of the Basel III regulations. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

Robustness checks: four-year window

	Log elasticity		Yield discount	
	TE β_{ij}	TE β_{ij}	Discount$_{ij}$	Discount$_{ij}$
$\mathbb{1}\{\text{Basel III}\}_j$	-0.14	-0.01	0.02	0.02
	(0.15)	(0.13)	(0.01)	(0.01)
$\mathbb{1}\{\text{DB}\}_i$	-0.22^{*}	-0.27^{***}	0.01	0.01
	(0.12)	(0.10)	(0.01)	(0.01)
$\mathbb{1}\{\text{Basel III}\}_j \times \mathbb{1}\{\text{DB}\}_i$	-0.66^{***}	-0.46^{**}	-0.04^{**}	-0.04^{**}
	(0.21)	(0.18)	(0.02)	(0.02)
Maturity		-0.05^{***}		-0.00
		(0.00)		(0.00)
Participants		-0.01		-0.00
		(0.02)		(0.00)
Constant	5.36^{***}	6.37^{***}	0.01	0.04
	(0.09)	(0.29)	(0.01)	(0.04)
Adj. R^2	0.12	0.34	0.00	0.00
N	465	465	1130	1130

Table 15: Coefficient estimates of the difference in differences specification (11). In the first and second column, the dependent variable is the total elasticity of demand (in logs). In the third and in the fourth column, the dependent variable is the quantity-weighted yield spread. $\mathbb{1}\{\text{Basel III}\}_j$ is a binary variable equal to if the auction occurs after January 2015. $\mathbb{1}\{\text{DB}\}_i$ is a binary variable equal to one if bidder i is a dealer bank. The sample period is from January 2011 to December 2018 and spans a four-year window around the introduction of the Basel III regulations. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

Robustness checks: dropping auctions around EURCHF floor removal

	Log elasticity		Yield discount	
	TE β_{ij}	TE β_{ij}	Discount$_{ij}$	Discount$_{ij}$
$\mathbb{1}\{\text{Basel III}\}_j$	-0.13	-0.04	0.02	0.02
	(0.14)	(0.12)	(0.01)	(0.01)
$\mathbb{1}\{\text{DB}\}_i$	-0.21^{**}	-0.26^{***}	0.01	0.01
	(0.10)	(0.09)	(0.01)	(0.01)
$\mathbb{1}\{\text{Basel III}\}_j \times \mathbb{1}\{\text{DB}\}_i$	-0.56^{***}	-0.42^{***}	-0.04^{***}	-0.04^{**}
	(0.19)	(0.16)	(0.02)	(0.02)
Maturity		-0.05^{***}		-0.00
		(0.00)		(0.00)
Participants		-0.03		-0.00
		(0.02)		(0.00)
Constant	5.35^{***}	6.53^{***}	0.01	0.03
	(0.08)	(0.26)	(0.01)	(0.04)
Adj. R^2	0.10	0.30	0.00	0.00
N	541	541	1302	1302

Table 16: Coefficient estimates of the difference in differences specification (11). In the first and second column, the dependent variable is the total elasticity of demand (in logs). In the third and in the fourth column, the dependent variable is the quantity-weighted yield spread. $\mathbb{1}\{\text{Basel III}\}_j$ is a binary variable equal to if the auction occurs after January 2015. $\mathbb{1}\{\text{DB}\}_i$ is a binary variable equal to one if bidder i is a dealer bank. The sample period is from January 2010 to December 2019 and spans a five-year window around the introduction of the Basel III regulations, but we drop auctions around the EURCHF cap removal on January 15, 2015. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

