Price elasticity of demand and risk-bearing capacity in sovereign bond auctions*

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Abstract

The paper uses bids submitted by primary dealer banks at auctions of sovereign bonds to quantify the price elasticity of demand. The price elasticity of demand correlates strongly with the volatility of returns of the same bonds traded in the secondary market but only weakly with their bid-ask spread. The price elasticity of demand predicts same-bond post-auction returns in the secondary market, even after controlling for pre-auction volatility. The evidence suggests that the price elasticity of demand is associated with the magnitude of price pressure in the secondary market around auction days, and proxies for primary dealer risk-bearing capacity.

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1 Introduction

This paper studies the behavior of primary dealers in the auction market for sovereign bonds. Primary dealers' fragility was a point of vulnerability of the U.S. financial sector during the 2007-9 crisis (Duffie 2013). Along the same lines, Goldberg (2020) shows that declines in broker-dealer inventory capacity are associated with future drops in liquidity across several asset classes and the availability of financing, and He et al. (2017) show that shocks to equity capital of primary dealers predict the cross section of returns across a broad class of assets (see also Etula 2013). These papers suggest that primary dealers' risk-bearing capacity is an important source of aggregate risk. In our paper, we study primary dealers' bidding in auctions of sovereign bonds, and the elasticity of demand thus revealed, to infer their risk-bearing capacity.

Several papers have documented a puzzling pattern of secondary market prices in reaction to uninformative supply (and demand) shocks that suggest that the demand for financial assets is not perfectly elastic, even in the most liquid markets (e.g., Duffie 2010). Possibly the prime example occurs in the U.S. sovereign bond market, which is one of the most liquid markets in the world (e.g., Fleming 2003). Fleming et al. (2022) and Lou, Yan, and Zhang (2013) find that, around auction days, the secondary-market yields of bonds of similar maturity to those being auctioned (and sometimes the same bond) display an inverted V-shaped pattern.[1] The authors argue that this finding is consistent with primary-dealer banks' limited risk-bearing capacity, and thus consistent with an imperfectly elastic demand curve. However, the lack of more direct evidence on the elasticity of demand as an explanation to the puzzling evidence –and to other, similar price-pressure effects– leaves much room for alternative hypotheses and may explain why still most asset pricing models assume a perfectly elastic demand. Below, we revisit the discussion of alternative hypotheses, some already suggested in Shleifer (1986).

The elasticity of demand is the marginal increase in quantity demanded by investors for

[1]Using Finnish sovereign bond market data, Keloharju, Malkamäki, Nyborg, and Rydqvist (2002) were the first to document this pattern. More recently, Beetsma, Giuliodori, de Jong, and Widijanto (2016) find the same pattern around German and especially Italian sovereign bond auctions.

a marginal decrease in the price of the bond. In a perfectly competitive market, an asset's price elasticity of demand is infinite meaning that investors absorb any shock to supply at the equilibrium price.[2] A less-than-perfectly elastic demand can be associated with primary dealers' limited risk-bearing capacity. Because an auction is a supply shock that significantly increases primary dealers' bond holdings in the short run, the ability of dealers to absorb this shock is likely to depend on their existing inventory, on how much dealers are able to offload of their portfolios prior to the auction in the secondary market (provided they know which bonds are being auctioned),[3] as well as on dealers' expectation of the ease with which they will be able to later turnover to other investors the bonds purchased at the auction (i.e., their expectation of other's risk-bearing capacity), besides naturally other secondary-market bond-specific characteristics such as return volatility and liquidity. We expect these secondary market conditions to be reflected in the elasticity of demand in the primary market. Specifically, we hypothesize that, if the elasticity of demand at the auction is high, then primary dealers expect to be able to sell the acquired bonds quickly without much price impact, and thus there is limited to no price drop followed by a price increase (i.e., a less noticeably inverted-V shape pattern in yields). Instead, with a low elasticity there is both a price drop and a slow price reversal. These hypotheses follow from Duffie (2010) who argues that "markets are effectively thinner in the short run" and that capital is slow moving.[4] In addition, in Kyle (1989), the slope of informed investors' auction demand functions (i.e., the derivative with respect to price) decreases in absolute value with investor risk aversion and asset volatility. A broad interpretation of risk aversion for financial agents is that these agents penalize volatility for reasons that include inventory costs, portfolio constraints (e.g., Allen and Wittwer 2021), and the difficulty in finding

[2]The assumption of infinite price elasticity of demand underlies prominent asset pricing models such as the Capital Asset Pricing Model or the Contingent Claims model. However, evidence on price pressure effects (e.g., Harris and Gurel 1986, Shleifer 1986, Duffie 2010 among others that we cite below) questions this assumption.

[3]Fleming et al. (2022) show that primary-dealer banks tend to sell futures before the auction to hedge some of their inventory risk and Lou et al. (2013) argue that primary dealers use the secondary market to short sell similar securities to those being auctioned.

[4]Grossman and Miller (1988), among others, discuss the return that market makers earn for bearing the inventory risk associated with bridging liquidity between the arrival of traders.

demand due to inattentive investors (e.g., Duffie 2010). A low elasticity is thus evidence of low risk-bearing capacity according to these models.

We analyze a unique, proprietary bid-level dataset from the Portuguese Treasury and Debt Management Agency (Portuguese acronym IGCP). The data used in the main analysis contain all the bids for 66 bond auctions conducted by the Portuguese State from 2014 to 2019. Auction-bid level data are generally not available for other markets including the U.S. In addition to being a unique dataset that allows us to estimate the elasticity of demand, there are several institutional features of the Portuguese market that are important for the analysis. Two additional, and relatively unique, institutional features of the Portuguese market can be used to provide better identification for a test of the risk-bearing capacity hypothesis. First, all auctions are re-openings of bonds already traded in the secondary market, so their effects can be measured in the primary and secondary markets.[5] In contrast, in the U.S. sovereign bond market, most auctions are not re-openings, which means that, for those auctions and before they occur, the researcher can only track the secondary-market prices of bonds of similar maturities, which are by construction imperfect substitutes. Second, only primary dealers can participate in the auctions whereas in the U.S. market institutional investors are also allowed. Risk-bearing capacity of primary dealers (which may depend indirectly on the risk-bearing capacity of other market participants) can be better identified in the Portuguese market. Two additional features, more common across markets, but also of relevance to the analysis, imply that during the sample period T-bond auctions were uninformative supply shocks anticipated by three trading days: T-bond auctions occurred on pre-determined Wednesdays of each month, and the lines to be auctioned were announced on the Friday prior to the Wednesday of the auction. On said Friday, the IGCP also announced an indicative issuance interval, often keeping the issue size close to the top of the interval.

We find that the Portuguese government secondary T-bond market displays a V-shape price

[5] Syndications are used for all new securities given that all auctions are re-openings.

pattern around T-bond auctions. On average, the secondary-market price of the bond being issued drops by 9 basis points in the three trading days prior to an auction, and subsequently increases by 6 basis points, relative to a benchmark representing the performance of all Portuguese government bonds. In the robustness section, we show that raw yields present the same inverted V-shape as in Lou et al. (2013) or Beetsma, Giuliodori, de Jong, and Widijanto (2016). We conduct a placebo test by looking at unused auction dates by the IGCP. We do not observe a V-shaped curve in the secondary-market price at any bond maturity for these placebo dates.

We compute a measure of the elasticity of (aggregate) demand at each auction using unsubscribed bids near the cut-off price. There are several noteworthy properties of the absolute value of this *marginal elasticity* of demand.[6] First, the average value of the estimated marginal elasticity is 332. According to this estimate, an increase in quantity supplied at an auction by roughly 3% is accommodated with only a 1 basis points drop in the price on average. This large elasticity value suggests that the Portuguese sovereign bond market was fairly liquid in the post 2014 period. For comparison, the average value we estimate is more than 10 times larger than Kandel, Sarig, and Wohl (1999)'s estimated average elasticity in Israeli IPO auctions.

Second, in the cross-section of all the auctions, the marginal elasticity has a strong negative correlation with the pre-auction volatility of the secondary-market returns of the bond being auctioned. This negative correlation suggests that the two variables may be proxies for dealer risk-bearing capacity, since return volatility is an important metric related to dealer inventory risk (e.g., Kyle 1989). The marginal elasticity also has a strong negative correlation with the bid-ask spread, but its significance disappears when controlling for the return volatility. This result suggests that the marginal elasticity has additional information content relative to the bid-ask spread, a usual proxy for market liquidity. Finally, the marginal elasticity has a positive correlation with the 3-day price drift prior to the auction, which is to be expected if a lower elasticity is associated with increased price pressure. However, this correlation is not statistically

[6] The elasticity is always negative. For brevity, and from now on, we shall discuss the absolute value of the elasticity without explicitly mentioning it.

significant.

Third, we find that the documented V-shaped pattern, is only statistically significant in the sub-sample of auctions where the measured elasticity is low (i.e., below the sample median). This finding is consistent with the hypothesis that there is only price impact when primary dealers anticipate that they are unable to quickly offload the bond purchases in the secondary market. For the low-elasticity sub-sample, the price drops by about 11 basis points in the three trading days prior to the auction date, increasing by about 21 basis points in the subsequent five trading days, relative to the benchmark. For comparability, the average bid-ask spread in our sample is 22 basis points. Thus, the price elasticity of demand in the primary market appears to proxy for dealers' risk-bearing capacity and to be related to price pressure observed in the secondary market as predicted.

Fourth, we run in-sample predictive regressions of *post-auction* secondary-market bond abnormal returns at various holding horizons, on the marginal elasticity, and various controls. To control for time variation in risk premia, we include in the regression the (pre-auction) return volatility of the bond being auctioned. Other controls include the relative bid-ask spread, the price drift in the three trading days prior to the auction, and the bid-to-cover ratio (Beetsma, Giuliodori, Hanson, and de Jong 2018). The marginal elasticity has a negative coefficient at every horizon and is statistically significant at all horizons up to ten days, except for the two-day horizon. The negative coefficient indicates that a low value of the elasticity (suggestive of low risk-bearing capacity) is associated with future price increases as predicted. A decrease in the marginal elasticity by one standard deviation predicts an 11 basis points increase in the price of the bond after 5 days. Price drift before the auction carries a negative sign for all holding periods suggesting that larger price declines before the auction are associated with larger price increases after the auction, as would be predicted if the prior price movement was motivated by price pressure, but this coefficient is statistically significant only up to the horizon of 5 days. The return volatility has a positive sign as predicted, but is also statistically insignificant. This evidence suggests that the return volatility, price drift, and the marginal elasticity may all proxy for primary dealers' risk-bearing capacity, but the marginal elasticity appears to be the less noisy of the three. These results are consistent with evidence in Allen and Wittwer (2021) who show using dealer-level information that the steepness of individual dealer demand in Canadian Treasury auctions is positively associated with dealer capitalization. We show too that, using as a benchmark the 5-day holding return, the inclusion of the elasticity leads to a large increase in adjusted R-squares. Finally, the relative bid-ask spread has a positive and generally significant coefficient, consistent with capturing a liquidity premium associated with transaction costs.

Fifth, we provide one additional test of the mechanism by studying the relationship for bonds with different maturities. We expect the effect of the marginal elasticity to be more pronounced for longer-duration bonds as these generally have higher interest rate risk and are thus more prone to impact traders' profit volatility. In fact, the IGCP recognizes dealers' lower willingness to trade longer-duration bonds by benefiting those dealers that participate more actively in these auctions (discussed below). When we add a short duration dummy and its interaction with the marginal elasticity to the predictive regression controls, we find an increase in the economic and statistical significance of the marginal elasticity on predictive regressions of the excess return across all holding horizons. This evidence suggests, as expected, that the effect of the marginal elasticity is stronger for longer-duration bonds. The effect on short-duration bonds is still negative but statistically insignificant.

