Which Bonds Characteristics Matter? Evidence from Retail Investors

Matheus Carrjio Brito *

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Abstract

This paper investigates which bond characteristics drive retail investors' allocation decisions using a novel transaction-level dataset of direct holdings in Brazilian government bonds from 2014 to 2024. Applying the methodology of Balasubramaniam, Campbell, Ramadorai, and Ranish (2023) to the fixed-income setting, I identify three investor clienteles organized around safety, duration exposure, and special bonds. The two characteristics generating the strongest portfolio heterogeneity are bond price and time-to-maturity. I show that the bond price factor better reflects a preference for floating-rate bonds rather than nominal price illusion. The time-to-maturity factor reflects persistent maturity habitat preferences: investors systematically return to the same maturity range after rebalancing, and initial maturity choices predict future choices well beyond what mechanical portfolio aging can explain.

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*Getulio Vargas Foundation - Sao Paulo School of Economics, Brazil. Email: matheus.brito@fgv.edu.br.

1 Introduction

Despite the central role of government bonds in household saving and wealth accumulation, remarkably little is known about how retail investors form preferences over fixed-income instruments. The household finance literature has extensively documented retail investor behavior in equity markets: individual investors trade too frequently on non-informative signals (Barber and Odean, 2008), systematically sell winning positions while holding losing ones (Ben-David and Hirshleifer, 2012), and treat low-priced stocks as lottery tickets (Kumar, 2009) or as a source of entertainment (Dorn and Sengmueller, 2009). Whether these patterns extend to fixed-income markets, or whether the distinct contractual structure of bonds disciplines investor behavior, remains an open question. This paper takes a step toward answering it by examining which bond characteristics drive retail portfolio decisions and whether investors sort into identifiable clienteles organized around those characteristics.

The question is economically relevant. Standard portfolio theory predicts that investors hold the market portfolio as their risky asset, with a riskless short-term bond as the safe component. Government bonds, however, span a wide spectrum of risk exposures, including interest rate risk, inflation risk, and duration risk, none of which are present in a riskless money-market instrument. Understanding which of these dimensions retail investors have a clientele for and which they neglect is therefore informative about the degree to which households solve their portfolio problem correctly.

To study these questions, I use a novel transaction-level dataset from the Tesouro Direto program, a retail bond platform launched by the Brazilian Treasury in 2002 to broaden household access to federal government securities. The program offers a diverse menu of bond types, including floating-rate bonds indexed to the overnight policy rate (Tesouro Selic), inflation-linked bonds (Tesouro IPCA+), fixed-rate bonds (Tesouro Prefixado), and goal-oriented instruments designed for retirement and education saving. The dataset covers the period from 2014 to 2024 and contains over 60 million transactions across more than 2.5 million individual investors, making it one of the most comprehensive retail fixed-income datasets available for academic research. Similar retail Treasury programs exist in other countries, including TreasuryDirect in the United States, but the Tesouro Direto is distinctive in providing universal transaction-level coverage with investor-level demographic information.[1]

The Brazilian setting offers several features that make it an attractive laboratory for studying retail bond behavior. Brazil has operated under an inflation-targeting regime with an independent central bank, providing the same institutional structure found in most advanced economies. At the same time, Brazil has experienced substantial variation in both nominal interest rates and inflation over the sample period, with the Selic rate ranging from approximately 2% to 14% and inflation exhibiting episodes well above target. This variation generates rich cross-sectional and time-series identification that is difficult to obtain in low-rate environments, while the underlying monetary policy framework ensures that findings are interpretable in terms of standard economic theory.

Empirically, I adapt the methodology of Balasubramaniam, Campbell, Ramadorai, and Ranish (2023) (hereafter BCRR) to the fixed-income setting. BCRR develop a factor model of direct stockholdings that identifies which stock characteristics generate the largest cross-sectional heterogeneity in retail portfolios and which investor attributes predict characteristic

[1] Retail government bond programs exist in many countries. Notable examples include: TreasuryDirect (United States, est. 1986), National Savings and Investments (United Kingdom, est. 1861), Bundesschatz (Austria, est. 2003), Buoni del Tesoro Poliennali—BTP (Italy, est. 2012), Certificados de Aforro and Certificados do Tesouro (Portugal, est. 1960), Hungarian Government Securities Plus—MÁP Plusz (Hungary, est. 2019), Retail Treasury Bonds (Poland), Kiwi Bonds (New Zealand), Cetesdirecto (Mexico, est. 2010), Japanese Government Bonds for Retail Investors (Japan, est. 2003), Korea Treasury Bonds (Korea, est. 1998), and Retail Sukuk and Retail Government Bonds (Indonesia, est. 2006), among others. See Table IA.2 for a detailed comparison of program characteristics across 22 countries.

tilts. The core object of their framework is the *bond co-holdings matrix*, a $B \times B$ positive semi-definite matrix constructed from the demeaned portfolio weights of I investors across B bonds, analogous to an empirical covariance matrix where the investor dimension replaces the time dimension. The diagonal elements of this matrix measure the cross-investor variance of holdings in each bond, capturing the degree to which bonds attract heterogeneous demand across investors. Projecting a vector of bond characteristics onto this matrix yields a scalar, the *clientele strength*, that summarizes how much cross-sectional dispersion in portfolio tilts a given characteristic generates. Characteristics with high clientele strength are those around which investors strongly disagree: some tilt heavily toward them while others avoid them entirely. Extracting the principal components of the characteristic co-holdings matrix then identifies the orthogonal directions of maximum portfolio heterogeneity, each interpretable as a distinct investor clientele defined by a bundle of bond characteristics that are systematically held together.

I apply this framework to bond holdings, replacing the size, value, and momentum characteristics that organize equity portfolios with the contractual features that differentiate government bonds: interest rate type, inflation indexation, coupon structure, yield to maturity, time to maturity, unit price, and recent return and volatility. I construct investor-level bond holdings by accumulating net transaction quantities for each investor-bond pair over the sample period. Since short-selling is not permitted in the Tesouro Direto program, cumulated positions are non-negative by construction, yielding a reliable measure of end-of-period holdings. In cases where a cumulated position becomes temporarily negative, indicating an unobserved initial holding predating the sample, I initialize the position at the absolute value of the minimum cumulated quantity observed for that investor-bond pair, ensuring non-negative holdings throughout. Following BCRR, I use the cross-section of holdings at the end of 2024 as the basis for the co-holdings matrix.

The bond characteristics with the highest clientele strength are unit price, time-to-maturity, and yield to maturity, indicating that these are the primary dimensions along which retail investors disagree in their portfolio allocations. The characteristic co-holdings matrix exhibits a strong factor structure: the first three principal components account for approximately 70% of the total co-holdings variance, each admitting a clear economic interpretation. The first principal component loads primarily on the floating-rate bond indicator and is interpreted as a *Safety* clientele, reflecting a preference for capital-preserving, liquid instruments. The second loads on time-to-maturity and fixed-rate bonds, capturing a *Duration Risk* clientele that takes active positions along the term structure. The third loads on goal-oriented instruments designed for retirement and education saving, identified as a *Special* clientele.

Examining which investor attributes predict membership in each clientele, I find that the Safety clientele is associated with larger portfolios and investors who are older, female, and married, consistent with capital preservation motives. The Duration Risk clientele disproportionately attracts younger, less experienced, and male investors, suggesting that term-structure risk-taking is concentrated among less financially sophisticated participants. For the two characteristics with the highest clientele strength, I show that the apparent sensitivity of retail demand to unit price reflects bond type selection rather than nominal price illusion: once bond-type fixed effects are included, the price coefficient loses statistical significance, while time-to-maturity and yield remain strong predictors of purchase decisions. Finally, I document that maturity preferences are persistent over horizons of up to ten years, with initial portfolio maturity predicting future maturity choices well beyond what passive portfolio aging can explain, consistent with preferred habitat behavior in the sense of Vayanos

(2021).

1.1 Related literature

This paper connects to three strands of the literature.

Retail Investors in Fixed Income. This paper is related to the household finance literature, which documents that individual investors combine rational responses with systematic biases in their portfolio decisions (Barber and Odean, 2013; Campbell, 2006). The bulk of this evidence concerns equity markets, where retail investors have been shown to trade too much, earn poor risk-adjusted returns, and exhibit behavioral biases including overconfidence, disposition effects, and attention-driven trading (Barber and Odean, 2001; Odean, 1999; Barber and Odean, 2008). A growing literature extends these findings to other asset classes, including cryptocurrencies (Kogan, Makarov, Niessner, and Schoar, 2024), foreign exchange (Heimer and Simsek, 2019; Hayley and Marsh, 2016), and derivatives (Bogousslavsky and Muravyev, 2024; Bryzgalova, Pavlova, and Sikorskaya, 2023).

Evidence on retail behavior in fixed income remains scarce relative to equities. deHaan, Li, and Watts (2023) show that retail investors rely heavily on credit ratings when selecting corporate bonds, consistent with limited attention and delegated information acquisition. Wei (2018) documents that corporate bonds heavily purchased by retail investors subsequently underperform those heavily sold, which he attributes to behavioral biases in retail demand. Liu, Wang, Wei, and Zhong (2019) provide evidence of yield-chasing behavior among retail investors in Chinese corporate bond markets. Nagel and Yan (2023) study retail demand for inflation protection using TIPS ETFs during inflation-scare episodes, documenting that retail participation responds sharply to salient inflation signals. Hilt, Jaremski, and Rahn (2022) examine the long-run effects of U.S. Liberty Bond ownership on household participation in capital markets.

A common thread in this literature is its focus on corporate bonds and retail-accessible fixed-income products, leaving retail behavior in sovereign debt markets largely unexplored. This paper fills that gap by documenting how retail investors form preferences over government bond characteristics, using a platform in which the full universe of investor-level transactions is directly observed.

Preferred Habitat Theory and Maturity Demand. The paper's central finding, that retail investors exhibit persistent preferences over specific maturity ranges, connects directly to the preferred habitat literature in fixed income. The preferred habitat hypothesis, originally proposed by Culbertson (1957), holds that investors have strong preferences for particular maturity segments and require a yield premium to hold bonds outside their preferred range. Vayanos (2021) provides a formal equilibrium model in which habitat preferences of bond investors interact with arbitrageur activity to determine the shape of the yield curve, showing that supply and demand shocks in specific maturity segments have persistent effects on yields. Greenwood and Vayanos (2014) and Greenwood, Hanson, and Vayanos (2024) provide empirical evidence that bond supply shifts affect yields differentially across maturities, consistent with imperfect substitutability driven by investor preferences.