B.4 Secondary Market Liquidity

Secondary Market Liquidity and Bidding Behavior

	Log demand elasticity			
	TE β_{ij}	TE β_{ij}	TE β_{ij}	TE β_{ij}
RBAS_j	-0.63^{***}	-0.43^{***}	-0.10	-0.01
	(0.05)	(0.06)	(0.09)	(0.09)
$\text{RBAS}_j \times \mathbb{1}\{\text{DB}\}_i$		-0.31^{***}	-0.31^{***}	-0.33^{***}
		(0.06)	(0.06)	(0.06)
Maturity			-0.03^{***}	-0.02^{**}
			(0.01)	(0.01)
Participants			0.02^{***}	0.02^{***}
			(0.01)	(0.01)
$\sigma_{j-21,j}$				-0.72^{***}
				(0.19)
Constant	5.63^{***}	5.65^{***}	5.56^{***}	5.57^{***}
	(0.07)	(0.08)	(0.13)	(0.14)
Macro	✓	✓	✓	✓
Adj. R^2	0.25	0.27	0.29	0.31
N	1087	1087	1087	993

Table 17: Coefficient estimates of regression (12). The dependent variable is the total elasticity (TE) of demand (in logs) at the bidder level. RBAS_j is the relative bid-ask spread at the auction date, whereas $\mathbb{1}\{\text{DB}\}_i$ is an indicator equal to one if bidder i is a dealer bank, and zero otherwise. Maturity is the time to maturity at the auction date. Participants is the number of bidders. $\sigma_{j-21,j}$ denotes the volatility of the bond in the month prior to the auction. Log issue size is the logarithm of supply. Macro controls include inflation, the short-term rate (SARON), the slope of the yield curve, and the KOF economic barometer. The sample is from 2000 to the present and only considers security reopenings. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively.

B.5 Predictive Regressions

Comparison with marginal elasticity of Albuquerque et al. (2024)

	Marginal elasticity		
	β_j^{ME}	β_j^{ME}	β_j^{ME}
$\bar{\beta}_j$	0.73***		
	(0.05)		
$\bar{\beta}_j^{\text{DB}}$		0.64***	
		(0.06)	
$\bar{\beta}_j^{\text{LT}}$			0.63***
			(0.06)
Constant	0.68**	1.24***	1.13***
	(0.28)	(0.28)	(0.31)
Adj. R^2	0.26	0.23	0.20
N	487	472	369

Table 18: Comparison of aggregate demand elasticity and investor-level measures of demand elasticity. We measure that aggregate demand elasticity β_j^{ME} using the marginal elasticity from Albuquerque et al. (2024)

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Predictive regressions with marginal elasticity of Albuquerque et al. (2024)

	Aggregate elasticity				Dealer banks vs. long-term investors			
	$rx_{j,j+1}$	$rx_{j,j+2}$	$rx_{j,j+5}$	$rx_{j,j+21}$	$rx_{j,j+1}$	$rx_{j,j+2}$	$rx_{j,j+5}$	$rx_{j,j+21}$
β_j^{ME}	-0.14^{***}	-0.13^{**}	-0.08	-0.21	-0.03	-0.06	-0.07	0.08
	(0.05)	(0.06)	(0.08)	(0.18)	(0.05)	(0.05)	(0.09)	(0.15)
Maturity					-0.00	0.00	-0.01	-0.01
					(0.01)	(0.01)	(0.02)	(0.03)
Participants					-0.00	-0.00	0.01	0.06^{*}
					(0.01)	(0.01)	(0.02)	(0.03)
RBAS_j					0.34^{**}	0.14	0.12	0.91^{*}
					(0.13)	(0.14)	(0.24)	(0.48)
Constant	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.03	0.02	0.00	0.01	0.08	0.03	-0.01	0.03
N	344	352	350	328	336	336	332	309

Table 19: The left panel regresses h-day ahead excess returns onto the marginal elasticity β_j^{ME} of Albuquerque et al. (2024). The right panel regresses h-day ahead excess returns onto the marginal elasticity β_j^{ME}, bond maturity, number of bidders, and the relative bid-ask spread. Excess returns are computed based on the auction price. The sample is from 2000 to present. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively

Comparison of predictive power across elasticity measures

	Aggregate elasticity				Dealer banks vs. long-term investors			
	$rx_{j,j+1}$	$rx_{j,j+2}$	$rx_{j,j+5}$	$rx_{j,j+21}$	$rx_{j,j+1}$	$rx_{j,j+2}$	$rx_{j,j+5}$	$rx_{j,j+21}$
$\bar{\beta}_j$	-0.20^{***}	-0.17^{*}	-0.27^{*}	-0.33				
	(0.08)	(0.09)	(0.15)	(0.30)				
$\bar{\beta}_j^{\text{LT}}$					-0.23^{**}	-0.30^{***}	-0.43^{***}	-0.71^{**}
					(0.09)	(0.10)	(0.12)	(0.32)
$\bar{\beta}_j^{\text{DB}}$					-0.22^{**}	-0.13	-0.09	0.31
					(0.10)	(0.11)	(0.15)	(0.31)
β_j^{ME}	-0.01	-0.05	-0.04	0.12	0.05	-0.01	-0.02	0.19
	(0.05)	(0.06)	(0.09)	(0.16)	(0.07)	(0.08)	(0.12)	(0.21)
Constant	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.10	0.03	0.00	0.03	0.11	0.06	0.03	0.04
N	326	326	322	299	216	216	213	196

Table 20: The left panel regresses h-day ahead excess returns onto the average total elasticity (TE) and the marginal elasticity β_j^{ME} of Albuquerque et al. (2024). TE is the average elasticity across all participants in the auction, which is computed as $\bar{\beta}_j = \frac{1}{I}\sum_{i=1}^{I}\beta_{ij}$. The right panel regresses h-day ahead excess returns onto the average demand elasticity of dealer banks $\bar{\beta}_j^{\text{DB}}$ and long-term investors $\bar{\beta}_j^{\text{LT}}$ separately. In addition, we include the marginal elasticity β_j^{ME}. Excess returns are computed based on the auction price. Controls include maturity, number of bidders, and the relative bid-ask spread. The sample is from 2000 to present. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively

Controlling for pre-auction drift and volatility

The pre-auction volatility is the standard deviation of daily returns in the month prior to the auction close, not including the daily return on the auction day. This variable is predetermined. The pre-auction drift is the cumulative yield change from h trading days prior to the auction to the day before the auction. We use $h = 5$, i.e. 5 trading days up to the day before the auction.

$$\text{Drift}_j = \sum_{k=1}^{h} \Delta y_{j-1-k}$$

	Aggregate elasticity				Dealer banks vs. long-term investors			
	$rx_{j\|j+1}$	$rx_{j\|j+2}$	$rx_{j\|j+5}$	$rx_{j\|j+21}$	$rx_{j\|j+1}$	$rx_{j\|j+2}$	$rx_{j\|j+5}$	$rx_{j\|j+21}$
$\bar{\beta}_j$	−0.09	−0.10	−0.35**	−0.24				
	(0.07)	(0.09)	(0.16)	(0.32)				
$\bar{\beta}_j^{\text{LT}}$					−0.11	−0.23**	−0.50***	−0.64***
					(0.09)	(0.10)	(0.17)	(0.24)
$\bar{\beta}_j^{\text{DB}}$					-0.09	−0.04	−0.11	0.32
					(0.09)	(0.11)	(0.15)	(0.26)
Vol	0.89**	0.23	−0.91	0.13	1.27**	0.62	−0.24	0.72
	(0.44)	(0.44)	(0.80)	(1.05)	(0.63)	(0.61)	(1.17)	(1.25)
Drift	−0.22	−0.53	−1.33	−1.50	0.32	−0.30	−1.03	−1.64
	(0.65)	(0.76)	(1.15)	(1.75)	(0.88)	(0.99)	(1.50)	(2.08)
Constant	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.16	0.03	0.02	0.00	0.14	0.06	0.03	0.05
N	294	294	291	290	226	226	223	205