Perhaps the main alternative hypothesis to the primary dealers' limited risk bearing capacity as an explanation of secondary market price pressures is the liquidity hypothesis. If the auctioned bond was being 'neglected' prior to the auction, then it will earn a higher return (see Shleifer 1986). This hypothesis has relatively less bite in our setting as the market participants are well-informed, large institutional investors. Further, the liquidity hypothesis would not predict a price drop ahead of the auction. In our tests, we control for standard liquidity measures, including the relative bid-ask spread and issue size. Second, the literature on price pressure often studies events that are uncommon at the firm level, such as an index inclusion. It is possible that these rare events change the profile of the firm allowing it to tap into new and more abundant capital, which would then be associated with higher valuations (see Chen et al. 2004). This alternative hypotheses is unlikely in our setting as we are dealing with the same issuer over time and bonds of the same maturity, and sometimes the same bond, are repeatedly issued. Third, Duffie (2010) and Sigaux (2020) discuss the alternative hypothesis that price pressure is due to an inability to contemporaneously observe the supply shock. In our setting, the auction size is fairly predictable as it often occurs at the maximum of the indicative interval announced ahead of the auction. Still, in our tests we include a control for how the auction size deviates from the top of the indicative interval and find no change in results. Finally, Amin and Tédongap (2020) and Fleming et al. (2022) note that primary dealers absorbed a decreasing fraction of the auction sales of U.S. sovereign debt post 2012 in favor of investment funds. Amin and Tédongap (2020) show that despite the investor composition change in the TIPS market post 2012, the V-shaped pattern does not disappear. They interpret this evidence as suggesting that it is not primary dealers' risk-bearing capacity that is causing the pattern in yields. Our interpretation of their evidence is that it is the aggregate risk-bearing capacity of all the various market participants that determines the amount of price pressure. While this is an interesting line of research, in our data primary dealers are the only ones able to acquire bonds sold at auctions, and moreover there is considerable stability over time in the dealers who are present at the auctions. Hence, our data gives a clean setting for testing the hypothesis that primary dealers' risk-bearing capacity is a first order determinant of price pressure (though as indicated above primary dealers risk-bearing capacity may depend indirectly on other investors' risk-bearing capacity). In addition, we provide cross-sectional tests of this hypothesis by linking the amount of price pressure around auction sales to the marginal elasticity estimated using the demand schedule from primary-dealer bids.

In a robustness test, we study the COVID-19 pandemic year of 2020. The volatility in financial markets but also the response of central banks is likely to have affected the risk-bearing capacity of primary dealer banks in more than one way. We therefore do not include data from 2020 in our main analysis so as not to taint the results in any direction. Our robustness tests show that including the auctions executed in 2020, except for the two auctions in March, does not significantly affect our results. Next, motivated by the existence of bid shading (e.g., Hortaçsu and Kastl 2012 and Hortaçsu, Kastl, and Zhang 2018), we add the bid discount observed in the auction as a control variable in the predictive regressions. The results are still qualitative the same. Third, we modify the procedure used to calculate the price elasticity of demand in several ways and these do not qualitatively affect the nature of our results.

The next section presents the related literature. Section 3 gives a brief description of the institutional setting of the Portuguese T-bond auctions and provides statistics on these auctions. Section 4 discusses estimates of the price elasticity of demand and introduces the remaining variables used in the analysis. The main results are presented in section 5, and section 6 discusses the pandemic year results. Section 7 discusses robustness tests and section 8 concludes.

2 Related literature

Recent literature points to primary dealer risk-bearing as an important driver of financial asset prices. Adrian, Etula, and Muir (2014) show that shocks to the leverage of securities broker-dealers are useful to explain cross sectional variation in expected returns in stocks and bonds, Etula (2013) shows that financial assets and liabilities for U.S. security broker-dealers contain information that can explain commodity returns, and He, Kelly, and Manela (2017) show that equity capital ratio of primary dealer counterparties of the New York Federal Reserve can explain the returns on a broad set of assets. Our evidence complements this work by tying the magnitude of price pressure from uninformative and predictable supply shocks to the magnitude of the primary-dealers' price elasticity of demand, a proxy for their risk-bearing capacity.[7]

[7]Bagwell (1992) and Kandel et al. (1999) are the first to estimate demand elasticities in financial markets. We extend their analysis by proposing alternative measures of elasticity and especially by relating the measure of

Several papers talk about price pressure effects due to financial intermediation constraints. Gabaix and Koijen (2021) show evidence of significant price pressure in the stock market which they hypothesize derives from the behavior of constrained financial intermediaries (see also Haddad et al. 2021). They use a structural model to infer the elasticity that is consistent with price changes around capital flows into the stock market. Instead, we estimate an elasticity associated with investor demand using their bidding behavior and show that this elasticity predicts subsequent price movements. Hendershott and Menkveld (2014) provide evidence consistent with intermediaries in the New York Stock Exchange causing price pressure to mean-revert their inventory. In a dealers market, Hansch, Naik, and Viswanathan (1998) show that an increase (decrease) in inventory may cause the market maker to go from offering a best bid (ask) to offering a best ask (bid). Gromb and Vayanos (2010) survey the literature that discusses the implications of institutional constraints for the ability of arbitrageurs to exploit apparent market mispricing. Duffie (2010) discusses evidence consistent with slow moving capital and Du, Tepper, and Verdelhan (2018) provide evidence of systematic violations of covered interest parity that are not arbitraged away. The asset pricing literature has identified price pressure effects from shocks to both supply and demand (e.g., Shleifer 1986, Harris and Gurel 1986, Loderer, Cooney, and Drunen 1991, Kaul, Mehrotra, and Morck 2000, Wurgler and Zhuravskaya 2002, Coval and Stafford 2007, Lou 2012, Wardlaw 2020, and Camanho and Faias 2020). Hartzmark and Solomon (2021) show that aggregate dividend payments to investors, which are uninformed and predictable flows, predict stock market returns around the day of payment.

Our paper extends the literature that studies the predictability of secondary-market yield variations around Treasury auctions. Fleming et al. (2022) and Lou et al. (2013) interpret their findings as reflecting hedging by primary dealers with limited risk-bearing capacity that is not sufficiently accompanied by other investors. Lou et al. (2013) document that the V-shaped pattern

marginal elasticity with secondary market price pressures.

is more pronounced for larger auction sizes, at times of low growth rate of aggregate broker-dealer leverage, or when the volatility of interest rates is high (see also Beetsma et al. 2016). They also discuss how the phenomenon is distinct from the on-the-run premium. We complement their work providing further evidence of limited primary-dealer risk-bearing capacity by showing that the price elasticity of demand subsumes some of the effects they describe. In subsequent work, Beetsma et al. (2018) show that euro-area sovereign auctions with high bid-to-cover ratios see a more pronounced increase in the secondary-market price on the day of the auction. Forest (2018) observes a similar finding in the U.S. 30-year T-bond market. For T-bond auctions in Portugal, the bid-to-cover ratio does not help predict post-auction returns in the secondary market and also does not remove the explanatory power of the price elasticity of demand.

3 Institutional background and auction data

The *Portuguese Treasury and Debt Management Agency* (IGCP) has conducted T-bond auctions using a uniform-price system since April 2014.[8] Data on auctions prior to 2011 (and on T-bill auctions) are available, but these auctions used a discriminatory-price method. For the purpose of this study, using data on uniform-price auctions allows for comparability with results in U.S. Treasury auctions (e.g., Lou, Yan, and Zhang 2013) where uniform-price auctions are used exclusivity since the late 1990s.

The IGCP auctions T-bonds using a primary dealership model. A small group of financial intermediaries (the primary dealers) participate in the auctions and are responsible for marketing Portuguese debt securities to final investors and for ensuring liquidity in the secondary market.

[8]The adoption of a uniform-price auction method in the aftermath of the euro-area sovereign debt crisis was perceived as more adequate in markets with higher volatility, as was still the case in Portugal at the time. Following Greece and Ireland, the Portuguese Republic requested international financial assistance in April 2011 and agreed on a 3-year economic adjustment program that allowed access to funding up to €78 billion (about 50% of the public debt outstanding at the time) from the IMF and EU institutions. For the ensuing 18 months, IGCP did not raise any medium- and long-term funding in the capital markets, though it continued issuing T-bills on a regular basis. In late 2012 and early 2013, IGCP conducted a number of medium- and long-term operations (through exchange offers and syndicated deals) that served as preparation to a full return to regular capital markets issuance, which occurred with the end of the EU-IMF Adjustment Program. In April 2014, IGCP announced the first T-bond auction in exactly 3 years.

The auctions comprise a competitive phase where each participant may submit multiple bids, each comprising a bidding quantity in multiples of €1 million and a bidding price in multiples of €0.01, without exceeding the upper limit of the auction indicative amount. There is no minimum bidding amount in each auction, but each primary dealer is expected to take up at least 2% of the total amount issued through auctions in every 2 years. In return for participation, the IGCP grants dealers intermediation gains resulting from exclusive direct access to the primary market, access to the post-auction non-competitive bidding phase, and issuance fees when selected as lead managers in syndicated deals.[9]

During our sample period, T-bond auctions can occur on pre-determined dates, the 2nd, 4th, or 5th Wednesdays of each month (though in the whole sample only two auctions occur in the month of August and none in the month of December). The week prior to each of these days, the IGCP contacts primary dealers to have their views on market conditions: it collects their opinion on whether an auction should be conducted, the lines to be auctioned, and the issuance amounts. From 2017 on, this exchange of views took the form of a detailed questionnaire sent out to all primary dealers on Thursday afternoon and returned to the IGCP by Friday morning of the week before the auction takes place. In the afternoon of that same Friday, the IGCP announced whether or not an auction would take place, and in the affirmative case, it disclosed the specific security (or securities) to be issued and the indicative issuance amount (typically announced as an interval for the total to be raised across the lines being offered). In practice, the IGCP tended to use only one of the available windows in each month, so the likelihood of conducting an auction when the previous window had not been used was relatively high.

Three institutional characteristics allow us to treat these auctions as uninformative supply

[9]In the competitive phase, bids are submitted electronically through the Bloomberg Auction System between 10:00am and 10:30am Lisbon time. Results are released until 10:45am. In addition to the competitive phase, a post-auction non-competitive bidding phase is also available during which the IGCP offers an additional amount up to 20% of the auctioned amount, which is allocated according to the dealers' participation in the competitive phase of the last three T-bond auctions. Non-competitive bids are allocated at the cut-off price of the competitive phase and are submitted in the trading day following the auction day until 10:30am. Dealers are selected as lead managers of syndicated deals based on an evaluation scorecard that depends on dealers' allocation in the competitive phase, compliance with market making obligations and other qualitative features.

shocks whose effects can be studied in both the primary and secondary markets. First, T-bond auctions occurred on pre-determined Wednesdays, following a predictable funding strategy: the IGCP announced a total annual issuance amount in the beginning of each year that was typically distributed evenly over the year. Dealers learn about the auctioned lines on the Friday prior to each auction. Second, at the announcement of the lines to be auctioned, the IGCP also announced an indicative issuance interval for the total of the lines. In practice, the IGCP issued at or close to the maximum of the indicative range in most auctions so the market could anticipate the total size of the issue. Third, all auctions were re-openings of existing bonds. These bonds were already traded in the secondary market. In addition, there is one aspect of the Portuguese bond auctions that help us identify the risk-bearing capacity of primary dealers viz-à-viz U.S. data: only registered primary dealers are allowed in Portuguese auctions whereas other institutional investors are also allowed in U.S. auctions.

We obtain unique, proprietary bid-level data from the IGCP. The data include all bids submitted by each primary dealer in all 90 T-bond auctions conducted between 2014 and 2020. The main analysis focuses on data through the end of 2019, that is, 74 auctions. We include the 2020 COVID-19 year data in a later section. We exclude from our main analysis 5 auctions with an issuance amount equal to the minimum of the indicative amount and 3 other auctions whose issue size is within a small margin of 5% of the minimum indicative amount, resulting in a final sample of 66 auctions. We filter these auctions because we want to focus on auctions whose size ultimately did not surprise investors and hence are more likely to be uninformative.