Most of the empirical preferred habitat literature focuses on institutional investors, such as insurance companies, pension funds, and central banks, as the primary source of maturity-segmented demand Jansen (2025), Guibaud, Nosbusch, and Vayanos (2013). Evidence on whether retail investors also exhibit habitat behavior is limited. Dorn and Huberman (2010) document that individual investors in German equity markets maintain persistent preferences over idiosyncratic risk exposures, a pattern analogous to preferred habitat behavior in the maturity dimension. Life-cycle portfolio choice models predict that maturity preferences should vary systematically with age and investment horizon (Gomes, 2020; Parker, Schoar, Cole, and Simester, 2025), but direct evidence linking these predictions to observed retail bond holdings has been scarce. This paper provides that evidence using a setting in which maturity preferences can be measured precisely at the transaction level over a decade-long horizon.

Investor Heterogeneity and Demand for Government Bonds. The methodology of this paper, applying a factor model of direct holdings to identify bond characteristic clienteles, builds on BCRR, who develop a framework for decomposing equity portfolio heterogeneity into characteristic-driven clienteles using direct stockholding data. This paper adapts their approach to the fixed income setting, where the relevant characteristics differ fundamentally from equities: maturity, coupon structure, inflation indexation, and interest rate type replace the size, value, and momentum factors that organize equity portfolios.

This paper also contributes to the broader literature on heterogeneous demand for government bonds. Jansen (2025) estimates demand curves for U.S. treasuries across institutional investor classes, documenting that long-term investors such as insurance companies and pension funds are the primary source of downward-sloping demand at the long end of the yield curve. While this literature has focused predominantly on institutional intermediaries, I shift attention to retail investors and provide direct evidence, from granular bond-level holdings data, on which bond characteristics matter most for this investor class, a question that has received limited attention due to data constraints.

The remainder of the paper is organized as follows. Section 2 describes the Tesouro

Direto program. Section 3 presents the data. Section 4 identifies which bond characteristics generate the strongest clientele effects and characterizes the investor profiles associated with each clientele. Section 5 examines the two highest-strength characteristics, unit price and time-to-maturity, in detail. Section 6 concludes.

2 Tesouro Direto Program

The *Tesouro Direto* program (hereafter TD) is a retail bond platform established by Brazil's National Treasury on January 7, 2002, in partnership with the Brazilian stock exchange (B3, formerly BM&F Bovespa), which serves as the central custodian of investor positions.[2] The program was designed with the dual objective of promoting financial inclusion and encouraging household saving by enabling retail investors to purchase federal government securities directly, without relying on costly financial intermediary products. TD also serves as an accessible entry point into financial literacy for first-time investors. Participation requires only a Brazilian individual taxpayer identification number (CPF) and registration with an accredited financial intermediary. The minimum investment is R$30.00 (approximately USD 7 at the sample-period average exchange rate), and monthly investments are capped at R$1,000,000 (approximately USD 240,000).[3]

Investors can trade through two channels: (i) by placing orders directly on the program's website, or (ii) via a financial intermediary (bank or brokerage) that provides access to TD.[4] The website centralizes information on available securities, including current and historical yields, prices, maturities, and contractual features. In addition, TD explicitly incorporates

[2]Retail government bond programs exist in many countries. See Table IA.2 for a detailed comparison of program characteristics across 27 countries.

[3]This maximum monthly investment cap was changed to USD 480,000 on 18/11/2024.

[4]Program website: Tesouro Direto. The appendix provides screenshots illustrating the investor interface.

financial education tools,such as simulators that map investment goals into bond choices,and extensive material describing bond pricing and risks, alongside a detailed FAQ section.

TD offers multiple categories of federal securities, including inflation-linked bonds (Tesouro IPCA+), floating-rate bonds (Tesouro Selic), and fixed-rate bonds (Tesouro Prefixado), as well as purpose-oriented products (e.g., Tesouro Educa+ and Tesouro Renda+), designed for educational and retirement investing. These instruments span a wide maturity spectrum (roughly from one year to several decades), currently the longest-maturity bond currently matures in 2065. Importantly, the TD program quotes the bond prices using the secondary treasury market prices, which provides a mark-to-market valuation and investors know the value of their position in case of early redemption. The prices are updated on the platform throughout the day based on secondary-market conditions, with the Treasury posting bid and ask quotes multiple times per day.

Trading through TD involves two main cost components: a custody fee charged by B3 and (potentially) a service fee charged by the intermediary. The B3 custody fee is 20 bps per year, accrued daily on the investor's position starting from the settlement date, typically D+1, one business day after the trade. This fee applies pro rata to floating-rate, inflation-linked, and fixed-rate securities, with an important exemption: investors holding up to R$10,000 in floating-rate bonds are not charged the custody fee on that position. Intermediary fees vary across banks and brokerages because they are contractually set by each institution; in practice, many intermediaries charge zero to attract clients.[5] Finally, TD transactions occur at posted bid and ask quotes, implying an effective spread between purchase and sale prices. Spreads are typically below 50 bps, but can be substantially higher for longer-maturity securities, occasionally reaching 250 bps for long-term bonds.

[5] List of institutions and their fees: Banks and brokerages.

Furthermore, purpose-oriented bonds are subject to a mandatory holding period of two months following purchase, during which investors are prohibited from selling, a restriction designed to discourage speculative trading. Investments in the program are also subject to two taxes. First, the *Imposto sobre Operações Financeiras* (IOF), a financial transactions tax, applies exclusively to positions held for less than 30 days. The IOF rate starts at 96% for a one-day holding period and declines by 3 percentage points per day, reaching zero after 30 days. Second, income tax is levied on investment returns at a rate that decreases with the holding period: 22.5% for investments held up to 180 days, declining progressively to 15% for investments held beyond 720 days.

Settlement and redemption in Tesouro Direto follow clear cutoffs. Purchases placed on business days before 6:00 p.m. are credited to the investor's account by 6:00 p.m. on the next business day (D+1). Orders submitted after 6:00 p.m. or on weekends/holidays are settled on the second business day (D+2). Redemptions (early sales back to the Treasury) also depend on the submission time. Requests made in the morning are paid out by 1:00 p.m. on the same business day; requests made in the afternoon or outside business hours are paid out on the next business day. The Treasury provides daily liquidity: investors can request redemption on any day, but execution occurs at prevailing market prices during trading hours and at the next business day's opening price when the request is submitted outside trading hours. Consequently, investors who hold a bond to maturity receive the contractual payoff implied at purchase, whereas early redemptions are settled at the bond's current mark-to-market value, which can differ from the purchase price.

3 Data

The dataset provided by the Brazilian Treasury contains transaction-level records from the Tesouro Direto Program. Each observation includes a de-identified investor code, the type of bond traded, a buy/sell indicator, the monetary value of the transaction, and the number of bond units transacted.[6] A supplementary file provided by the Brazilian Treasury contains investor-level demographic characteristics, including gender, marital status, occupation, and municipality and state of residence.

Investors holding accounts with multiple brokerages that operate within the program appear as separate entries sharing a common investor code, which allows the same individual to be tracked across platforms. However, the transaction records do not identify the specific brokerage through which each trade was executed; they only indicate whether the trade was placed directly through the program's own website.[7]

Panel A of Table 1 presents descriptive statistics at the aggregate time-series level. On an average trading day, total transaction volume in the program amounts to approximately USD 50 million, with a single-day peak of USD 4 billion. Average daily buy volume is approximately USD 31 million and average daily sell volume approximately USD 17 million, representing 65% and 35% of total average daily volume, respectively. On a typical day, nearly 20,000 investors execute at least one transaction, trading across an average of 22 distinct bond series with an average time-to-maturity of 7.34 years. By maturity segment, short-term bonds (maturity below 3 years) account for 25.82% of total transaction volume, medium-term bonds (maturity between 3 and 5 years) for 28.54%, and long-term bonds

[6]The dataset also contains indicators for bond redemptions and for the inclusion of bonds in the program. Initially, bonds could move between the Tesouro Direto Program and the secondary market. This practice was permitted until 2015, at which point it was prohibited.

[7]The share of transactions executed through the program's website is 12% in number and representing approximately 22% of quantity shares.

(maturity exceeding 5 years) for 45.64%.

The data set contains transaction flows but not portfolio holdings. However, under a set of assumptions, investor-level holdings can be constructed from the flow data. Specifically, for each investor-bond pair, I initialize the position at the start of the sample period (January 2014) and cumulate net flows forward until either the bond matures or the end of the sample (December 2024), whichever occurs first. For some investor-bond pairs, particularly those active at the beginning of the sample, the true initial position is unobserved, which can produce negative cumulated positions in certain periods. Since short selling is not permitted in the TD Program, any such negative values indicate a missing initial holding rather than an actual short position. To correct for this, I set the initial position equal to the absolute value of the minimum cumulated quantity observed over the sample period, thereby ensuring non-negative holdings throughout.[8]

Finally, constructing a balanced panel of holdings for the full investor population is computationally prohibitive, as tracking portfolio positions across more than five million investor-bond pairs would require substantial memory resources. To manage this constraint, I randomly select 1% of all investors, yielding a sample of 286,000 individuals, to form the holdings panel used in the empirical analysis.[9]

Panel B of Table 1 reports summary statistics for the portfolio holdings of the randomly selected investors. The average portfolio value is approximately USD 5,000, with a standard deviation of USD 22,000. The distribution is highly right-skewed, as evidenced by a median holding of only USD 200, indicating that a small number of investors account for a

[8]Investors who held positive positions at the start of the sample but did not subsequently sell are subject to a portfolio measurement error, as their initial holdings remain unobserved. This concern is likely to be of limited practical importance, however, since the majority of bonds in the sample were issued after January 2014, and most investors in the program initiated their participation during the sample window.