Table 21: The top panel regresses h-day ahead excess returns onto the average total elasticity (TE) across all participants in the auction, which is computed as $\bar{\beta}_j = \frac{1}{I}\sum_{i=1}^{I} \beta_{ij}$. The bottom panel regresses h-day ahead excess returns onto the average demand elasticity of dealer banks $\bar{\beta}_j^{\text{DB}}$ and long-term investors $\bar{\beta}_j^{\text{LT}}$ separately. Excess returns are computed based on the auction price. Controls include maturity, number of bidders, the relative bid-ask spread, pre-auction yield drift and pre-auction volatility. The sample is from 2000 to present. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively

Abnormal returns

To control for market trends, Albuquerque et al. (2024) construct bond abnormal returns. Abnormal log returns is the cumulative residual from the close of auction day until the close of h-ahead days. The residual is computed with a market model by subtracting the daily log return on the SBI Government (SBIDGT from SIX) times a shrinkage beta.

First, we estimate the intercept α and the slope β by regressing daily bond log returns on daily index log returns in three months prior to the auction.

$$r_{t|t+1} = \alpha + \beta \cdot r^m_{t|t+1} + \varepsilon_{t+1} \qquad : \qquad \hat{\varepsilon}_{t+1} = r_{t|t+1} - \hat{\alpha} - \underbrace{\{\lambda \cdot 1\hat{\beta} + (1-\lambda) \cdot 1\}}_{\text{shrinkage beta}} r^m_{t|t+1}$$

Second, we construct abnormal log-returns $\text{AR}_{j|j+h}$ in the five days prior to the auction and in the month after as the cumulative residual $\hat{\varepsilon}_{t+1}$ in the h trading days after the auction. For the auction return, we construct abnormal log-returns using the market clearing price at the auction. This exercise computes the holding period return from the perspective of an auction participant. For comparison with Albuquerque et al. (2024), we use a weight of $\lambda = 0.6$.

	Aggregate elasticity				Dealer banks vs. long-term investors			
	$AR_{j\|j+1}$	$AR_{j\|j+2}$	$AR_{j\|j+5}$	$AR_{j\|j+21}$	$AR_{j\|j+1}$	$AR_{j\|j+2}$	$AR_{j\|j+5}$	$AR_{j\|j+21}$
$\bar{\beta}_j$	-0.25^{***}	-0.23^{***}	-0.21^{***}	-0.24^{*}				
	(0.05)	(0.05)	(0.07)	(0.13)				
$\bar{\beta}_j^{\text{LT}}$					-0.17^{***}	-0.19^{***}	-0.22^{***}	-0.19^{*}
					(0.07)	(0.06)	(0.06)	(0.10)
$\bar{\beta}_j^{\text{DB}}$					-0.17^{***}	-0.12^{**}	-0.08	-0.04
					(0.05)	(0.05)	(0.06)	(0.11)
Constant	✓	✓	✓	✓	✓	✓	✓	✓
Controls	×	×	×	×	×	×	×	×
Adj. R^2	0.13	0.11	0.07	0.03	0.18	0.14	0.12	0.02
N	295	295	295	295	197	197	197	197

Table 22: The top panel regresses h-day ahead abnormal log-returns onto the average total elasticity (TE) across all participants in the auction, which is computed as $\bar{\beta}_j = \frac{1}{I}\sum_{i=1}^{I} \beta_{ij}$. The bottom panel regresses h-day ahead abnormal log-returns onto the average demand elasticity of dealer banks $\bar{\beta}_j^{\text{DB}}$ and long-term investors $\bar{\beta}_j^{\text{LT}}$ separately. Abnormal log-returns are computed based on the auction price. Robust standard errors are in parentheses. *, **, *** correspond to significance levels of 10%, 5% and 1%, respectively