[10] Table 1 reports summary statistics of T-bond auctions per year. In the beginning of the

[10]In all the auctions dropped, the secondary-market price of the issued bonds fell significantly prior to these auctions, a sign of low risk bearing capacity, yet our estimated marginal elasticity is high, which may be related with the fact that the IGCP surprised the market by issuing at the lower limit of the indicative range. If we increase the quantity sold to equal the maximum of the indicative interval for these auctions (assigning the quantity needed to reach the top of the indicative interval equally to both auctions when two auctions are held in the same day), in all but one case the elasticity drops by at least 30% (with an average drop of 63%). We believe this counterfactual would be more in line with market expectations. In one of the auctions the elasticity increases, but at the cost of a significantly lower cut-off price. We exclude these "surprise" auctions from our main analysis, but results do not change significantly when they are included. The remaining auctions have substantially higher issue size relative to the lower limit of the indicative interval. The distribution of issue sizes is in Figure 1 of the Online Appendix.

sample, which coincides with the aftermath of the sovereign debt crisis, the number of auctions was low, with only 4 auctions conducted in 2014. Portugal was slowly returning to issuing T-bonds and syndicated deals played a more important role. Since 2016, the number of T-bond auctions has oscillated between 13 and 16. T-bonds are issued with maturities between 2 and 30 years with an average duration between 7 and 11 years. $SIZE$ describes the total subscribed amount. The auctions in 2014 and 2015 had an average size close to €1 billion; auction size declined to about €600 million from 2016 onward, a consequence of the IGCP starting to conduct regularly simultaneous auctions on two lines.

[Table 1 here]

Over the sample period, there were 24 registered primary dealers, of which 19 were present in all years. In any single year the mode of the number of registered dealers was 21. The average number of participants in each auction was 19, and only 13-15 primary dealers were allocated on average. The average number of bids was quite large, about 60 in the main sample, representing an average of 3 bids per bidder. Of these, only 26 bids on average were allocated. The bid-to-cover ratio, $COVER$, is the ratio between the total amount bid and the allocated amount. The average bid-to-cover ratio was about 2 in the main sample, reaching an average of 2.52 in 2018 another sign of the liquidity of the market.

4 Data description and elasticity measures

Our main data, described above, is a unique bid-level data obtained from the IGCP. From Bloomberg, we obtain the secondary-market bid, ask, and mid prices at the daily frequency for all T-Bonds for the same time-span. As a benchmark for market performance, we collect also from Bloomberg the total return index of Portuguese government bonds.[11] We obtain the

[11] We use Bloomberg Generic Prices for all bonds. These prices are computed using a Bloomberg proprietary methodology that aims at providing "consensus" prices and is based on different price contributions and other relevant information (i.e., transaction prices and indicative quotes). The total return index is also computed by Bloomberg and considers the performance of all Portuguese government bonds, weighted by total amount outstanding.

spread between 10-year Portuguese T-bonds and German Bunds of the same maturity also from Bloomberg.

4.1 Price elasticity of demand

If P and Q describe price and quantity demanded at the price P, respectively, then the price elasticity of demand is $(\partial Q/\partial P)(P/Q)$. A large (absolute) value of the elasticity means that small price decreases are associated with large increases in demanded quantities. Thus, with high elasticity, a shock to supply such as a pre-announced re-opening through an auction, is absorbed by demand without much of a price decrease.

The main question in estimating the price elasticity is which point in the demand curve to use. We describe several different measures. Our main measure of the price elasticity of demand uses bids from untapped liquidity. We take the four price points from unsubscribed bids next to the cut-off price, together with the cut-off price point itself. These five price points generally correspond to more than five bids, as more than one dealer may submit a bid at the same price point: across all auctions, the 25th (75th) percentile of the number of bids used in the calculation of the elasticity is seven (nine). The five pairs (Q_i, P_i) are constructed such that Q_i equals the sum of the quantities bid at price point P_i or higher. In 38% of the auctions all of the quantity bid at the cut-off price is allocated. In the rest of the auctions, there is a small amount of quantity that is not allocated. This unsubscribed quantity represents on average about 2.4% of the total allocated amount or 25% of the total quantity bid at the cut-off price. In practice, this means that in these auctions the IGCP could have increased quantity marginally at the same price. Even though this represents a very small portion of the demand curve, it is a portion with infinite elasticity of demand, nonetheless. To take this into account, in every auction with a pro rata allocation, we add to the quantity-price point at the cut-off, (Q_c, P_c), one additional point, (Q_a, P_c), such that Q_a is the allocated quantity at the cut-off.[12]

[12]The robustness section contains additional analysis regarding rationing.

Using these quantity-price pairs, we estimate a linear regression model of Q_i on P_i and a constant. The slope in the model is an estimate of $\partial Q/\partial P$. We multiply this estimated slope by the ratio of the cut-off price to the cut-off quantity to get an elasticity. All elasticity estimates are negative. For ease of interpretation, we take the negative of the estimated elasticity. We label this measure as the marginal elasticity of demand, ME. This measure is close in spirit to the second measure calculated in Kandel et al. (1999) that uses all unfilled orders. ME describes how much the price would have to decline if the IGCP were to increase the quantity sold into the untapped liquidity.

We construct alternative measures of the elasticity of demand. Figure 1 plots the (aggregate) demand curve for a 10-year T-bond auctioned on May 11, 2016. Depicted in the figure are the slope of the lines used to estimate two other elasticities, in addition to that used for ME and discussed above.[13] Total elasticity (TE) differs from ME in that it uses all the demand price points to estimate the slope $\partial Q/\partial P$ from a linear regression of Q on P and a constant. Gross elasticity (GE) is obtained from the slope of the demand curve estimated using only the maximum price and the cut-off price points and corresponding quantities (see the points identified with the diamonds in the figure). For the auction depicted in the figure, the values of ME, TE, and GE (expressed in logarithms) are 5.23, 4.89, and 5.60, respectively. A feature of this and many other auctions in our sample is that ME and TE are significantly lower than GE, evidence of a demand quasi-kink close to the cut-off price of the auction. We return to the significance of such demand kinks in subsection 4.4. Lastly, we construct another marginal elasticity measure, denoted SE, that uses the four price points (possibly the same number of bids or more) from *subscribed* bids next to the cut-off price, together with the cut-off price point. Note that SE differs from ME only in the estimated slope, $\partial Q/\partial P$, since the other term in these elasticities, P/Q, is identical. SE is similar to Kandel et al. (1999)'s first measure that uses the

[13]Another measure, a variant of ME, uses all the price points of the unsubscribed bids next to the cut-off point that fall within a fixed price interval. We take the price interval to be the minimum interval across all auctions that guarantees at least one point besides the cut-off point. The results are qualitatively the same.

last filled orders in the auction. For clarity, the slope of the regression line that identifies SE is not depicted as it would overlap almost perfectly with that of GE in this auction.

[Figure 1 here]

As Figure 1 illustrates, ME is likely to contain different information from that in SE, GE or TE. GE and TE may be distorted by extreme bids, namely bids of relatively small quantities at very high prices. These bids guarantee that the dealer is allocated since the cut-off price is likely to be significantly lower. Since dealer allocation (even of a small quantity) is an important determinant of side benefits identified above, this bidding behavior may be strategic and not revealing of dealers' valuations of the specific bond being auctioned. To alleviate this concern, the IGCP introduced in 2017 an 'overbidding penalty' affecting dealers' evaluation scorecard, which suggests that this type of behavior has indeed occurred (see afme/Finance for Europe 2020). Table 2 contains descriptive statistics of the various elasticity measures. All of the elasticity measures display relatively large figures, but on average ME, SE and GE are larger than TE. That ME is smaller on average than SE, as in the example above, is a reflection of the quasi-kink in the demand curve.

[Table 2 here]

4.2 Auxiliary variables

Table 2 contains descriptive statistics of the variables used in the analysis (Table A.1 in the Appendix contains all the variable definitions). $SIZE$ and $COVER$ were defined and described above. $RBAS$ is the average of the previous 5-trading day period (excluding the auction day) of the daily relative bid-ask spread of the same bond being auctioned, calculated as the difference between the ask and the bid prices divided by the mid price (in percent). The average relative bid-ask spread is 0.24%. $DRIFT$ is the log return of the bond being auctioned computed from the end of day on Thursday to the end of day on Tuesday prior to the auction (in percent) adjusted for the return on Bloomberg's index of Portuguese government bonds over the same period times a shrinkage beta. There is a negative drift of 9 basis points on average with a standard deviation that is about three times as large as the absolute value of its mean. $SPREAD$ is the average of the previous 5-trading day period (excluding the auction day) of the difference between the 10-year Portuguese T-bond and the 10-year Bund (in basis points). The average spread in the sample is about 216 basis points. The spread declined significantly over the sample as the Portuguese economy improved, so the higher values are from the earlier part of the sample and the lower values from the later part of the sample. VOL is the standard deviation of daily log returns in the secondary market of the bond being auctioned over the 20 trading days prior to the auction date. The average daily volatility of log returns is 0.42%. $SDUR$ is a dummy equal to one for bonds of duration shorter than the median duration of the bonds in the sample (i.e., 8.3 years). We measure duration using the Macaulay measure and as an alternative we have also redone the tests using the bonds' residual maturity. The correlation between the two duration dummies is 0.98 and not surprisingly our results are not affected when the dummy with bond maturity is used instead.

Table 3 presents the linear correlations between variables. Larger auctions ($SIZE$) are associated with lower bid-ask spreads ($RBAS$), suggesting that the IGCP sees market appetite for larger auctions in lower pre-auction bid-ask spreads. The correlations between each of the elasticity measures and $DRIFT$ are positive as expected, but surprisingly, with the exception of TE, they are not statistically significant. The lack of significance could be explained by the existence of residual uncertainty about the size of the auction that is only resolved at the auction (Sigaux 2020). Higher $SPREAD$ and higher VOL are associated with higher $RBAS$, and with lower $DRIFT$. All four elasticity measures are strongly positively correlated with each other. The positive correlation between ME and $SDUR$ indicates that shorter duration bonds have more elastic demand in general. $SDUR$ correlates positively with $SPREAD$ suggesting that the IGCP tends to issue shorter duration bonds when the spread on the 10-year Portuguese bond to the 10-year German Bund is higher. We now discuss how the price elasticity is related to other liquidity measures.

[Table 3 here]

4.3 Price elasticity and other liquidity measures

The price elasticity describes the ability of demand to absorb a supply shock, and as such it is a measure of liquidity. In Kyle (1989), the slope of the demand curve carries two components, one linked to risk aversion and the risk-bearing capacity of informed investors and another linked to market liquidity associated with the presence or lack thereof of noise traders. Table 3 shows that, not surprisingly, all elasticity measures correlate negatively with the relative bid-ask spread, especially GE and TE (only the correlation between SE and $RBAS$ is not statistically significant). All the elasticity measures also correlate significantly with VOL, displaying correlations between -0.68 and -0.29. These high correlations suggest that there is common information between the elasticity measures and both $RBAS$ and VOL. Specifically, they may all share complementary information about liquidity (see also Allen et al. 2021). The elasticity measures also correlate positively with $COVER$, an indication that deals that are highly demanded relative to the allocated amount are also deals where the demand elasticity, and hence the risk-bearing capacity, is highest. Somewhat unexpectedly, the elasticity does not display a statistically significant correlation with auction size.