[9]Tracking portfolio positions for 286,000 investors and their respective bond holdings produces a dataset exceeding 600 million observations and approximately 40GB of storage.

disproportionate share of total assets. In terms of maturity composition, 38.87% of average holdings are allocated to short-term bonds, 27.87% to medium-term bonds, and 33.26% to long-term bonds, corresponding to average monetary values of USD 1,933, USD 1,444, and USD 1,633, respectively. The average portfolio maturity is approximately 7 years. Investors tend to hold highly concentrated portfolios, with an average of 1.77 distinct bond series and a Herfindahl-Hirschman Index (HHI) of 0.70. Over the sample period, the average investor executes nearly seven transactions in total, with more than five purchases and fewer than two sales. Annual buy-side turnover averages 22.57% and sell-side turnover 14.08%. Taken together, these patterns are consistent with a buy-and-hold investment strategy, in which investors accumulate positions over time but seldom liquidate them.

Panel C of table 1 reports the distribution of investor demographic characteristics, including age, investment experience, gender, educational attainment, and geographic location. Experience is measured as the number of years elapsed between an investor's first recorded transaction and the end of the sample period. The typical investor is approximately 36 years old. Men represent 68.27% of the sample and women represent 31.63%. In terms of marital status, 55% of investors are single and 45% are not. Regarding educational attainment, 30% of investors hold a college degree, while the remaining 70% do not; this distinction is used to classify investors into occupations that require higher education and those that do not. Geographically, the investor base is heavily concentrated in the Southeast region of Brazil, which accounts for nearly 59% of all investors. The South is the second most represented region at 15.26%, followed by the Northeast at 13.92%, the Center-West at 7.96%, and the North at 4.00%.

[Table 1 about here]

4 Which Bond Characteristics Matters?

To identify which bond characteristics matter most for retail investors, I use the method proposed by BCRR that uses the direct holdings. Using the final period of the data set I select the investors with positive holding in at least one of the 51 available bond. From the 286 thousand investors that have a portfolio position in the data set, 156 thousand have a positive holding at the final of the data set. Let $\mathbf{q}_i'$ denote the 1 dimensional vector of bond holdings for investor i, where $B = 51$ and each entry records the portfolio weight allocated to a given bond at that December of 2024. Because retail investors tend to hold concentrated portfolios, $\mathbf{q}_i'$ typically contains many zero entries. Stacking all vectors $\mathbf{q}_i'$ among investors results in the *bond holding matrix* $\mathbf{Q_i}$, with dimension $I \times B$, where I denotes the number of investors.

The Bond Coholdings Matrix. Let $\tilde{\mathbf{Q}}_\mathbf{i}$ denote the demeaned bond-holdings matrix, in which demeaning is performed across the investor dimension:

$$\tilde{\mathbf{Q}}_i = \mathbf{Q}_i - I^{-1} \sum_{i'=1}^{I} \mathbf{Q}_{i'}, \tag{1}$$

where the subtracted term is the cross-investor average portfolio weight for each bond. From this demeaned matrix it is straightforward to construct the *bond coholdings matrix*, defined over the B bonds and with dimension $B \times B$:

$$\boldsymbol{\Omega}_\mathbf{i} = I^{-1} \sum_{i=1}^{I} \tilde{\mathbf{Q}}_i \tilde{\mathbf{Q}}_i'. \tag{2}$$

The bond coholdings matrix $\boldsymbol{\Omega}_\mathbf{i}$ shares the structural properties of the empirical covariance matrix of asset returns, with the investor dimension replacing the time dimension. In particular, $\mathbf{\Omega_i}$ is positive semidefinite whenever $I > B$.

The diagonal elements of $\mathbf{\Omega_i}$ measure the cross-investor dispersion of holdings in each bond. If every investor allocated identical portfolio weights, these variances would equal zero and $\mathbf{\Omega_i}$ would be ill-conditioned. In practice, retail investors hold not-diversified portfolios with many concentrated positions, so the diagonal element for bond j is large when ownership is highly heterogeneous across investors, that is, when some investors hold substantial positions while the majority holds none. In this sense, the diagonal of $\mathbf{\Omega_i}$ captures the degree of clientele segmentation in each bond: a large value signals that the bond attracts a distinct subset of investors rather than being held uniformly across the population.

The off-diagonal elements measure co-holding intensity across bond pairs. A large positive off-diagonal value for the pair (j, k) indicates that investors who overweight bond j also tend to overweight bond k, reflecting complementarity in portfolio composition. Conversely, a negative value indicates a substitution pattern, in which investors who concentrate in bond j systematically underweight bond k. Values close to zero indicate that holdings of the two bonds are orthogonal across investors.

Characteristic Clientele Strength. While the bond coholdings matrix captures which bonds are held together, the primary goal is to understand which *bond characteristics* drive investor heterogeneity, rather than the identity of specific bonds. To this end, I define c as a zero-mean B-vector of the cross-sectional rank of a given characteristic, rescaled to the interval $[-0.5, 0.5]$. By construction, the equal-weighted average of c across all bonds equals zero. The inner product $c'\mathbf{Q_i'}$ then gives the holdings-weighted average characteristic tilt of investor i's portfolio. Because investors tilt their holdings toward certain types of bonds, $c'\mathbf{Q_i'}$ need not have mean zero across investors.

Using the characteristic vector c, the quadratic form $c'\mathbf{\Omega_i}c$ summarizes the cross-investor dispersion in the characteristic tilt $c'\mathbf{Q_i'}$. Then, following BCRR, the definition of the *clientele strength* of a characteristic as this empirical variance:

$$\sigma^2(c'\mathbf{Q_i'}) = c'\mathbf{\Omega_i}c. \tag{3}$$

A large value of $c'\mathbf{\Omega_i}c$ indicates that the characteristic is strongly favored by some investors and strongly disfavored by others, that is, it generates a significant clientele effect.

The quadratic form in equation (3) can be decomposed into two components. The diagonal component reflects the extent to which intensely held bonds carry extreme values of the characteristic, while the off-diagonal component reflects the extent to which bonds with extreme characteristic values tend to be held together across investors. Both components are reported separately in the empirical analysis.

Characteristic Coholdings and Clusters. A further dimension of interest is whether bond characteristics cluster together in investor portfolios. To investigate this, define the matrix C_K with the dimension $K \times B$ where the K is the number of bonds characteristics and B the number of bonds. Then, for each column proceed to cross-section rank normalization. Then, denote the *characteristic holdings matrix* as the matrix multiplication of bonds holdings by the bond characteristics tilts $\mathbf{Q}^* = \mathbf{C_K'}\mathbf{Q_i}$.

Proceeding analogously to equation (2), I demean Q^* across the investor dimension to obtain $\tilde{Q}_i^*$, and then construct the *bond characteristic coholdings matrix* of dimension $K \times K$:

$$\Omega_i^* = I^{-1} \sum_{i=1}^{I} \tilde{Q}_i^* \tilde{Q}_i^{*\prime}. \tag{4}$$

The diagonal elements of Ω_i^* recover the clientele strengths in equation (3) for each bonds characteristic, while the off-diagonal elements capture the extent to which pairs of characteristics tend to be held together across investor portfolios. Extracting the principal components of Ω_i^* allows me to decompose investor preferences into orthogonal characteristic clusters.

Bond Characteristics. I consider the following $K = 10$ bond characteristics. Five are continuous variables: share price, time-to-maturity as of December 2024, yield-to-maturity, return volatility computed over the preceding three months, and the cumulative return over the preceding three months. The remaining five are indicator variables: a dummy for floating-rate bonds, a dummy for inflation-linked bonds, a dummy for fixed-rate bonds, a dummy for special bonds, and a dummy for bonds with a scheduled coupon payment. For continuous characteristics, I rank bonds by their characteristic value and rescale the ranks to the interval $[-0.5, 0.5]$ with mean zero. For indicator variables, I use the raw dummy value as the portfolio-weighted tilt $\mathbf{C}'_{\mathbf{K}}\mathbf{Q}_{\mathbf{i}}$, which corresponds to the fraction of the investor's portfolio allocated to bonds with the given attribute. This yields a continuous measure on $[0, 1]$ that is directly comparable across characteristics.

I estimate the characteristic coholdings matrix defined in equation (4) and report its diagonal elements, the clientele strengths, in Table 2.

[Table 2 about here]

Table 2 reports results under two specifications. The first three columns present results in which the bond characteristics are orthogonalized sequentially, following an iterative procedure that ensures each characteristic captures investor heterogeneity not already explained by stronger characteristics.[10] This addresses the concern that clientele effects for a

[10] This orthogonalization procedure follows BCRR and proceeds iteratively via multivariate kernel regression. A detailed description is provided in Section 1.1.

given characteristic may simply reflect its correlation with other characteristics in the cross-section of bonds. The last three columns present results without this orthogonalization, using the raw ranked characteristics. In both specifications, the first column reports the variance of the characteristic tilt $c_k' \mathbf{Q}_i$ across investors, that is, the diagonal element of Ω_i^*, which measures clientele strength. The second column converts this variance into a standard deviation for ease of interpretation. The third column reports the share of the total variance attributable to the off-diagonal elements of $\mathbf{\Omega_i}$, which captures the role of coholding propensities in driving characteristic clientele strength.

Among the bond characteristics, price exhibits the highest cross-sectional variance in investor tilts, followed by time-to-maturity and yield-to-maturity, based on orthogonalized characteristics. The prominence of price is consistent with evidence from the equity literature, where stock price ranks as the third most important characteristic in BCRR. The retail investor preference for lower-priced assets is well-documented and is typically attributed to lottery-like return features or budget constraints that preclude investment in higher-priced securities (Kumar, 2009; Gomes, Haliassos, and Ramadorai, 2021). The relevance of time-to-maturity as the second most important characteristic aligns with life-cycle models of portfolio choice (Parker, Schoar, Cole, and Simester, 2025; Campbell and Viceira, 2002), which predict systematic variation in maturity preferences over the investor lifecycle, as well as with preferred-habitat theories that assign investors to specific maturity segments (Vayanos, 2021). Finally, the importance of yield is consistent with a growing literature documenting yield-chasing behavior among retail investors (Liu, Wang, Wei, and Zhong, 2019; Gomes, Peng, Smirnova, and Zhu, 2022; Lian, Ma, and Wang, 2019), as well as reaching-for-yield patterns among institutional investors (Campbell and Sigalov, 2022).

Further, since each bonds is a bundle of characteristics, it is important to investigate in which of them are associated with one another. Thus, I extract the three principal components of the characteristics tilt matrix given by Equation 4. The *coholding characteristics* matrix displays a strong factor structure, the three principal components account for more than 70% of the explained variance, the first with 30%, the second with 25%, and the third with 15%. To have an economic interpretation of each principal component I regress the principal portfolio on characteristics tilts separately. The regression coefficient thus allows the interpretation of the how the principal components are associated with the characteristics and also, the R^2 gives a measure of how the principal components explaining the bond characteristics. Figure 1 shows the results of the regression for each characteristics. In red is the first principal component, in blue the second and in green the third component. The first one has the largest positive loading on the floating rate share and negative on low price characteristics. The second one has a positive loading on fixed-rate and negative on inflation-linked and also a positive on the time-to-maturity. The third one has a negative loading on the coupon, positive on the special share indicator and the volatility.

The principal components of the co-holding matrix capture directions of maximum cross-sectional variance in portfolio tilts rather than levels of holdings. A characteristic with a large loading on a given principal component therefore identifies a dimension along which investors strongly disagree, some tilting heavily toward that characteristic while others avoid it entirely. This property allows each principal component to be interpreted as a distinct investor clientele defined by a bundle of bond characteristics that are systematically held together.

Figure 1 displays the factor loadings for the first three principal components. The first principal component loads most heavily on the floating-rate indicator and is labeled the *Safety* clientele. In the Brazilian context, floating-rate bonds offer a yield tied to the overnight policy rate, providing protection against both duration risk and inflation while avoiding mark-to-market losses. Investors tilting toward this component effectively treat their bond holdings as a high-yield liquid savings account rather than a long-term investment vehicle. The second principal component loads positively on time-to-maturity and fixed-rate bonds, and negatively on inflation-linked bonds, and is labeled the *Duration* clientele.[11] Investors loading on this component take an active position along the term structure, accepting interest rate risk in exchange for a fixed nominal return. The third principal component loads primarily on the special bonds indicator, instruments contractually designed for retirement and education savings, and is labeled the *Special* clientele. Unlike the first two components, this clientele is defined not by a risk-return tradeoff but by a goal-oriented savings motive embedded in the bond's contractual structure.

[Figure 1 about here]

Investor Profiles and Bond Characteristics. Having established that bond characteristics form economically interpretable clusters, the natural next question is which types of investors tilt their portfolios toward each characteristic and each bundle of characteristics. To address this question, I estimate univariate cross-sectional regressions of each bond characteristic tilt on a set of investor-level attributes, following the "who owns what" approach of BCRR.

The investor attributes considered are the log value of bond holdings, the number of bonds currently held, the total number of bonds ever traded, age, platform experience measured from the date of the first trade, portfolio concentration measured by the Herfindahl-

[11] This component also loads on fixed-rate and inflation-linked bonds. As shown in Appendix Figure IA.1, decomposing time-to-maturity into short, medium, and long-term indicators reveals a pronounced maturity exposure for this component, while preserving the same pattern of loadings on fixed-rate and inflation-linked bonds.

Hirschman index, and indicator variables for gender, marital status, and Brazilian region. Each investor attribute is rank-normalized to the interval $[-0.5, 0.5]$ following the same procedure used to construct the bond characteristic vectors c_k.

Table 3 reports the results. Investors with a positive tilt toward floating-rate bonds, the defining characteristic of the *Safety* clientele, tend to hold larger and more concentrated portfolios, are older and less experienced on the platform, and are more likely to be female and married. This profile is consistent with the use of floating-rate bonds as a liquid savings vehicle by wealthier and more risk-averse investors. By contrast, investors with a positive tilt toward fixed-rate bonds and longer maturities, the characteristics most associated with the *Duration* clientele, tend to hold smaller portfolios with fewer bonds, are younger and less experienced, and are more likely to be male and single. Investors associated with the *Special* clientele display a similar profile in terms of portfolio size and age, though with no systematic gender distinction.

[Table 3 about here]

To characterize each clientele more precisely at the portfolio level, table 4 reports univariate regressions of each investor attribute on the first three principal components of the bond co-holding matrix, corresponding to the *Safety*, *Duration*, and *Special* clienteles respectively.

Column (1) shows that the *Safety* clientele is positively associated with portfolio size, number of bonds held, and trading frequency. This pattern is consistent with the use of floating-rate bonds as a cash management instrument by wealthier and more active investors. The clientele is also disproportionately female, married, and college educated, suggesting a demographic profile oriented toward capital preservation rather than return maximization. Column (2) shows that the *Duration* clientele is characterized by smaller portfolios, fewer bonds held and traded, and lower overall trading activity. The demographic profile is younger, male, single, and without a college degree, suggesting that duration-bearing bonds attract less financially sophisticated retail investors who accept term-structure risk, potentially without fully understanding its implications. Column (3) shows that the *Special* clientele is also associated with smaller portfolios and younger investors, consistent with the goal-oriented design of these instruments for retirement and education savings. Unlike the *Duration* clientele, however, the *Special* clientele displays no statistically distinguishable gender pattern, suggesting that the appeal of goal-oriented products cuts across gender lines in a way that pure duration risk taking does not.

[Table 4 about here]

5 Main Bond Characteristics

5.1 Bonds Price

The first bond characteristic that generates strong clientele effects is the bond price. From a theoretical standpoint, the nominal price of a bond is a deterministic function of its payment coupon, yield to maturity, and time-to-maturity, it contains no information beyond what is already captured by these fundamental characteristics. A rational investor who conditions on yield and maturity should therefore treat nominal price as entirely redundant: two bonds offering identical yields and maturities are equivalent investments regardless of their nominal prices. It is interesting then that price emerges as the first bond characteristic. Thus, I explore two explanations for the price effect. First, a financial constraint that implies that investors are restricted to cheap bonds. Second, I examine with retail investors suffer from nominal illusion.

Financial Constraints. As documented by Campbell (2006), financial constraints can deter participation in asset markets, particularly among low-income households. While potentially relevant, financial constraints alone are unlikely to account for bond price having the highest clientele strength in this setting. Panel A of Table 5 reports descriptive statistics for bond prices across all bond types. Floating-rate bonds carry the highest average price at USD 2,863, implying a minimum tradeable amount of USD 28 given the program's 1% tick size. Fixed-rate coupon bonds have the lowest average price at USD 174, implying a minimum trade of USD 1.74. With an average minimum wage of USD 336 over the sample period, these minimum investments represent 8% and 0.5% of monthly minimum wage, respectively, suggesting that price-based sorting across bond types is not primarily driven by budget constraints. Consistent with this, floating-rate bonds, despite having the highest price, also record the highest trading volume at over 25 million transactions.

A more direct explanation lies in the rank normalization applied to bond prices. Panel B of Table 5 assigns bonds to daily price quintiles and reports the time-averaged share of each bond type within each quintile. The top quintile is consistently dominated by floating-rate bonds, while all other types concentrate in lower quintiles. After rank normalization, the price characteristic therefore effectively identifies bond type, particularly for floating-rate bonds, which is precisely the pattern captured by the first principal component in Figure 1.

[Table 5 about here]

Nominal Price Illusion. Although nominal price does not have theoretical relevance to choose a bonds, there is substantial evidence that investors respond to nominal prices in equity markets. Baker, Greenwood, and Wurgler (2009), Weld, Michaely, Thaler, and Benartzi (2009), Green and Hwang (2009), Birru and Wang (2016) document that investors systematically favor low-price stocks, a pattern consistent with the belief that cheaper stocks have more "room to grow" in percentage terms. Kumar (2009) connects this preference to lottery-seeking behavior, showing that low-price stocks share characteristics with lottery tickets and attract investors with a taste for skewness. While the precise mechanism may differ in bond markets, where contractual cash flows bound the return distribution and the lottery analogy does not apply directly, the broader phenomenon of nominal price sensitivity reflects a cognitive tendency to treat price levels as informative signals of value or affordability, independent of the underlying fundamentals. Whether this tendency extends beyond equity markets to the bond context is an empirical question worth investigating, particularly among retail investors who have been shown to exhibit behavioral biases in the Brazilian equity market Birru, Chague, De-Losso, and Giovannetti (2023).

To investigate whether nominal price independently influences bond purchase decisions, I estimate panel regressions of the form:

$$\mathrm{Buy}_{i,j,t} = \beta^p\, p_{j,t} + \beta^y\, y_{j,t} + \beta^\tau\, \tau_{j,t} + \lambda_i + \varepsilon_{i,j,t}, \tag{1}$$

$$\mathrm{Buy}_{i,j,t} = \beta^p\, p_{j,t} + \beta^y\, y_{j,t} + \beta^\tau\, \tau_{j,t} + \lambda_i + \lambda_{\mathrm{yq}(t)} + \varepsilon_{i,j,t}, \tag{2}$$

$$\mathrm{Buy}_{i,j,t} = \beta^p\, p_{j,t} + \beta^y\, y_{j,t} + \beta^\tau\, \tau_{j,t} + \lambda_i + \lambda_{\mathrm{yq}(t)} + \lambda_{\mathrm{type}(j)} + \varepsilon_{i,j,t}, \tag{3}$$

$$\mathrm{Buy}_{i,j,t} = \beta^p\, p_{j,t} + \beta^y\, y_{j,t} + \beta^\tau\, \tau_{j,t} + \lambda_i + \lambda_{\mathrm{type}(j)\times\mathrm{yq}(t)} + \varepsilon_{i,j,t}, \tag{4}$$

$$\mathrm{Buy}_{i,j,t} = \beta^p\, p_{j,t} + \beta^y\, y_{j,t} + \beta^\tau\, \tau_{j,t} + \lambda_i + \lambda_{\mathrm{type}(j)\times t} + \varepsilon_{i,j,t}. \tag{5}$$

where the outcome variable $\mathrm{Buy}_{i,j,t}$ is an indicator equal to one if investor i purchases bond j at time t, $p_{j,t}$ is the nominal bonds price, $y_{j,t}$ is the yield to maturity, $\tau_{j,t}$ is the time-to-maturity, and λ_i is an investor fixed effect absorbing stable heterogeneity in trading propensity, present in all specifications. The specifications differ in how they control for time-varying aggregate conditions. Specification (1) includes only investor fixed effects. Specification (2) adds year-quarter fixed effects $\lambda_{\text{yq}(t)}$ to absorb low-frequency aggregate shocks common to all bonds. Specification (3) further includes bond-type fixed effects $\lambda_{\text{type}(j)}$, controlling for time-invariant differences in demand across bond categories. Specifications (4) and (5) replace these with the interaction $\lambda_{\text{type}(j)\times\text{yq}(t)}$ and $\lambda_{\text{type}(j)\times t}$, respectively, allowing aggregate demand shocks to vary across bond types at a quarterly and daily frequency. The specification (5) effectively compares investors trading the same bond type on the same day, leaving price, yield, and maturity as the only sources of cross-sectional identification. Across all specifications, the coefficient of interest is β^p, which tests whether nominal price carries independent predictive content for buying decisions after conditioning on the two characteristics that determine bond value for a rational investor.