Figure 2 plots the time series of quarterly averages of ME, $RBAS$, and VOL. The figure shows both a positive co-movement between $RBAS$ and VOL and a negative co-movement between ME and each of the other two liquidity measures.[14]

One important factor affecting liquidity in this market during our sample period is the the Asset Purchase Programme (APP) implemented by the European Central Bank (ECB). Figure 2

[14]Monteiro (2022) shows a significant drop in the price elasticity of demand during the period of the sovereign debt crisis in Portugal, followed by a sustained recovery in the case of T-bills auctions. For T-bonds auctions the recovery was not so strong, but in this case the change in auction method (from discriminatory- to uniform-price auctions) may also have played a role.

also indicates the increases and decreases by the ECB of bond purchases related with the APP, denoted in bold font and normal font, respectively. These large-scale asset purchases by the ECB are likely to have generated at least two effects on liquidity, one being the direct increase in demand by the ECB (e.g., Pelizzon et al. 2022), and the other being the reduction in the float from the ever increasing level of securities held by the ECB, which may have lead some investors to exit the market (see Ferdinandusse, Freier, and Ristiniemi 2020). While the net effect of these on demand and thus on the risk-bearing capacity of primary dealers is unclear, at least initially before the float declined significantly, the effect on primary dealers is likely an increase in their risk-bearing capacity and thus in ME. Indeed, the introduction of the APP in 2015 and especially the expansion of the program in March of 2016 seem to be associated with a higher ME and lower $RBAS$ and VOL, but the effect is less clear in 2017-18, as purchases start to be phased out.[15]

[Figure 2 here]

Next, we study the cross-sectional determinants of the marginal elasticity. The results are displayed in Table 4. We regress ME on $RBAS$, $DRIFT$, $SIZE$, $SPREAD$, VOL, and $SDUR$, though only the first two sets of regressions include VOL.[16] The regression specifications allow for year and quarter fixed effects (second and fourth columns). When VOL is present, it is the only statistically significant variable, with significance levels at 1% or better. One standard

[15]We have used the total monthly amount of actual purchases of Portuguese government bonds in our regressions below to control for the effect around each auction, but this additional control does not affect our results. We report this set of results in the Online Appendix. The evolution of actual purchases of Portuguese sovereign bonds was somewhat different from the evolution of total ECB purchases, as the APP includes limits on the percentage of outstanding that the Eurosystem may hold of each issuer and each particular security, which implied proportionately lower purchases in Portugal in 2016-17. The Programme also included other operational features aimed at ensuring market neutrality, namely that purchases should be spread evenly over each month, along all the lines with residual maturity between 1 and 30 years, and respecting a blackout period for lines being offered in the primary market and those with a residual maturity that are close in time.

[16]We do not include $COVER$ because it uses information contemporaneous to that used to construct the ME. Including $COVER$ in the regressions produces the following results: i) it does not change the qualitative nature of the results discussed in the text regarding Table 4; ii) it has a statistically strong positive relation to ME, after controlling for the other variables; and iii) increases significantly the regressions' adjusted R-square. These results are available in the Online Appendix.

deviation increase in VOL is associated with a decrease in ME of about 0.40, equivalent to a little more than one half of a standard deviation of ME. $RBAS$, which has a statistically significant negative correlation with ME, is not significant after controlling for volatility or when including fixed effects. $DRIFT$ shows an insignificant positive association with ME that turns negative and still insignificant when the regressions also include VOL, a possible effect of the multicollinearity between $DRIFT$ and VOL. Shorter duration bonds have higher ME, but the effect is not significant. The strong correlation between VOL and ME suggests that they capture similar aspects of liquidity arising possibly from inventory risk, the effect that VOL has on risk-bearing capacity through dealers' portfolio constraints (see also Goldstein and Hotchkiss 2020 for the U.S. corporate bond market), and from time variation in risk premia.

[Table 4 here]

4.4 IGCP behavior and the cut-off price

The negative difference observed on average between ME and SE (or GE) suggests that the demand curve often depicts a kink around the cut-off price (see Table 2 and Figure 1). While the elasticity at any given point of the demand curve is completely determined by bidder behavior, the elasticity observed around the cut-off price also depends on the particular choice of cut-off price by the seller because the supply is not fixed but is chosen at the auction by the IGCP.[17]

Keloharju et al. (2005) discuss the strategic behavior of the Finnish Treasury when conducting uniform-price bond auctions and show that the seller usually chooses the cut-off price to maximize marginal revenue (marginal revenue defined with respect to quantity). Although this strategy does not maximize the total revenue in any particular auction, it may be justified by the fact that the Treasury repeatedly engages the market using auctions. They argue that if the Treasury were to maximize revenue at any one auction, the Treasury would choose the minimum

[17] In our sample, the IGCP typically chose an issuance amount equal to the top of the indicative range announced. In addition, in roughly 45% of the auction days the IGCP defined a cut-off price that resulted in an issuance amount either below or above this threshold, with the distance to the interval upper bound being −8% at the 10th percentile and +14% at the 90th percentile (see the Online Appendix).

bid price at that auction, which would likely have a significant negative impact in the secondary market and compromise future auctions. Keloharju et al. (2005) argue that, by maximizing the marginal revenue around the most preferred price among bidders the Treasury promotes more competition in subsequent auctions.

We demonstrate a similar strategy in the Portuguese Treasury auctions. Figure 3 presents evidence that the IGCP maximizes marginal revenue. The figure plots for intervals of €0.01 around the auction cut-off price—with the central bar representing the cut-off price—the proportion of auctions where the marginal revenue is maximized. Compared to prices in the vicinity of the cut-off price, there is a significantly higher fraction of auctions where the marginal revenue is maximized at exactly the cut-off price. Note too that in our sample, the average difference between cut-off price and the secondary-market price is €0.10 (i.e., there is overpricing on average in the auctions), which means that on average the IGCP is not choosing the cut-off price to equal the price in the secondary market.[18]

[Figure 3 here]

Further evidence is presented in the Online Appendix. There we present a plot of the average bid amount for intervals of €0.01 around the auction cut-off price and show that demand at the cut-off price is generally significantly higher, with about twice the bid amount relative to any other price in the vicinity.

Choosing the cut-off point to maximize marginal revenue implies that the IGCP picks a point on the demand curve where the elasticity of demand estimated using price points to the left of the cut-off price (SE) is significantly higher than that estimated using price points to the right of the cut-off price (ME), that is at a demand kink.[19] Because ME uses unsubscribed

[18]The literature usually finds that Treasury auctions are underpriced relative to the secondary market, in line with theories that emphasize the winner's curse. In contrast, Cardoso-Costa, Faias, Herb, and Wu (2022) show that auctions tend to be overpriced in some Euro area countries and relate this to specific institutional features of the primary dealership model used in these countries. The authors explore the particular case of Portugal, showing suggestive evidence that overpricing may be related with aggressive bidding behavior driven by competition for syndication fees.

[19]To see this, let total revenue equal PQ. Then, marginal revenue equals $Q+P(\partial Q/\partial P)$. The first order necessary

bids, we hypothesize that it captures the primary dealers' remaining risk-bearing capacity in the aftermath of a bond auction (i.e., untapped liquidity). In the next section we will relate ME with the post-auction abnormal return. Including SE in the regressions allows us to control for the tapped liquidity in the market and the kink in demand. We also control for GE instead of SE in a robustness test available in the Online Appendix.

5 Secondary-market price dynamics around Treasury auctions

In this section, we analyze the secondary market price of the bond being auctioned around the auction day. Our hypothesis is that the marginal elasticity captures dealers' expectations of their ability to sell in the secondary market the recently acquired bonds. When capital is slow to respond in the short term, dealers' may expect that they have to hold more of the issued bonds for longer. These expectations reduce their risk-bearing capacity and are reflected in a lower marginal elasticity of demand. We therefore expect that a low elasticity of demand is associated with a slow price adjustment in the secondary market. As Duffie (2010) argues, the response to a supply shock "typically involves [...] a subsequent and more extended reversal." We first analyze secondary-market bond prices in a window of 11 trading days centered at the auction day. Second, we conduct in-sample predictive return regressions on ME and other variables. Third, we conduct a cross-sectional test focusing on bond duration. Overall, our tests complement the literature by offering direct evidence that demand conditions matter for how the shock is absorbed.

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condition for an interior solution that maximizes marginal revenue is

$$2\frac{\partial Q}{\partial P} + P\frac{\partial}{\partial P}\frac{\partial Q}{\partial P} = 0.$$

Noting that SE and ME are defined as the negatives of the elasticities, the second term can be approximated by $(SE - ME)\,Q$.

5.1 Event-study analysis

We plot the cumulative log abnormal return (i.e., the adjusted price) in the secondary market of the bond being auctioned starting 5 trading days prior to the auction date and ending 5 trading days after the auction date. This analysis is somewhat different from Lou et al. (2013) that use yields instead of prices. Because Portuguese government bond prices showed a significant upward trend through most of the sample period, using prices allows us to subtract the log return of Bloomberg's index of Portuguese government bonds, multiplied by a shrinkage beta (see Vasicek 1973 and Frazzini and Pedersen 2014), from the log return of the bond being auctioned to control for these market trends, something we would not be able to do with yields.[20] Nonetheless, in the robustness section, we repeat this exercise using raw yields instead of adjusted returns. The top panel of Figure 4 displays the average cumulative log abnormal return (solid line) and corresponding 90% confidence bands (grey area). Note that day 0 represents the closing price at the end of the auction day, which we normalize to 0.

[Figure 4 here]

The top panel of the figure shows that there is a price decline from end-of-day -4 to end-of-day -1, with a large drop occurring on day -3, the Friday before the auction when the line(s) to be auctioned is (are) announced. This price decline starts to reverse on the day of the auction (recall that the day 0 price is the closing price on the day of the auction) and generally continues to increase in the days following the auction. The mean price decline prior to the auction is the mean of $DRIFT$ (of 9 bps).[21] Skipping the day of the auction, the abnormal log return in the 5 days following the auction is about 6 basis points. Price reversal is not immediate as it is not in other instances of price pressure (see the discussions in Kaul, Mehrotra, and Morck 2000,

[20]We also estimate a residual cumulative return from simply subtracting the log-daily bond market index returns from the log-daily bond returns. In the online appendix, we show that the results are qualitative the same using this model of abnormal returns.

[21]In the U.S., and for sovereign debt auctions through 2012, Fleming and Weiling (2017) show that the price continues to decline during the trading day through the start of the auction.

Duffie 2010, and Hendershott, Menkveld, Praz, and Seasholes 2022).[22] This V-shaped pattern is consistent with the evidence in Lou et al. (2013) for U.S. Treasury auctions of an inverted V-shaped pattern in yields around auction dates.

In the bottom panel of Figure 4, we split the auction sample by the median value of ME. Under the hypothesis that the V-shaped pattern in prices is due to primary dealers' limited risk-bearing capacity, we expect to find such pattern primarily when the elasticity of demand is low. For periods of high elasticity (black line), there is no statistically significant price change through the event window. However, for periods of low elasticity (gray line), the V-shaped price pattern is more pronounced than the unconditional pattern in the top panel of the figure. In the subsample of low elasticity, the average price drift prior to the auction is close to -11 bps, and the log abnormal return in the 5 days after the auction is about 21 basis points. This evidence suggests that the liquidity left untapped by the IGCP, as captured by ME that uses unsubscribed bids, contains information about the remaining risk-bearing capacity of primary dealers. In the robustness section, we conduct the same analysis using SE, TE and GE. Preempting our results, we find the same V-shaped pattern in prices from these measures of the elasticity of demand, but weaker significance, suggesting that ME is a better proxy of dealers' *remaining* risk-bearing capacity. One possible reason for why ME is a less noisy proxy of dealers' risk-bearing capacity relates to the choice of cut-off price as discussed above. Another reason is that the other measures may suffer from a bias related to the issue of overbidding also discussed above.

5.2 Predictive regressions

We run a series of cross-sectional regressions of the log abnormal return for auction i measured from the close on the auction day to trading day h after the auction, $AR_{i,h}$. For each h, we

[22]We do not have data to study who benefits from the post-auction gains. Evidence in Goldstein et al. (2021) for corporate bonds suggests that these gains appear to accrue mainly to non-underwriters. However, their setting is quite different from ours because we ignore syndicated bond issues and also because in the sovereign bond market all auctions are re-openings, that is the same bond already trades in the secondary market prior to the auction.

estimate the model

$$AR_{i,h} = \beta X_i + \epsilon_{i,h}, \tag{1}$$

where the variables X_i include the marginal elasticity, ME_i, and control variables for auction i. We normalize the variables X_i by their respective sample standard deviation for ease of interpretation of economic significance. The control variables are the relative bid-ask spread ($RBAS$), the price drift prior to the auction ($DRIFT$), the auction size ($SIZE$), the bid-to-cover ratio ($COVER$), the spread between Portuguese and German 10-year T-Bonds ($SPREAD$), the return volatility of the bond being auctioned (VOL), and (SE) to capture the kink in demand. A liquidity premium would suggest a positive coefficient associated with $RBAS$; $DRIFT$ and $SIZE$ are both expected to load negatively given the evidence in Lou et al. (2013); VOL is expected to be positively associated with the holding period return because it is related to both market liquidity and time-varying risk premia; and higher $COVER$ should imply greater liquidity and be associated with a lower ex-post return or as Beetsma et al. (2018) predict be associated with high ex-post returns as it proxies for investors' valuations. In the Online Appendix we show results where we control for how the auction size deviates from the lower limit of the indicative interval and find no change in our results (see Sigaux 2020).