The three coefficients capture conceptually distinct mechanisms within a unified framework. β^p measures the sensitivity of purchase decisions to nominal price levels; a negative and statistically significant estimate constitutes evidence of price illusion. β^y captures yield-chasing behavior of the kind documented by Liu, Wang, Wei, and Zhong (2019) in the Chinese bond market, with a positive and significant estimate indicating that investors systematically favor higher-yielding bonds. β^τ captures maturity preferences, with a positive estimate indicating a preference for longer-duration bonds. Estimating these three channels simultaneously allows us to assess the relative importance of each dimension of bond choice and to evaluate whether price illusion persists after controlling for the economically meaningful characteristics that should govern rational investment decisions.

Table 6 reports the results. Column (1), which includes only investor fixed effects, reveals a negative and statistically significant relation between nominal price and buying probability, alongside a positive and significant relation with time-to-maturity. Column (2) adds year-quarter fixed effects to absorb aggregate time-series variation. The price coefficient falls by roughly half in magnitude but remains statistically significant, indicating that part of the raw price-buying relation reflects macroeconomic conditions rather than a pure cross-sectional preference for low-priced bonds. The time-to-maturity coefficient is virtually unchanged, suggesting it captures a stable investor preference.

Column (3) further adds bond-type fixed effects. The price coefficient loses statistical significance while time-to-maturity remains large and highly significant. This pattern is consistent with two reinforcing mechanisms: nominal price is strongly correlated with bond type, leaving little residual price variation within types; and floating-rate bonds, which dominate retail demand, constitute only a handful of distinct securities per quarter, further limiting within-type price variation. Taken together, this suggests that investors first select a bond type and then screen on maturity, rather than on price.

Column (4) replaces separate bond-type and year-quarter fixed effects with their interaction, restricting identification to variation across bonds of the same type within the same quarter. The price coefficient remains insignificant, while yield and time-to-maturity retain their magnitude and significance. Column (5) further tightens identification by interacting bond type with date, so that comparisons are made across bonds of the same type traded on the same day. Price remains insignificant, while yield and time-to-maturity are highly significant. The persistence of these effects under the most demanding specification confirms that, conditional on bond type, investors screen primarily on fundamental value metrics and are not systematically attracted to lower-priced bonds.

[Table 6 about here]

5.2 Time-to-Maturity

The second strongest bond clientele is formed around time-to-maturity. The findings in the previous section suggest a two-stage decision process: retail investors first select a bond type and then, conditional on that choice, screen on time-to-maturity and yield. Preferences over maturity horizons are well-grounded in theory. A long-standing literature on preferred habitats documents that investors concentrate their demand in specific maturity segments, generating segmented markets in which yield-curve shape reflects the distribution of habitat preferences rather than pure expectations (Culbertson, 1957; Vayanos, 2021; Greenwood, Hanson, and Vayanos, 2024). At the household level, life-cycle models further predict that maturity preferences are tied to investment horizons and shift systematically with age and wealth accumulation (Gomes, 2020; Parker, Schoar, Cole, and Simester, 2025).

Motivated by this evidence, I examine the extent to which retail investors concentrate their purchases in specific maturity ranges, consistent with habitat-type preferences, and whether these preferences are stable over time or shift as market conditions evolve. To assess maturity concentration, I construct a transition matrix that tracks whether investors move across maturity brackets between consecutive purchases. To assess persistence, I estimate cross-sectional regressions that relate an investor's current maturity choice to her past choices, controlling for bond-level characteristics and investor fixed effects.

Transition Matrix. Following a procedure similar to Dorn and Huberman (2010), who study transitions across volatility regimes, I construct transition matrices based on transaction-level average maturity choices. I focus on investors who sell a bond within a given quarter and subsequently purchase a different bond in the same quarter, thereby excluding round-trip transactions that might be due to temporary liquidity needs.

Investors are classified into maturity bins separately for selling and buying decisions using two alternative schemes. The first relies on fixed maturity categories: short ($\tau < 3$ years), medium ($3 < \tau \leq 5$ years), long ($5 < \tau \leq 10$ years), and very long ($\tau > 10$ years). The second scheme uses quartiles of the empirical distribution of transaction maturities.

Sorting investors independently by the maturity of the bond sold and the bond purchased yields a 4×4 transition matrix with 16 possible cells, where under random choice each cell would contain 6.25% of observations. If investors exhibit maturity preferences, the transition matrix should display a higher concentration of mass along the diagonal relative to off-diagonal cells.

I compute these transition matrices quarterly over the 2014–2024 period, then average cell probabilities across time and estimate heteroskedasticity-robust standard errors based on the time-series variation. Figure 2 presents the results, with selling maturity bins on the y-axis and buying maturity bins on the x-axis. Panels A and C report transition matrices using fixed maturity bins, with Panel C displaying conditional probabilities normalized so that each row sums to 100%. Panels B and D present the corresponding results using quartile-based bins, with Panel D reporting row-normalized conditional probabilities.

The transition matrix reveals substantial persistence in maturity choice. After selling a bond the probability of remaining in the same maturity for short, medium, long, and very long-term bond are 8.73%, 13.78%, 14.14%, and 6.16%, respectively. Overall, diagonal elements account for 42.81% of total transition probability, indicating strong maturity persistence relative to the benchmark of 25% along the diagonal.

The quartile-based classification yields a similar pattern: diagonal cells display elevated probabilities, particularly in the lowest and highest maturity buckets, consistent with preferred-habitat behavior. Moreover, cells above the main diagonal (i.e., transitions toward shorter maturities) tend to exhibit probabilities above the random benchmark, suggesting some downward migration in maturity.

Panels C and D in Figure 2 report conditional transition probabilities (rows normalized to sum to 100%), which reinforce these findings. Persistence is strongest among long and very long maturities. For instance, under the fixed-bin classification, selling a long-term bond is followed by a purchase in the same maturity range with probability 43.85%; using quartile bins, the corresponding probability for the top quartile is 38.77%. For very long maturities, the conditional persistence reaches 48.20% under fixed bins and 30.88% under quartile bins. Short- and medium-term maturities also exhibit persistence. Under fixed bins, the probability of remaining in the same bucket is 25.04% (short) and 35.43% (medium); under quartile bins, these probabilities are 34.34% and 27.70%, respectively.

Overall, the transition matrices provide evidence of maturity-specific habitat preferences. At the same time, there is some tendency toward shorter maturities. This pattern may partly reflect mechanical effects: as time passes, time-to-maturity declines, and because the transition matrix averages behavior across time, such downward drift is likely—particularly under the quartile-based classification, where maturity thresholds vary dynamically over time.

[Figure 2 about here]

Persistence of maturity choice. If retail investors exhibit a preferred maturity habitat, their initial portfolio maturity should be a strong predictor of their future portfolio maturity. I examine this hypothesis using a series of cross-sectional regressions in which the outcome variable is the average portfolio time-to-maturity $\tau_{i,y+k}$ in year $y+k$ and the main regressor is the average portfolio time-to-maturity $\tau_{i,y}$ in year y, for horizon shifts $k = 1, \ldots, 10$. I also include a set of investor-level controls $X_{i,y}$ measured in the initial period, including the log value of bond holdings, the number of bonds in the portfolio, age, marital status, college degree status, and gender.

A central identification concern is that current time-to-maturity declines mechanically over time, even in the absence of active trading. This passive aging of the portfolio may induce spurious persistence in maturity measures. To address this issue, I construct an alternative measure based on the time-to-maturity at purchase, that is, the remaining maturity at the date the investor acquired each bond that is on their portfolio at time $y+k$. Let $\tau_{i,y}^{\text{cur}}$ denote the value-weighted average maturity computed using the remaining time-to-maturity in year y, and let $\tau_{i,y}^{\text{purch}}$ denote the corresponding average computed using the original time-to-maturity at the date each bond was acquired. Because $\tau_{i,y}^{\text{purch}}$ is not mechanically affected by the passage of time for any given bond held in the portfolio, it better captures the investor's active maturity choice and provides a measure that is immune to passive portfolio aging. The two specifications are given by:

$$\tau_{i,y+k}^{\text{cur}} = \alpha + \beta\, \tau_{i,y}^{\text{cur}} + \gamma' X_{i,y} + \varepsilon_i, \tag{5}$$

$$\tau_{i,y+k}^{\text{purch}} = \alpha + \beta\, \tau_{i,y}^{\text{purch}} + \gamma' X_{i,y} + \varepsilon_i. \tag{6}$$

The coefficient β measures the degree to which cross-sectional differences in initial maturity predict cross-sectional differences in future maturity. A β close to one indicates that investors who initially chose longer maturities than their peers continue to do so, consistent with a stable maturity habitat. A β close to zero indicates that initial maturity choices have no predictive power for future choices, suggesting that investors do not maintain a persistent preference over maturity buckets.

Figure 3 plots the estimated $\hat{\beta}$ coefficients from Equations (5) and (6) for horizon shifts $k = 1$ to 10 years, together with 95% confidence bands. Both specifications reveal a similar and economically meaningful pattern: the persistence coefficient declines with the forecast horizon but remains positive and statistically significant throughout, indicating that cross-sectional differences in initial portfolio maturity retain predictive power for future maturity choices even a decade later.

At $k = 1$, both measures yield a $\hat{\beta}$ close to 0.92, indicating that nearly all of the initial cross-sectional dispersion in maturity choices is preserved after one year. The coefficient then declines gradually, reaching approximately 0.59 under τ^{purch} and 0.49 under τ^{cur} at $k = 5$. Importantly, the two estimates diverge as the horizon lengthens: $\hat{\beta}^{\text{cur}}$ declines faster than $\hat{\beta}^{\text{purch}}$, consistent with the mechanical aging of τ^{cur}. Because τ^{purch} is immune to this passive decay, its estimate provides the cleaner measure of active preference persistence. Beyond $k = 5$, both coefficients stabilize and do not converge to zero, suggesting the existence of a permanent component in maturity preferences within each entry cohort. This long-run stability is corroborated by the Spearman rank correlation, which remains well above zero even at $k = 10$, confirming that the persistence result is not driven by a small number of outliers in the maturity distribution.

[Figure 3 about here]

Table 7 reports the full set of regression coefficients for each horizon. Panel A presents estimates based on current time-to-maturity (τ^{cur}) and Panel B based on purchase time-to-maturity (τ^{purch}). Each column corresponds to an entry cohort defined by the year in which investors first appear in the sample with positive bond holdings; the outcome variable is measured k years later. Because TD program expanded substantially over the sample period, the number of investors grows from 1,806 in the 2014 cohort to 126,789 in the 2023 cohort. The age is negative and statistically significant across all cohorts and both specifications, indicating that older investors systematically hold bonds with shorter remaining maturities. This pattern is consistent with life-cycle theories of portfolio choice Parker, Schoar, Cole, and Simester (2025), in which proximity to retirement shortens the desired investment horizon. Male investors hold bonds with significantly longer maturities than female investors, a finding that is robust across all cohorts and specifications. Investors holding more than two bonds in their portfolio also display longer average maturities, which may reflect greater engagement with the term structure or a deliberate duration-extension strategy among more active participants. The coefficient on log portfolio value changes sign across cohorts: it is positive for early cohorts and negative for later ones. A plausible interpretation is that the program's expansion attracted a broader, less financially sophisticated clientele that allocated relatively more to shorter-maturity instruments despite holding larger nominal positions,a pattern consistent with the declining intercept noted above. Finally, marital status and college degree are not consistently significant across specifications, suggesting that maturity choice is not primarily determined by these demographic characteristics.

[Table 7 about here]

6 Conclusion

The household finance literature has extensively documented retail investor behavior in equity markets, yet the fixed-income counterpart remains comparatively understudied. This paper addresses that gap using a novel transaction-level dataset on retail investors' direct holdings of Brazilian government bonds from 2014 to 2024. Adapting the methodology of

BCRR to the fixed-income setting, I examine which bond characteristics drive heterogeneity in retail portfolios and how investor attributes map onto characteristic tilts.

Three bond characteristics generate the strongest clientele effects: unit price, time-to-maturity, and yield to maturity. Applying principal component analysis to the bond characteristic variance-covariance matrix, I uncover a strong factor structure in which the first three principal components account for more than 70% of the explained variance. These components are interpretable as three distinct investor clienteles: *Safety*, *Duration Risk*, and *Special*. The Safety clientele is defined by a preference for floating-rate bonds, which offer protection against duration and inflation risk. The Duration Risk clientele concentrates demand in medium- to long-term fixed-rate and inflation-linked bonds, taking an active position along the term structure. The Special clientele captures demand for goal-oriented instruments designed specifically for retirement and education saving.

Profiling these clienteles against investor attributes reveals systematic patterns. The Safety clientele is associated with larger portfolios, more diversified holdings, and investors who are older, female, and married, a demographic profile consistent with capital preservation motives. Duration Risk clientele is characterized by smaller portfolios, fewer trades, and investors who are younger, male, and single, suggesting that term-structure risk-taking is disproportionately concentrated among less financially experienced participants. The Special clientele similarly attracts younger investors with smaller portfolios, with no statistically distinguishable gender difference, consistent with the goal-oriented design of these instruments appealing broadly across demographic groups.

Then I investigate the two bond characteristics with the highest clientele strength: bond price and time-to-maturity. For bond price, I evaluate two candidate explanations. The budget constraint hypothesis predicts that financially constrained investors select bonds primarily on the basis of affordability; however, the data reveal that the bond type with the highest bond price, floating-rate bonds, also records the largest transaction volume, providing no support for a binding budget constraint. The nominal price illusion hypothesis, which is well-documented in equity markets (Weld, Michaely, Thaler, and Benartzi, 2009; Baker, Greenwood, and Wurgler, 2009; Birru and Wang, 2016), posits that investors systematically favor lower-priced assets irrespective of fundamental value. A panel regression of purchase decisions on price, yield, and time-to-maturity with progressively stringent fixed-effect structures shows that the price coefficient loses statistical significance once bond-type fixed effects are included. This result is consistent with a two-stage decision process in which investors first select a bond type and subsequently screen on other characteristics: the apparent price sensitivity reflects the predominance of floating-rate bonds, the highest-priced bond type, in retail portfolios rather than a genuine preference for low-price bonds.

For time-to-maturity, I provide direct evidence that retail investors exhibit preferred habitat behavior in the sense of Vayanos (2021). Using a transition matrix that tracks the maturity of bonds sold and subsequently repurchased by the same investor within a quarter, I document a strong diagonal structure: investors who sell a bond in a given maturity range predominantly repurchase within the same range, consistent with stable maturity habitat preferences. I corroborate this finding with cross-sectional persistence regressions, showing that initial portfolio maturity is a strong predictor of future maturity choices at horizons of up to ten years, even after controlling for passive portfolio aging. Taken together, these results establish that time-to-maturity preferences are active, persistent, and economically meaningful among retail investors in sovereign bond markets.

Figures

Figure 1: Characteristic Loadings

This figure presents the loadings of investor characteristic tilts on the first three principal components (PCs) extracted from a matrix of bond characteristic tilts of dimension 156,000 × 10. Characteristic tilts are constructed using orthogonalized investor characteristics. The ten bond characteristics considered are: time-to-maturity, yield, low price, floating rate, past 3-month volatility, past 3-month return, inflation-linked, fixed rate, special bonds, and coupon payment. The x-axis reports each bond characteristic alongside the R^2 from a univariate regression of the respective PC loading on that characteristic.

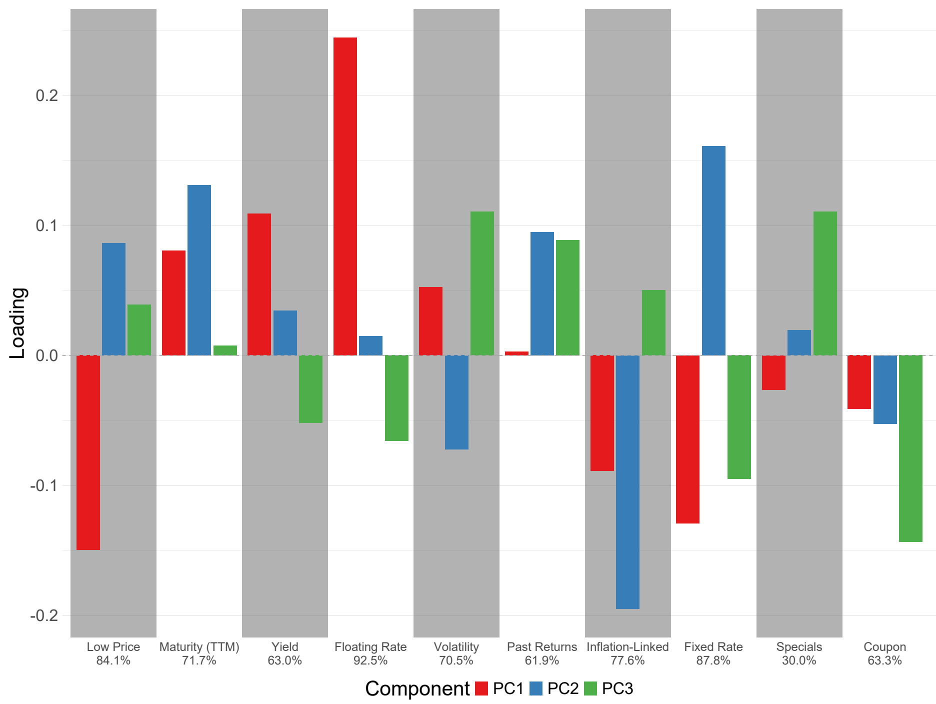


Figure 2: Maturity Transition Matrices: Where Do Investors Reinvest?

This figure displays heatmaps of the maturity transition matrix for investors who both sold and bought Treasury bonds in the same month. For each investor-month, I compute the value-weighted average time-to-maturity (TTM) on the sell side and on the buy side separately. Panel A sorts investors into within-month quartiles of average maturity; each cell reports the time-series average share (in %) of active investors who sold from the column quartile and bought into the row quartile, with heteroskedasticity-robust standard errors in parentheses. Under independence, each cell equals 6.25%. Panel B uses fixed maturity bins—Short ($\leq$3y), Medium (3–5y), Long (5–10y), and Very Long (>10y)—and reports the joint distribution of (buy, sell) pairs; cells sum to 100% over the entire matrix. Panel C normalises Panel B by column, so that entry (i, j) gives the probability of buying into bin i conditional on having sold from bin j; each column sums to 100%. Darker shading indicates a higher share of investors. The strong diagonal pattern across all three panels indicates that investors predominantly reinvest at maturities similar to those they sold, consistent with a preferred maturity habitat.