Our regression model is different from the regression models in Beetsma et al. (2016) and Beetsma et al. (2018) for two reasons. Their models use the time series of the daily yield or daily yield change over the whole sample (the dependent variables of interest). They regress these variables on a dummy for days when auctions occur (or days with nearby auctions) possibly interacted with other variables. Using time series data brings in a problem of overlapping observations when the holding period horizon is longer than one day, such as in our exercise. We avoid this concern by running cross-sectional regressions with non-overlapping observations. In addition, our regression model is predictive in the sense that our dependent variable is measured after the auction. We do this to test whether the price change that follows the auction is positively associated with an existing risk premium as captured by ME.[23] Ideally, we would measure returns starting shortly after the auction results are announced, but because we only have daily data, we measure returns from the close of the auction day. We expect to still be able to capture the effects from price pressure as these tend to take time to reverse (e.g., Duffie 2010). Our regression model is closer in spirit to Lou et al. (2013) because they also use cross-sectional, predictive in sample regressions. However, they measure returns from a trading strategy that spans a window that is centered in the auction day and thus cannot use information that is available only at the auction day such as ME or $COVER$.

Table 5 summarizes the results for a specific horizon of 5 days ($h = 5$) after the auction date, AR_5, to match the evidence presented in Figure 4. The first two columns show regressions without ME, but where we include variables previously proposed in the literature. They serve as a benchmark for our results. The other three columns include ME as an independent variable. The results show that $RBAS$ is significantly positively associated with the 5-day return, consistent with $RBAS$ capturing a liquidity premium associated with transaction costs (see, for example, Albuquerque, Song, and Yao 2020). As the regressors have been standardized by dividing them by the respective sample standard deviation, we infer that one standard deviation increase in $RBAS$ is associated with a 10 to 13 basis points increase in the 5-day post-auction return. The bid-to-cover ratio does not have any predictive ability. This result contrasts with evidence in Beetsma et al. (2018) and may be due to the return-measurement timing assumptions we use as explained above. $SIZE$ is negatively associated with future returns, but the coefficients are not statistically significant. Other control variables do not have a statistically significant predictive power except for SE that measures the marginal elasticity of demand allocated in the auction and is used to control for the kink in demand around the cut-off price.

Table 5 shows that ME is a significant predictor of returns. ME is statistically significant at

[23]The elasticities ME and SE (not disclosed to the market) and $COVER$ (disclosed to the market) are measured with information from the auction that may or may not already be incorporated by the market in the closing price at the end of the day of the auction.

the 1% level or better and carries a negative coefficient estimate in all specifications as predicted. In addition, adding ME to the regression contributes to an increase in the adjusted R^2 between 7 and 8 percentage points, depending on the specification. Since the table displays standardized coefficients, an estimate of -11.37 in the last column implies that a one standard deviation decrease in ME translates into a 11 basis points price increase following the auction. This evidence is consistent with ME being a proxy for dealers' risk bearing capacity.

[Table 5 about here]

Next, we present results that use the specification in the last column of Table 5, but with returns measured at different horizons ($h = 1, 2, ..., 10$). The results are in Table 6. The table shows that the coefficient associated with ME is negative at all horizons, and is statistically significant except at horizon of 2 days. $RBAS$ is positive and significant at most horizons. $DRIFT$ is always negative and significant at the shorter horizons indicating that some of the pre-auction price movement reverts back independently of ME. The other controls are mostly statistically insignificant. In the Online Appendix, we present results where we exclude VOL from the regression because VOL and ME are strongly correlated (see Table 4) and they may be proxies for the same effect. Adding all controls but VOL results in higher estimated coefficients associated with ME with somewhat higher significance. We conclude that the evidence is consistent with ME being a proxy for primary dealers ability to absorb the supply shock, and a better proxy than VOL.

[Table 6 here]

5.3 Bond duration: A cross-sectional test

This subsection provides a cross-sectional test that the elasticity of demand is related to dealers' risk bearing capacity. Longer-duration bonds weigh negatively on dealers' risk bearing capacity for four reasons. First, longer-duration bonds carry higher interest rate risk and are thus relatively more prone to impact traders' overall profits. Second, while all public debt securities are eligible to serve as collateral in the European Central Bank's open-market operations, they are subject to different valuation haircuts that increase with the residual bond maturity. Third, and perhaps more importantly given our conversations with IGCP, dealers' appear to have a lower willingness to trade longer-duration bonds, which the IGCP counters by weighing dealers' performance in the competitive auction phase by the auction's bond's duration. Fourth, in Table 3, shorter-duration bonds tend to have more elastic demand (i.e., $SDUR$ correlates positively with ME, as well as with other elasticity measures), which suggests that dealers have a higher risk-bearing capacity for shorter-duration bonds on average. We therefore expect a differential effect of ME on post-auction bond prices for longer-duration bonds.

We repeat the predictive regressions including $SDUR$ and an interaction term between ME and $SDUR$. The results are available in Table 7. We find that shorter-duration bonds are on average associated with lower post-auction returns, but the effect is mitigated when taking into account the interaction with ME. More interestingly, the economic and statistical significance of ME is now higher in these regressions, as it captures the effect for longer-duration bonds only. The negative coefficient associated with ME is now also statistically significant across all holding period returns. As the estimated coefficient of the interaction term between ME and $SDUR$ is negative but lower in absolute value than the estimated coefficient on ME, risk-bearing capacity concerns still appear relevant for shorter-duration bonds, but the effect is statistically insignificant (untabulated t-statistics). Using the level of bond duration as opposed to a dummy variable leads to similar results, but these results are not as easily interpretable. This evidence is consistent with ME capturing risk bearing capacity concerns that appear particularly relevant for longer-duration bonds.

[Table 7 here]

6 The COVID-19 pandemic

The COVID-19 pandemic brought about significant volatility in financial markets that may have affected the risk-bearing capacity of primary dealer banks. On the one hand, this additional volatility should work as an ideal test to the risk-bearing capacity hypothesis. On the other hand, the unexpected nature, timing, and magnitude of the events means that no risk model was prepared to account for what happened. For this last reason, we do not include the year of 2020 in the main analysis so that results are not tainted by a potentially atypical year as related to the COVID-19 crisis. However, the auctions in the COVID-19 pandemic era are interesting on their own.

The only auctions conducted in March 2020 occurred on the 11th. March 11 is also the day the World Health Organization declares COVID-19 a pandemic. The next day, the European Central Bank announced arguably timid policy initiatives to contain the macroeconomic impact of the pandemic. At the press conference, Ms. Lagarde said that the ECB is "not here to close [bond] spreads. This is not the function or the mission of the ECB."[24] In the ensuing days government bond yields increased significantly in most euro area countries including Portugal, until March 18th when the ECB announced the Pandemic Emergency Purchase Programme for €750 billion intended at ensuring a proper functioning of the monetary policy transmission mechanism by reducing the dispersion in spreads. The prices of the lines auctioned on the 11th (5-year and 10-year re-openings) fell dramatically on the days after the auction, conditioned by events that were arguably unanticipated at the time of the auction. Of note, the average ME for the two lines was low, 5.14, but only about half of one standard deviation away from the pre-pandemic ME average. Clearly, primary dealers did not price in the small demand presence after March 11, as the 'ECB shock' could not have been anticipated. For this reason, in the analysis that follows, we exclude the two auctions from March 2020.

We repeat the predictive regressions including all the auctions in 2020, except for the two

[24]See https://www.ecb.europa.eu/press/pressconf/2020/html/ecb.is200312 f857a21b6c.en.htmlqa.

lines auctioned on March 11. The sample size increases to 82 observations. We report in Table 8 the predictive regressions for 5-day holding-period returns and leave the rest of the analysis for the Online Appendix. There are no noticeable qualitative changes relative to our main results. Quantitatively, the estimated coefficients associated with ME drop slightly. Note though that the Adjusted R-squares of all the regressions are quite similar, even those that exclude ME, despite the increase in the number of observations. This behavior of the R-squares is consistent with the significant increases in volatility in financial markets in the COVID-19 pandemic era, which makes the regressions including 2020 noisier. Despite the potential for confounding effects and additional noise from the 2020 data, our findings are generally consistent with those displayed in the main analysis.

[Table 8 here]

7 Robustness analysis

In this section we present a number of robustness exercises.

Bid shading. Bid shading, the practice of bidding below ones' valuation, has been documented in many countries and across different auction formats (e.g., Nyborg et al. 2002 and Hortaçsu et al. 2018). It typically leads to under-pricing relative to the secondary market. In the case of Portugal, bid shading behavior may be mitigated by benefits that the IGCP gives to dealers – syndication fees and post-auction non-competitive offerings – that depend on their allocations across multiple auctions (Cardoso-Costa et al. 2022). In fact, Treasury bond auctions in Portugal were on average over-priced in our sample. In addition, Treasury bond auctions in Portugal often are rationed (see below), which can be optimal in order to minimize bid shading (Parlour and Rajan 2005). Still, dealers' strategic behavior may bias the estimated elasticity from the aggregate demand schedule.

In order to study the effect of bid shading in our results, we construct two variables that proxy for bid shading: under-pricing (UP), measured as the difference between the secondary-market price at the end of the auction day and the cut-off auction price; bid discount ($DISC$), measured as the cross-dealer average of the difference between the secondary-market price at the end of the auction day and the quantity weighted average bid price of each dealer. First, we repeat the regressions in Table 4 adding the two additional controls UP and $DISC$. The Online Appendix reports that both of these variables are positively related to ME, though they are only weakly so. This confirms our suspicion that the marginal elasticity might be correlated with proxies for bid shading. We note that, like $COVER$, these two variables are observable only at the time of the auction and cannot be used to predict ME.

Second, we repeat our predictive regressions including UP and $DISC$ as controls.The Online Appendix reports that our results regarding the ability of ME to predict holding period returns remain quantitatively unaffected. In addition, the coefficients associated with these two variables are mostly statistically insignificant. Overall, our results suggest that the demand schedule revealed in the auction has important information content regarding dealers' risk-bearing capacity, even if the demand schedule is biased due to potential dealer strategic behavior.

Pro-rata allocation. As discussed above, in about 60% of the auctions in our sample, the IGCP opts for not fulfilling all bids offered at the cut-off price, thus rationing the bidders. To describe when rationing occurs, recall that the indicative issuance range is set on the sum of the lines auctioned on any single day. Often, rationing occurs to limit the issuance amount to the maximum of the indicative range: this happens in 55% of the rationed auctions in single auction dates and in 77% of the occasions in double auction dates. In other occasions it simply results in rounding the allocation amount (almost always a multiple of €50 million). In our baseline definition of ME, we already incorporate the effects of rationing. In every auction with rationing, ME is estimated by including two points of the demand schedule at the cut-off price (one for the quantity allocated and another also including the quantity unfilled at the cut-off).

Here, we analyze if secondary-market price pressure is related to rationing. We define PRS as the pro-rata share in an auction (i.e., the fraction of filled orders at the cut-off price); PRS is higher when there is less rationing. In the Online Appendix, we report that PRS is negatively related to ME, but the association is not statistically significant. We also find that more rationing is associated with higher post-auction returns, especially over horizons under 5 trading days. This effect is larger as $SIZE$ is smaller, but typically not statistically significant. In sum, there is a weak relationship between rationing and the amount of price pressure. Moreover, adding these variables contributes to an increase of the economic and statistical significance of ME. In these regressions, the negative coefficient associated with ME is now statistically significant for all holding period returns from 4 days after the auction onwards.