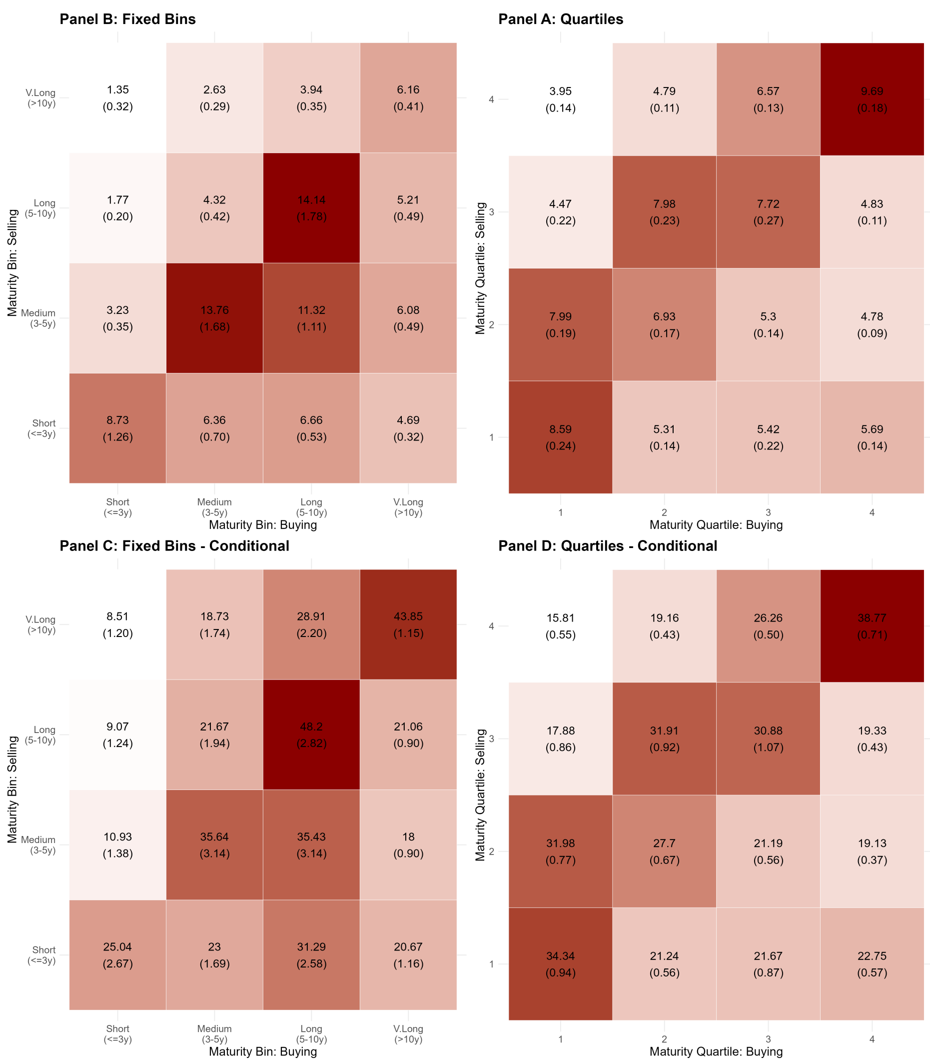
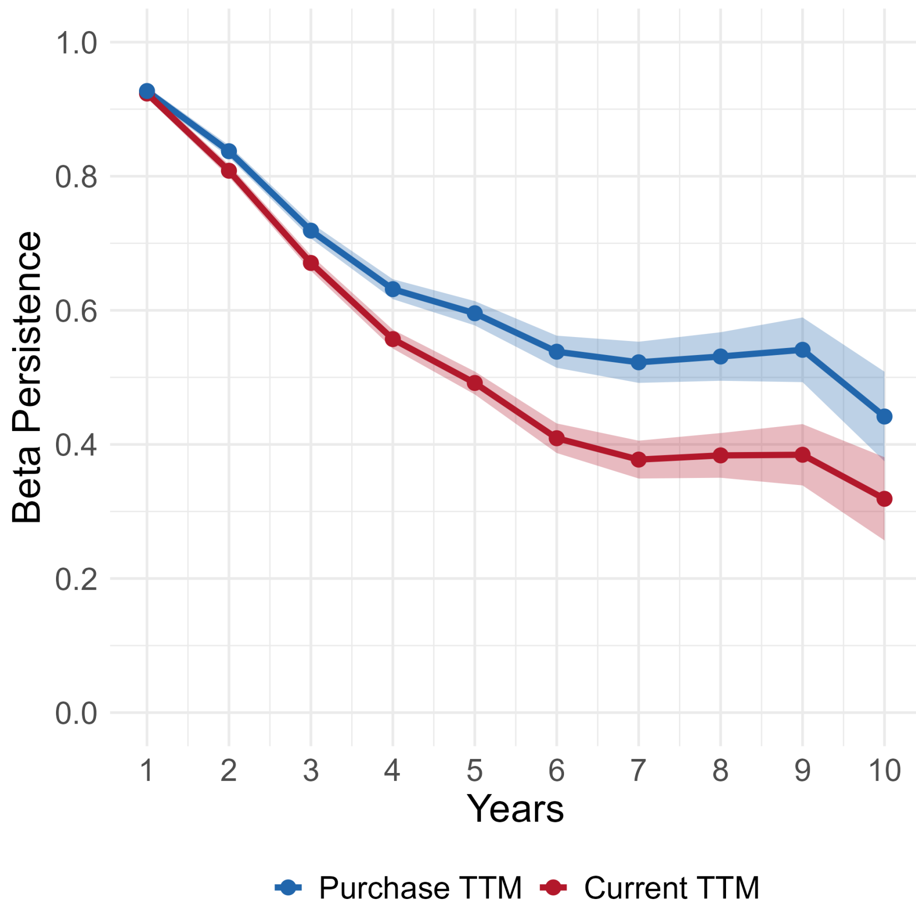


Figure 3: Persistence across cohorts

This figure plots the β coefficients from the cross-sectional regressions $\tau^{\text{cur}}_{i,y+k} = \alpha + \beta\, \tau^{\text{cur}}_{i,y} + \gamma' X_{i,y} + \varepsilon_i$ and $\tau^{\text{purch}}_{i,y+k} = \alpha + \beta\, \tau^{\text{purch}}_{i,y} + \gamma' X_{i,y} + \varepsilon_i$, estimated separately for each horizon $k \in \{1, \ldots, 10\}$ years. The dependent variables $\tau^{\text{cur}}_{i,y+k}$ and $\tau^{\text{purch}}_{i,y+k}$ measure, respectively, the current portfolio maturity and the purchase-weighted maturity of investor i at year $y + k$. Each regression retains only investors present in both the initial year y and the terminal year $y + k$. The control vector $X_{i,y}$ includes the log of portfolio value, an indicator for holding more than one bond, gender, marital status, an indicator for college-level education, and age, all measured at the initial year y. Shaded bands denote 95% confidence intervals based on heteroskedasticity-robust standard errors.



Tables

Table 1: Descriptive Statistics Tesouro Direto

This table reports descriptive statistics for retail investor activity on the Tesouro Direto platform. Panel (a) summarizes platform-level daily trading activity, including volumes, average maturity, investor participation, and the maturity composition of trading volume. Panel (b) presents investor-level holdings and trading measures, covering portfolio size, maturity allocation, portfolio concentration (HHI), and trading intensity. Panel (c) reports investor demographics, including gender shares, marital status, and occupation categories. For each variable, the table reports the mean, standard deviation, minimum, 25th percentile, median, 75th percentile, maximum, and number of observations. Monetary values are expressed in U.S. dollars, converted using an exchange rate of R$4.19 per US$1.

	Mean	SD	Min	25th Perc	Median	75th Perc	Max	N
Panel a) Trading Activity								
Daily Volume	48.619,06	82.594,58	62,01	24.294,82	41.340,62	62.755,48	3.963.457,58	2.806
Daily Buy Volume	31.194,59	79.825,13	0,00	15.327,06	23.365,82	37.764,57	3.962.989,61	2.806
Daily Sel Volume	17.424,47	11.923,57	0,00	7.663,96	16.972,65	25.303,35	112.463,29	2.806
Median Volume	272,28	352,62	42,86	142,14	214,52	343,91	14.736,47	2.806
Average Quantity	4,56	2,85	1,42	2,56	3,42	5,88	26,65	2.806
Average Maturity (Years)	7,34	1,10	3,94	6,38	7,48	8,23	10,79	2.806
Number of Bonds	22,73	4,53	5,00	21,00	22,00	26,00	32,00	2.806
Number of Investors (1000)	19,84	13,71	0,01	7,98	19,76	29,58	87,28	2.806
Proportion Volume Short ($\leq$ 3 Years)	25,82	14,77	1,91	12,71	22,60	40,00	99,66	2.806
Proportion Volume Medium ($3-5$ Years)	28,54	14,81	0,00	15,01	29,52	40,30	66,75	2.806
Proportion Volume Long ($>$ 5 Years)	45,64	18,46	0,24	33,94	43,37	55,11	95,72	2.806
Panel b) Holdings Measures								
Holdings	5.010,79	22.689,70	0,00	28,72	213,06	1.985,08	1.659.895,82	286.261
Short-term Holdings	1.933,70	10.561,59	0,00	0,00	16,72	328,73	898.449,82	286.261
Medium-term Holdings	1.443,44	7.123,37	0,00	0,00	15,95	374,73	370.910,99	286.261
Long-term Holdings	1.633,66	11.212,85	0,00	0,00	10,18	258,53	808.675,70	286.261
Share Short-term (%)	38,87	39,45	0,00	0,00	28,67	75,68	100,00	279.551
Share Medium-term (%)	27,87	32,25	0,00	0,00	17,29	46,44	100,00	279.551
Share Long-term (%)	33,26	37,93	0,00	0,00	16,03	62,09	100,00	279.551
Time to Maturity (Years)	7,09	9,88	0,42	2,66	4,32	7,01	61,52	286.261
Number of Bonds	1,77	1,32	1,00	1,00	1,00	2,00	35,00	286.261
HHI	0,70	0,28	0,00	0,49	0,74	1,00	1,00	286.261
# Distinct Bonds	2,80	2,95	1,00	1,00	2,00	3,00	68,00	286.261
# Purchases	5,32	24,88	0,00	0,00	1,00	4,00	8.622,00	286.261
# Sales	1,57	6,11	0,00	0,00	0,00	1,00	912,00	286.261
# Trades	6,89	27,31	0,00	0,00	1,00	5,00	8.624,00	286.261
Turnover Positive (%)	22,57	37,19	0,00	0,00	0,26	32,25	195,03	279.551
Turnover Negative (%)	14,08	36,54	0,00	0,00	0,00	5,52	223,34	279.551
Investor Characteristics								
Average Age	35,69	12,57	17,00	26,33	33,64	42,10	86,00	286.261
Experience (Years)	3,49	2,65	0,00	1,22	3,14	5,45	11,00	286.261
Male (%)	68,27	46,54	0,00	0,00	100,00	100,00	100,00	286.261
Female (%)	31,73	46,54	0,00	0,00	0,00	100,00	100,00	286.261
Single (%)	55,31	49,72	0,00	0,00	100,00	100,00	100,00	286.261
Not Single (%)	44,69	49,72	0,00	0,00	0,00	100,00	100,00	286.261
College or Higher (%)	29,98	45,82	0,00	0,00	0,00	100,00	100,00	286.261
Not College or Higher (%)	70,02	45,82	0,00	0,00	100,00	100,00	100,00	286.261
Southeast (%)	58,85	49,21	0,00	0,00	100,00	100,00	100,00	286.261
South (%)	15,26	35,96	0,00	0,00	0,00	0,00	100,00	286.261
Northeast (%)	13,92	34,61	0,00	0,00	0,00	0,00	100,00	286.261
Center-West (%)	7,96	27,07	0,00	0,00	0,00	0,00	100,00	286.261
North (%)	4,00	19,60	0,00	0,00	0,00	0,00	100,00	286.261

Table 2: Clientele Strength: Raw and Orthogonalized Characteristic Tilts

This table reports clientele strength measured as the variance of characteristic tilts across investors in December 2024 using both orthogonalized and raw characteristics tilts following the procedure explained in section 4 the same used by Balasubramaniam, Campbell, Ramadorai, and Ranish (2023). The bonds characteristics are ordered from the highest orthogonality variance. The second column transform the variance into the standard deviations. The third column "Off-Diagonal" column presents the percentage of the variance that can be attributed to off-diagonal elements of the co-holding matrix. All statistics equally weight investors.