Placebo analysis. We conduct a placebo test by looking at unused auction dates by the IGCP. Recall that the IGCP can issue on the 2nd, 4th and 5th Wednesdays of each month, but leaves many of these dates unused. There are 82 unused auction dates between April 2014 and the end of 2019.[25] In the Online Appendix, we replicate the graphical event-study analysis of the top plot in Figure 4 for bonds of three maturities, 2, 5 and 10 years. Specifically, at each unused auction date, we obtain the secondary-market prices of the bonds that are closest to each of these maturities. The figure plots the average cumulative log abnormal returns in the 11-day window centered at the unused dates. The main result is that the secondary-market prices do not present the V-shaped pattern observed around executed auctions. Interestingly, the abnormal return of the 10-year bond seems to increase throughout the window, while the abnormal returns of the 2-year and 5-year bonds decrease. The trends observed over the 11-day windows suggest under- or over-performance relative to the aggregate index throughout the sample period. The 10-year bond upward trend may be justified by the fact that this is usually the most liquid on-the-run bond in the sample; the sample vastly coincides with a period of search for yield in international bond markets especially in long term bonds, also supported by the European Central Bank's Asset Purchase Programme, which is consistent with the relative under-performance observed for 2- and 5-year bonds. Nonetheless, there is no V-shaped pattern observed over the 11-day

[25]We exclude Wednesdays in late December that typically fall in the Christmas season, as well as those Wednesdays immediately following a syndicated deal, as the IGCP tends to avoid an excessive issuance concentration.

windows.

Yields versus prices. We run the event-study analysis using yields instead of prices, to confirm the statistical and economic significance of the impact of the marginal elasticity on price pressure on the secondary market. Yields allow us to address in a sole measure the heterogeneity of features between different Treasury bonds, namely maturity and coupon rate. However, the advantage of using prices – and the reason that we chose prices for the main analysis – is the fact that we can compute abnormal returns by adjusting Treasury bond raw returns using the Portuguese Treasury bond index returns.

In the Online Appendix, we plot the evolution of the raw yields of the bonds being auctioned. As expected, consistent with the results above, yields around auction dates follow an inverted V-shape, with an average reduction of 3 bps in the 5 day post-auction period. The order of magnitude of these movements is in line with the results obtained by Lou et al. (2013) or Beetsma et al. (2016). In addition, the inverted V-shape is only present in auctions where the marginal elasticity of demand is low.

Further, we run predictive regressions using yield cumulative changes from the auction day to h-days ahead rather than log-abnormal returns. The online appendix shows that the coefficient estimates associated with ME on these regressions are positive and significant, which is expected since there is a negative relationship between prices and yields. Thus, the results are robust to the use of yield changes.

Alternative measures of elasticity. We study the significance of using ME versus any of the other estimated elasticities. The relevant question is where in the demand curve should we estimate an elasticity of demand that best captures dealers' risk-bearing capacity? In the Online Appendix, we repeat the event-study analysis where we split the sample using each of the other proposed elasticity measures. Like with ME, for TE, GE, and SE there is a V-shape pattern in abnormal returns around auctions only in the low elasticity sub-samples, though the shape is less pronounced. In addition, as noted when discussing the predictive regressions, these measures do not show that same power to predict post-auction excess returns, at some horizons. A possible reason is the noise associated with the problem of overbidding. We interpret our combined findings as revealing that dealers' risk-bearing capacity is best identified by the marginal elasticity associated with untapped, residual liquidity.

8 Conclusion

In this paper, we show that the elasticity of demand obtained from the primary market is a proxy for primary dealers' risk-bearing capacity and thus should be studied as a potential source of information on risks about the aggregate economy. Our analysis proceeds by revisiting a common assumption in prominent financial-asset market models that supply shocks are absorbed with no price variation, i.e., the price elasticity of demand is infinite. However, the empirical finance literature has uncovered many examples where prices appear to move in response to supply shocks even in the most liquid of markets, a possible manifestation of limited risk-bearing capacity in the short run. One step missing in this literature is to demonstrate that the observed price response to the supply shock is linked to the elasticity of demand, that is to the revealed ability of demand to absorb these shocks in the short run. This paper uses the observed aggregate demand data in auctions of sovereign debt to calculate the price elasticity of demand. It then shows that an apparent price pressure phenomenon in the secondary market around auction days is connected to the price elasticity of demand obtained with auction data, suggesting that this elasticity captures dealers' perceptions of the ease with which they can turnover the bonds purchased in the auction to their secondary-market clients.

From a policy perspective, policy makers' monitoring of financial markets can benefit from using primary dealers' price elasticity as a barometer to assess the risk-bearing capacity of these agents, as this is a higher frequency proxy for their risk bearing capacity than others used in the literature (Goldberg 2020). In addition, issuers may benefit from knowing the value of the price elasticity of demand when determining the cut-off price of the auction since the elasticity correlates with the price in secondary market in the days after the auction (see Allen, Kastl, and Wittwer 2022 for another argument on how knowing the elasticity of demand can be used to increase auction revenue). Finally, understanding the price volatility induced by auctions, when and why it happens, can help banks develop better models of Value-at-Risk that use historical data to predict future volatility. Banks use these models to determine their risk-bearing capacity and auction-induced price volatility may be exactly the kind of volatility that banks should give more weight to.

In future work, and because changes in the price-elasticity of demand can signal changes in aggregate risk, we would like to study the predictive power of the price elasticity of demand over aggregate real and financial variables. Also, we would like to better understand the incentives of primary dealers in the selection of securities to be auctioned. Are primary dealers interested in securities whose demand is expected to be high post auction, or securities whose price has been going up prior to the auction? In addition, there may be fewer auctions when demand is low, a dimension of liquidity in the extensive margin that remains understudied.

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Table 1. T-bond auction characteristics

The table reports auction properties per year and for the full sample. The first column reports the number of auctions in each year or sample period. All other statistics are sample means of the respective variable in the indicated period. COVER is the ratio of all bid amount to the actual issuance amount. Participant (part.) bidders are the bidders that participate with at least one bid in an auction. These are a subset of the registered (regist.) bidders. Allocated (alloc.) bidders are the ones that had at least one bid satisfied on the auction.

Year	Nr auctions	Duration (years)	SIZE (€million)	COVER	Nr regist. bidders	Nr part. bidders	Nr alloc. bidders	Nr bids	Nr alloc. bids
2014	4	7	981	2.44	22	21	14	91	29
2015	8	10	943	1.80	21	20	15	71	32
2016	13	7	633	1.77	21	19	15	54	28
2017	16	7	650	2.02	21	19	13	56	24
2018	14	9	565	2.52	21	19	12	58	26
2019	11	11	611	1.96	20	18	13	69	32
2014-19	66	8	678	2.06	24	19	13	60	26
2020	16	9	622	2.20	20	18	13	69	32
2014-20	82	8	667	2.09	24	19	13	62	27

Table 2. Summary statistics of main variables

The table reports summary statistics for all the variables across the 66 auctions from 2014 to 2019. The variable definitions are in Table A.1. Mean is the sample mean of the variable, SD is the sample standard deviation, Min and Max are the minimum and maximum observations, and p25, p50, and p75 indicate the observation in percentile 25, 50, or 75, respectively.

	Mean	SD	Min	p25	p50	p75	Max
RBASx100	0.24	0.14	0.05	0.15	0.21	0.28	0.85
DRIFTx100	-0.09	0.21	-0.75	-0.18	-0.07	0.03	0.40
SIZE	677.50	258.18	275.00	500.00	625.00	800.00	1499.00
COVER	2.06	0.50	1.46	1.72	1.92	2.28	3.76
SPREAD	215.53	86.70	59.26	148.56	194.56	296.06	378.50
VOL	0.42	0.27	0.08	0.24	0.35	0.51	1.43
ME	5.56	0.69	4.14	5.10	5.44	5.98	7.22
SE	5.88	0.78	4.40	5.28	5.95	6.45	7.38
GE	5.55	0.41	4.46	5.31	5.53	5.87	6.39
TE	5.34	0.43	4.51	5.08	5.28	5.59	6.52
SDUR	0.50	0.50	0.00	0.00	0.60	1.00	1.00

Table 3. Correlations

The table reports linear correlations among the main variables across the 66 auctions from 2014 to 2019. The variable definitions are in Table A.1. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

Variables	RBAS	DRIFT	SIZE	COVER	SPREAD	VOL	ME	SE	GE	TE	SDUR
RBAS	1.00										
DRIFT	-0.34**	1.00									
SIZE	-0.20	-0.08	1.00								
COVER	-0.06	0.31**	-0.37***	1.00							
SPREAD	0.32**	-0.37***	-0.03	-0.24*	1.00						
VOL	0.52***	-0.45***	0.04	-0.31**	0.09	1.00					
ME	-0.23*	0.09	-0.03	0.36***	0.13	-0.48***	1.00				
SE	-0.12	0.08	-0.06	0.44***	-0.03	-0.29**	0.46***	1.00			
GE	-0.50***	0.13	0.08	0.23*	-0.01	-0.56***	0.37***	0.45***	1.00		
TE	-0.45***	0.23*	-0.14	0.53***	0.00	-0.68***	0.51***	0.45***	0.69***	1.00	
SDUR	-0.08	0.14	-0.02	0.26**	0.45***	-0.36***	0.27**	0.16	0.32**	0.59***	1.00

Table 4. Determinants of the marginal elasticity

The table reports coefficients of regressions of ME on RBAS, DRIFT, SIZE, SPREAD, VOL and SDUR between 2014 and 2019. The independent variables are normalized by the respective sample standard deviation. The variable definitions are in Table A.1. Some specifications include year and quarter fixed effects. *t-stats* calculated using robust standard errors are reported in parenthesis below the coefficients. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

	ME	ME	ME	ME
RBAS	-0.039	-0.100	-0.188**	-0.294*
	(-0.447)	(-0.779)	(-2.143)	(-1.804)
DRIFT	-0.082	-0.023	0.009	0.042
	(-0.880)	(-0.234)	(0.092)	(0.407)
SIZE	-0.014	-0.061	-0.048	0.006
	(-0.175)	(-0.617)	(-0.576)	(0.060)
SPREAD	0.081	0.036	0.093	0.253
	(0.804)	(0.172)	(0.809)	(1.179)
VOL	-0.335***	-0.421***		
	(-3.646)	(-3.695)		
SDUR	0.079	-0.119	0.256	0.151
	(0.414)	(-0.478)	(1.288)	(0.598)
Constant	5.912***		5.640***	
	(17.474)		(16.097)	
Year FE	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes
Obs.	66	66	66	66
Adj R^2	0.19	0.23	0.06	0.10

Table 5. Predictive regressions of the 5-day ahead abnormal return

The table reports coefficients of predictive regressions of the 5-day ahead abnormal return on different sets of independent variables between 2014 and 2019. The independent variables are normalized by the respective sample standard deviation. The variable definitions are in Table A.1. *t-stats* calculated using robust standard errors are reported in parenthesis below the coefficients. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

	AR_5	AR_5	AR_5	AR_5	AR_5
ME			-12.68***	-9.55***	-11.37***
			(-3.23)	(-3.07)	(-3.21)
RBAS	12.79***	11.00***		10.58***	9.83***
	(3.82)	(2.84)		(3.31)	(2.71)
DRIFT	-7.50	-6.38		-7.41*	-7.62**
	(-1.63)	(-1.52)		(-1.83)	(-2.00)
SIZE		-1.87			-1.03
		(-0.40)			(-0.24)
COVER		-2.72			0.04
		(-0.51)			(0.01)
SPREAD		-6.44			-3.95
		(-1.57)			(-1.09)
VOL		8.64*			4.77
		(1.69)			(0.99)
SE		6.50*			9.49**
		(1.69)			(2.38)
Constant	-18.45***	-45.53	108.52***	62.55**	11.63
	(-3.32)	(-1.27)	(3.23)	(2.35)	(0.30)
Obs.	66	66	66	66	66
Adj R^2	0.26	0.31	0.15	0.33	0.39

Table 6. Predictive regressions at various holding horizons with all controls

The table reports coefficients of predictive regressions of the h-day ahead abnormal return on all the independent variables between 2014 and 2019 (h varies from 1 to 10 days). The independent variables are normalized by the respective sample standard deviation. The variable definitions are in Table A.1. *t-stats* calculated using robust standard errors are reported in parenthesis below the coefficients. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

	AR_1	AR_2	AR_3	AR_4	AR_5	AR_6	AR_7	AR_8	AR_9	AR_{10}
ME	-2.74*	-3.11	-6.34*	-7.73**	-11.37***	-10.18**	-10.51**	-12.85**	-15.61***	-11.53**
	(-1.90)	(-1.40)	(-1.82)	(-2.27)	(-3.21)	(-2.30)	(-2.07)	(-2.58)	(-2.70)	(-2.26)
RBAS	1.11	3.30	7.41**	10.07***	9.83***	10.62*	13.49*	9.57*	5.12	10.48**
	(0.41)	(1.31)	(2.01)	(3.67)	(2.71)	(1.82)	(1.93)	(1.70)	(0.98)	(2.20)
DRIFT	-0.46	-4.43*	-6.50*	-8.88***	-7.62**	-7.66	-6.17	-8.47	-9.99	-2.66
	(-0.31)	(-1.91)	(-1.93)	(-2.77)	(-2.00)	(-1.57)	(-1.06)	(-1.40)	(-1.50)	(-0.48)
SIZE	3.49*	1.51	2.45	-1.41	-1.03	-3.76	-3.77	-2.96	-4.28	-1.92
	(1.75)	(0.54)	(0.69)	(-0.38)	(-0.24)	(-0.69)	(-0.61)	(-0.48)	(-0.67)	(-0.30)
COVER	0.58	1.15	0.96	-0.16	0.04	-3.19	-5.16	-4.33	-2.88	-2.29
	(0.35)	(0.52)	(0.32)	(-0.05)	(0.01)	(-0.64)	(-0.86)	(-0.71)	(-0.50)	(-0.42)
SPREAD	-3.46*	-3.80	-3.67	-5.61*	-3.95	-6.80	-6.27	-6.35	-5.01	-4.80
	(-1.96)	(-1.63)	(-1.32)	(-1.96)	(-1.09)	(-1.47)	(-1.14)	(-1.07)	(-0.86)	(-0.98)
VOL	-0.49	5.50*	2.76	3.64	4.77	7.15	5.98	6.66	3.45	-0.22
	(-0.15)	(1.75)	(0.75)	(0.90)	(0.99)	(1.21)	(0.77)	(0.79)	(0.42)	(-0.03)
SE	3.26*	5.36**	6.14*	6.79**	9.49**	9.25*	14.27**	16.01**	13.89*	10.66*
	(1.93)	(2.63)	(1.87)	(2.02)	(2.38)	(1.87)	(2.12)	(2.13)	(1.85)	(1.91)
Constant	-6.02	-26.00	-9.95	11.06	11.63	29.32	-4.06	1.95	44.53	29.35
	(-0.37)	(-1.07)	(-0.33)	(0.32)	(0.30)	(0.65)	(-0.07)	(0.03)	(0.70)	(0.48)
Obs.	66	66	66	66	66	66	66	66	66	66
Adj R^2	0.10	0.25	0.23	0.39	0.39	0.32	0.24	0.24	0.15	0.08

Table 7. Cross sectional test with bond duration

The table reports coefficients of predictive regressions of the h-day ahead abnormal return on all the independent variables between 2014 and 2019 (h varies from 1 to 10 days). The independent variables are normalized by the respective sample standard deviation. The variable definitions are in Table A.1. *t-stats* calculated using robust standard errors are reported in parenthesis below the coefficients. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

	AR_1	AR_2	AR_3	AR_4	AR_5	AR_6	AR_7	AR_8	AR_9	AR_{10}
ME	-5.92***	-8.99***	-12.71***	-14.79***	-17.57***	-17.58***	-17.79**	-22.04***	-24.02**	-17.58**
	(-2.77)	(-3.34)	(-2.98)	(-3.02)	(-3.29)	(-2.86)	(-2.20)	(-2.78)	(-2.63)	(-2.13)
RBAS	1.12	3.41	7.86**	10.81***	10.29**	11.53*	14.93**	11.45*	7.34	11.68**
	(0.41)	(1.33)	(2.01)	(3.76)	(2.66)	(1.88)	(2.08)	(1.97)	(1.41)	(2.45)
DRIFT	0.54	-2.68	-5.08	-7.64**	-6.27*	-6.56	-5.86	-8.17	-10.42	-2.41
	(0.39)	(-1.57)	(-1.60)	(-2.44)	(-1.69)	(-1.34)	(-1.02)	(-1.34)	(-1.55)	(-0.44)
SIZE	4.81**	3.84*	4.56	0.63	1.00	-1.78	-2.49	-1.42	-3.49	-0.86
	(2.58)	(1.70)	(1.44)	(0.18)	(0.25)	(-0.32)	(-0.41)	(-0.23)	(-0.54)	(-0.13)
COVER	2.60	4.61**	3.48	1.75	2.42	-1.68	-5.67	-5.21	-5.52	-2.73
	(1.58)	(2.02)	(1.04)	(0.47)	(0.53)	(-0.31)	(-0.84)	(-0.78)	(-0.88)	(-0.49)
SPREAD	0.07	2.24	0.82	-2.14	0.29	-3.99	-6.86	-7.50	-9.17	-5.32
	(0.03)	(0.86)	(0.20)	(-0.51)	(0.06)	(-0.67)	(-0.88)	(-0.91)	(-1.07)	(-0.78)
VOL	-2.44	2.05	-0.34	0.67	1.79	4.29	4.22	4.57	2.50	-1.68
	(-0.74)	(0.76)	(-0.10)	(0.16)	(0.36)	(0.71)	(0.54)	(0.55)	(0.32)	(-0.25)
SE	2.91*	4.74***	5.58*	6.24*	8.95**	8.73*	13.93**	15.60**	13.68*	10.38*
	(1.87)	(2.87)	(1.70)	(1.85)	(2.25)	(1.79)	(2.12)	(2.17)	(1.92)	(1.88)
SDUR	-50.63**	-93.06***	-97.88**	-106.21**	-94.94*	-110.03**	-103.50	-130.05	-114.48	-85.95
	(-2.50)	(-3.31)	(-2.36)	(-2.27)	(-1.88)	(-2.03)	(-1.38)	(-1.67)	(-1.25)	(-1.01)
SDUR_ME	4.91*	9.18***	10.35**	11.74**	10.08	12.45*	12.91	16.36*	15.56	10.73
	(1.98)	(2.82)	(2.15)	(2.16)	(1.67)	(1.90)	(1.44)	(1.71)	(1.41)	(1.07)
Constant	10.02	5.03	29.22	58.41	50.00	81.11	55.96	78.78	123.10	79.29
	(0.53)	(0.23)	(0.92)	(1.45)	(1.06)	(1.66)	(0.78)	(1.16)	(1.53)	(0.99)
Obs.	66	66	66	66	66	66	66	66	66	66
Adj R^2	0.21	0.43	0.29	0.43	0.42	0.33	0.23	0.25	0.15	0.07

Table 8. Predictive regressions including the year 2020

The table reports standardized coefficients of predictive regressions of the 5-day ahead abnormal return on different sets of independent variables between 2014 and 2020. The independent variables are normalized by the respective sample standard deviation. The variable definitions are in Table A.1. *t-stats* calculated using robust standard errors are reported in parenthesis below the coefficients. *, **, *** correspond to significance levels of 10%, 5%, and 1%, respectively.

	AR_5	AR_5	AR_5	AR_5	AR_5	AR_5
ME			-11.63***	-7.70***	-10.68***	-15.00***
			(-3.43)	(-2.87)	(-3.25)	(-3.20)
RBAS	11.54***	12.29***		9.14***	10.33***	10.24***
	(3.90)	(3.31)		(3.09)	(2.87)	(2.71)
DRIFT	-7.76*	-6.87*		-7.56**	-8.12**	-6.99**
	(-1.92)	(-1.88)		(-2.05)	(-2.40)	(-2.13)
SIZE		-0.08			-0.23	0.76
		(-0.02)			(-0.06)	(0.21)
COVER		-0.86			1.96	3.64
		(-0.19)			(0.50)	(0.92)
SPREAD		-6.42*			-5.01	-2.03
		(-1.80)			(-1.54)	(-0.60)
VOL		6.81			3.78	2.32
		(1.65)			(0.94)	(0.55)
SE		4.17			7.55**	7.26**
		(1.27)			(2.18)	(2.06)
SDUR						-79.00*
						(-1.84)
SDUR_ME						9.04
						(1.67)
Constant	-15.73***	-41.96	93.77***	47.22**	7.22	33.02
	(-3.81)	(-1.32)	(3.38)	(2.13)	(0.22)	(0.85)
Obs.	82	82	82	82	82	82
Adj R^2	0.27	0.32	0.14	0.32	0.39	0.41

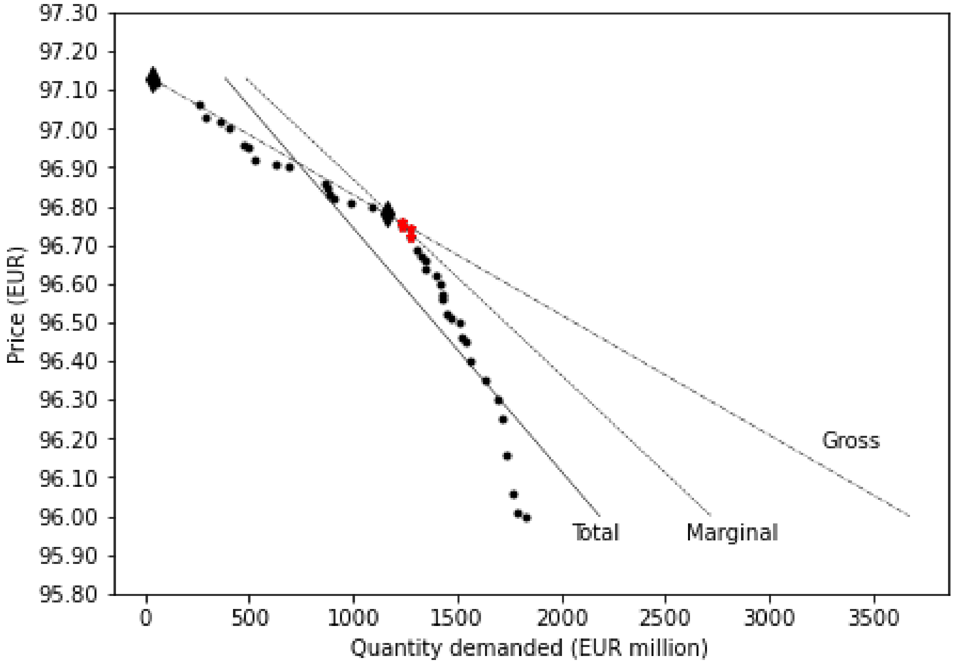

Figure 1. Example of an auction demand curve.
The figure presents all the bid prices for the auction of May 11, 2016 of a 10-year Treasury Bond. The range of bids was between 96.00 and 97.13 with a cut-off price of 96.78. The secondary market price at the end of the day on the same bond was 96.993. The IGCP indicated it would like to issue between €750 million and €1 billion, the bid amount was €1.83 billion, and the final allocated amount was €1.15 billion. The figure also presents three slopes used to construct three different elasticities of demand. *Gross* represents the slope of the gross demand curve using just the cut-off price point and the maximum price point. *Total* represents the slope of the total demand curve using all price points. *Marginal* represents the slope of the marginal demand curve using untapped demand as given by the cut-off price point and 4 unsubscribed price points to the right of the cut-off price. In this auction, the value of ME, TE and GE are 5.23, 4.89, and 5.60, respectively.

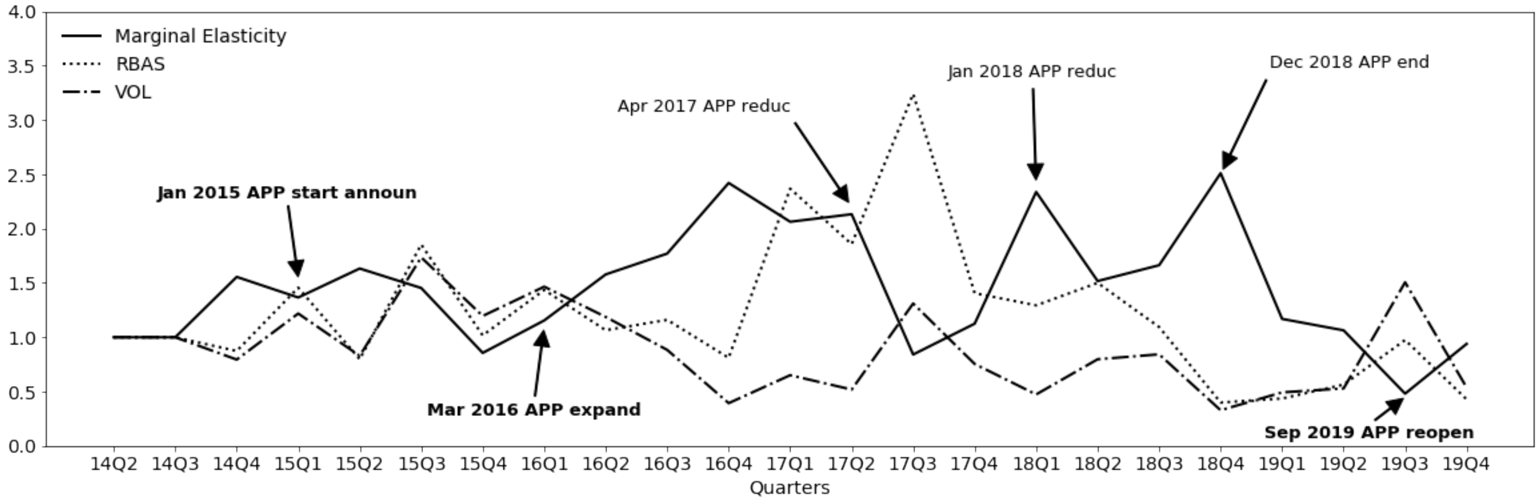

Figure 2. Time series of marginal elasticity, relative bid-ask spread, and volatility.
The figure presents quarterly average values of the marginal elasticity (ME), relative bid-ask spread (RBAS), and volatility (VOL). The three series are normalized to 1 at the initial point for ease of comparison. In boldface, we indicate events by the European Central Bank of programs that increase liquidity, and in normal font, we indicate events by the ECB of programs that decrease liquidity. APP stands for Asset Purchase Program.

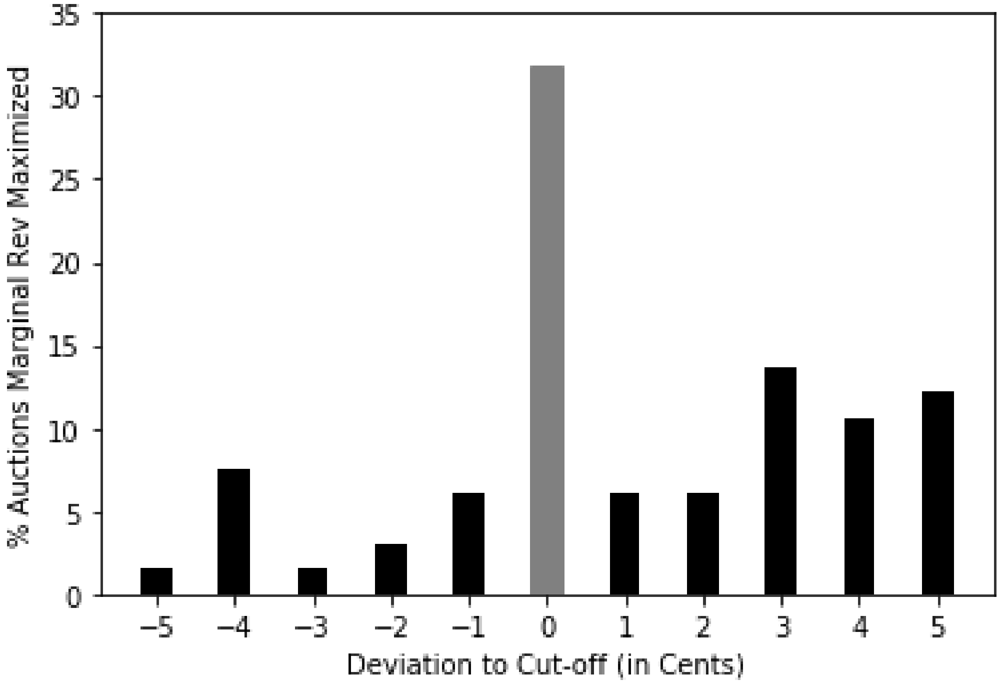

Figure 3. Proportion of bins with maximum marginal revenue at and around the cut-off price.
For each auction and conditional on an interval of +/- €0.05 around the cut-off price, the figure plots the fraction of auctions between 2014 and 2019 whose marginal revenue is maximized at each price. Negative values to the left of the cut-off price indicate unsubscribed prices €-0.05 to €-0.01 below the cut-off price. Positive values to the right of the cut-off price indicate subscribed prices €0.01 to €0.05 above the cut-off price.

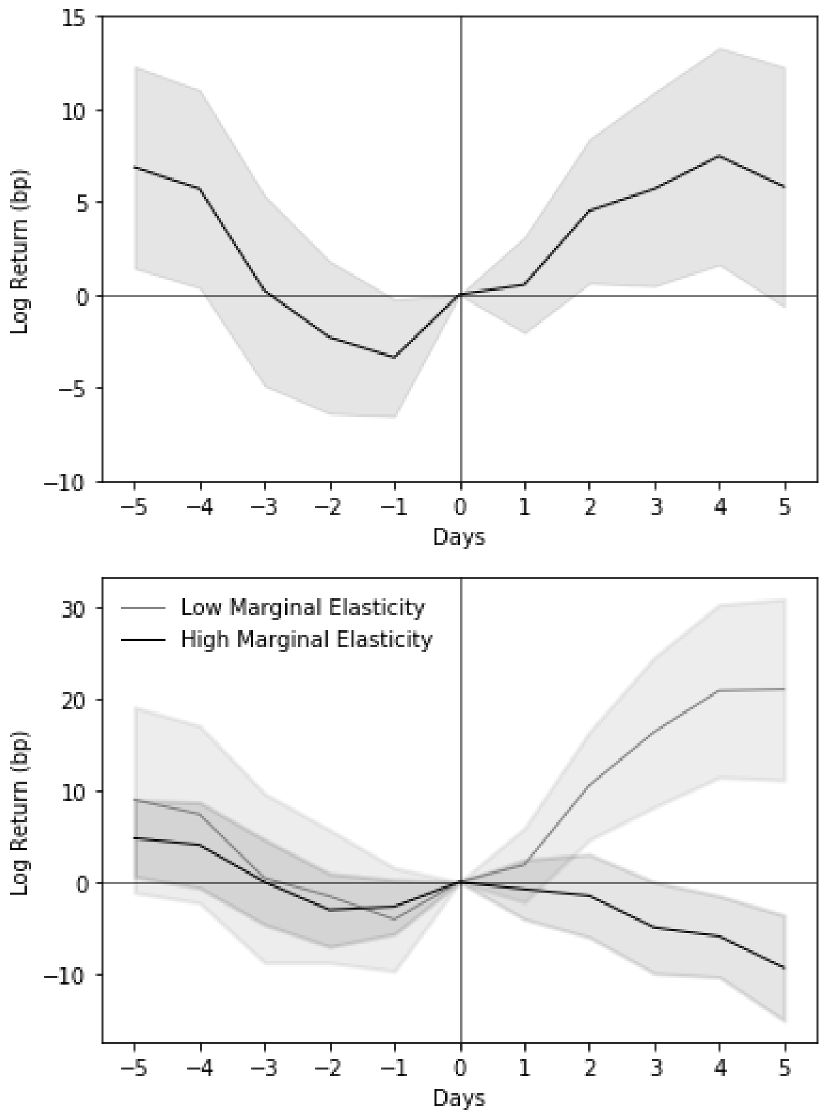

Figure 4. Cumulative log abnormal returns around auction day.
The figure displays the average cumulative log abnormal returns (in bps) between 5 days prior and 5 days after the auction day for all auctions between 2014 and 2019. The returns are normalized to 0 at the close of auction day (day 0). 90% confidence bands are also reported. The top panel presents the results for all auctions. The bottom panel presents the results partitioning the auctions between high (black line) and low (gray line) marginal elasticity according to the median value of ME.

Table A.1. Variable definitions

Variable	Description
AR_h	*Abnormal log-return* 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 of Bloomberg's Portuguese bond index multiplied by a shrinkage beta and the estimated constant from the secondary-market daily log returns of the auctioned bond. The shrinkage beta is the result of a weight of 0.4 applied to the market beta of 1 and a weight of 0.6 applied to the bond's market beta (see Vasicek 1973 and Frazzini and Pedersen 2014). For each bond/auction, we use the period from 65 days to 6 days prior to the day of the auction and data from the bond being auctioned to estimate the market beta and constant. Source for prices: Bloomberg.
COVER	*Bid-to-cover ratio* is the total bid amount divided by the allocated amount. This variable is observed at the end of the auction. Source for bids: IGCP.
DRIFT	*Previous 3-day log abnormal return* is the secondary-market abnormal log return of the T-bond being auctioned from end-of-trading day Thursday to end-of-trading day Tuesday prior to the auction (variable is based on Lou et al. 2013). We obtain the abnormal return by subtracting the log return of Bloomberg's Portuguese Government Bond index for the same period times the shrinkage beta (see definition of AR_h). This variable is observed prior to the auction. Source for prices: Bloomberg.
GE	*Gross elasticity* is the price elasticity of demand obtained using two points of the demand curve: the cut-off price point and the maximum price, and the total quantities bid at those points. The elasticity uses the slope of the line that goes through these two points multiplied by the ratio of the cut-off price to the cut-off quantity. Gross elasticity is the log of the negative of this value. This variable is observed only by the Treasury at the auction. Source for bids: IGCP.
ME	*Marginal elasticity* is the price elasticity of demand obtained using the cut-off price/quantity and the first four price points that are unsubscribed. The elasticity uses the slope from the linear regression that goes through these five points multiplied by the ratio of the cut-off price to the cut-off quantity. Marginal elasticity is the logarithm of the negative of this value. When there is pro-rata share at the cut-off price, we substitute the point in the demand curve by two points with the same price and still use the first four price points that are unsubscribed. This variable is observed only by the Treasury at the auction. Source for bids: IGCP.
RBAS	*Relative bid-ask spread* is the average over the 5-day period prior to the auction of the daily difference between ask and bid prices divided by the mid price. Prices are close-of-day prices of the T-bond being auctioned. This variable is observed prior to the auction. Source for prices: Bloomberg.
SDUR	*Short duration* is a dummy variable that takes value 1 if the Macaulay duration of the security being auctioned is shorter than the median Macaulay duration across all auctions and 0 otherwise. Source: Bloomberg.
SE	*Marginal elasticity subscribed* is the price elasticity of demand obtained using the cut-off price/quantity and the first four price points that are subscribed. The elasticity uses the slope from the linear regression that goes through these five points multiplied by the ratio of the cut-off price to the cut-off quantity. SE is the logarithm of the negative of this value. This variable is observed only by the Treasury. Source for bids: IGCP.
SIZE	*Size* is the allocated amount in the auction (in EUR million), observed at end of auction. Source: IGCP.
SPREAD	*Spread* is the average spread between the 10-year Portuguese government bond yield and the German government bond yield (in basis points) in the 5 days prior to the auction. This variable is observed prior to the auction. Source for time-series: Bloomberg.
TE	*Total elasticity* is the price elasticity of demand obtained using all the price points. The elasticity uses the slope from the linear regression that goes through all the points multiplied by the ratio of the cut-off price to the cut-off quantity. Total elasticity is the logarithm of the negative of this value. This variable is observed only by the Treasury at the auction. Source for bids: IGCP.
VOL	*Volatility* is the standard deviation of log returns of the bond being auctioned over the 20 trading days prior to the auction (in one auction we have only 19 trading days). This variable is observed prior to the auction. Source for prices: Bloomberg.