	Orthogonalized			**Raw**		
Characteristic	Variance	Std. Dev.	% Off-Diag.	Variance	Std. Dev.	% Off-Diag.
Unit Price	0.106	0.326	0.083	0.106	0.277	0.083
Maturity (TTM)	0.088	0.297	8.493	0.068	0.231	9.664
Yield	0.068	0.261	5.786	0.040	0.173	-58.805
Floating Rate	0.068	0.451	-40.717	0.068	0.408	-40.717
Volatility	0.056	0.236	4.274	0.071	0.228	-40.082
Past Return	0.055	0.235	-26.616	0.081	0.243	-33.855
Inflation-Linked	0.053	0.400	-22.591	0.053	0.364	-22.591
Fixed Rate	0.049	0.384	-20.289	0.049	0.329	-20.289
Specials	0.023	0.264	-3.491	0.023	0.210	-3.491
Coupon	0.022	0.258	-1.079	0.022	0.236	-1.079

Table 3: Investor's Characteristics Across Bonds Characteristics

This table reports estimates from univariate regressions of each bond characteristic tilt (columns) on each investor characteristic (rows). Bond characteristic tilts are orthogonalized prior to estimation. Standard errors are heteroskedasticity-robust and reported in parentheses; R^2 values are reported in brackets. All regressions are estimated with equal weights across investors.

Investor Attribute	Maturity (TTM)	Volatility	Past Returns	Yield	Unit Price	Fixed Rate	Specials	Inflation-Linked	Floating Rate	Coupon
Portfolio Size	-0.034***	-0.101***	0.135***	-0.017***	-0.252***	-0.221***	-0.175***	0.200***	0.196***	-0.043***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
	[0.18%]	[1.63%]	[2.55%]	[0.08%]	[6.87%]	[3.74%]	[5.81%]	[2.50%]	[1.92%]	[0.28%]
No. Bonds (Current)	0.003*	-0.019***	0.023***	-0.031***	-0.097***	-0.067***	-0.088***	0.183***	-0.028***	0.052***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
	[0.00%]	[0.05%]	[0.07%]	[0.26%]	[0.99%]	[0.33%]	[1.43%]	[2.03%]	[0.04%]	[0.39%]
No. Bonds (Ever)	0.023***	-0.002	0.011***	-0.042***	-0.092***	-0.081***	-0.086***	0.192***	-0.025***	0.049***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
	[0.08%]	[0.00%]	[0.02%]	[0.49%]	[0.91%]	[0.49%]	[1.38%]	[2.28%]	[0.03%]	[0.35%]
No. of Trades	0.050***	-0.006***	0.039***	-0.056***	-0.152***	-0.189***	-0.090***	0.162***	0.117***	-0.025***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
	[0.38%]	[0.01%]	[0.21%]	[0.87%]	[2.46%]	[2.70%]	[1.52%]	[1.63%]	[0.67%]	[0.10%]
Age	-0.091***	-0.086***	0.089***	0.014***	-0.106***	-0.048***	-0.072***	0.064***	0.056***	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
	[1.29%]	[1.18%]	[1.11%]	[0.06%]	[1.23%]	[0.18%]	[0.98%]	[0.26%]	[0.16%]	[0.01%]
Experience	-0.083***	-0.033***	0.033***	-0.059***	-0.099***	-0.050***	-0.142***	0.273***	-0.081***	0.093***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
	[1.09%]	[0.17%]	[0.15%]	[0.99%]	[1.07%]	[0.19%]	[3.80%]	[4.67%]	[0.33%]	[1.29%]
Concentration (HHI)	-0.003*	0.004**	0.002	0.030***	0.055***	0.017***	0.082***	-0.204***	0.105***	-0.072***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
	[0.00%]	[0.00%]	[0.00%]	[0.24%]	[0.32%]	[0.02%]	[1.25%]	[2.55%]	[0.53%]	[0.77%]
Male	0.038***	0.030***	-0.031***	-0.003***	0.034***	0.018***	0.016***	0.009***	-0.043***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
	[0.63%]	[0.39%]	[0.37%]	[0.01%]	[0.35%]	[0.07%]	[0.13%]	[0.01%]	[0.25%]	[0.11%]
Single	0.020***	0.022***	-0.024***	-0.001*	0.032***	0.018***	0.024***	-0.029***	-0.012***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.19%]	[0.22%]	[0.24%]	[0.00%]	[0.33%]	[0.07%]	[0.34%]	[0.16%]	[0.02%]	[0.00%]
College Educated	-0.009***	-0.014***	0.016***	-0.004***	-0.032***	-0.021***	-0.032***	0.045***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
	[0.03%]	[0.08%]	[0.10%]	[0.01%]	[0.29%]	[0.09%]	[0.52%]	[0.35%]	[0.01%]	[0.02%]
Southeast	-0.007***	-0.004***	0.004***	-0.004***	-0.009***	-0.005***	-0.010***	0.023***	-0.008***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
	[0.02%]	[0.01%]	[0.01%]	[0.01%]	[0.03%]	[0.01%]	[0.06%]	[0.10%]	[0.01%]	[0.02%]
Northeast	0.002**	-0.002*	0.005***	0.006***	-0.001	-0.009***	0.015***	-0.041***	0.035***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
	[0.00%]	[0.00%]	[0.01%]	[0.01%]	[0.00%]	[0.01%]	[0.06%]	[0.15%]	[0.08%]	[0.06%]
South	0.008***	0.008***	-0.009***	-0.001	0.011***	0.011***	-0.003***	0.015***	-0.023***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
	[0.02%]	[0.01%]	[0.02%]	[0.00%]	[0.02%]	[0.01%]	[0.00%]	[0.02%]	[0.04%]	[0.00%]
Central-West	0.005***	0.003**	-0.003*	-0.001	0.004**	0.001	0.006***	-0.012***	0.004	-0.003*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)
	[0.00%]	[0.00%]	[0.00%]	[0.00%]	[0.00%]	[0.00%]	[0.01%]	[0.01%]	[0.00%]	[0.00%]
North	0.002	0.003	-0.005*	0.012***	0.019***	0.021***	0.024***	-0.064***	0.019***	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)
	[0.00%]	[0.00%]	[0.00%]	[0.01%]	[0.01%]	[0.01%]	[0.04%]	[0.10%]	[0.01%]	[0.00%]

Table 4: Investor's Characteristic Loading on PCA

This table reports the factor loadings, heteroskedasticity-robuststandard errors, and R^2 from univariate regressions of each investor characteristic on the firstthree principal components of the investor characteristic tilt matrix. All investorcharacteristics are standardized to have unit variance prior to estimation.

Account Attribute	PC1	PC2	PC3
Portfolio Size	0.403***	-0.318***	-0.045***
	(0.004)	(0.004)	(0.003)
	[5.36%]	[3.98%]	[0.14%]
No. of Bonds (Current)	0.051***	-0.212***	-0.050***
	(0.004)	(0.004)	(0.003)
	[0.08%]	[1.77%]	[0.17%]
No. of Distinct Bonds (Ever)	0.068***	-0.227***	-0.035***
	(0.004)	(0.004)	(0.003)
	[0.15%]	[2.04%]	[0.09%]
No. of Trades	0.276***	-0.227***	0.001
	(0.004)	(0.004)	(0.003)
	[2.52%]	[2.03%]	[0.00%]
Turnover	0.374***	-0.088***	-0.009***
	(0.004)	(0.004)	(0.003)
	[4.61%]	[0.30%]	[0.01%]
Age	0.097***	-0.114***	-0.039***
	(0.004)	(0.004)	(0.003)
	[0.31%]	[0.51%]	[0.10%]
Experience	-0.105***	-0.413***	-0.118***
	(0.004)	(0.004)	(0.003)
	[0.36%]	[6.74%]	[0.97%]
Concentration (HHI)	0.010**	0.209***	0.057***
	(0.004)	(0.004)	(0.003)
	[0.00%]	[1.72%]	[0.23%]
Male	-0.050***	0.072***	0.001
	(0.004)	(0.004)	(0.003)
	[0.08%]	[0.21%]	[0.00%]
Single	-0.042***	0.081***	0.021***
	(0.004)	(0.004)	(0.003)
	[0.06%]	[0.26%]	[0.03%]
College Education	0.044***	-0.110***	-0.046***
	(0.004)	(0.004)	(0.003)
	[0.06%]	[0.48%]	[0.15%]
Southeast	-0.001	-0.049***	-0.006**
	(0.004)	(0.004)	(0.003)
	[0.00%]	[0.09%]	[0.00%]
South	-0.038***	-0.016***	-0.012***
	(0.004)	(0.004)	(0.003)
	[0.05%]	[0.01%]	[0.01%]
Northeast	0.045***	0.052***	0.024***
	(0.004)	(0.004)	(0.003)
	[0.07%]	[0.11%]	[0.04%]
Central-West	-0.006	0.012***	-0.004
	(0.004)	(0.004)	(0.003)
	[0.00%]	[0.01%]	[0.00%]
North	0.003	0.045***	0.001
	(0.004)	(0.004)	(0.003)
	[0.00%]	[0.08%]	[0.00%]

Table 5: Descriptive of Bond Share by Unit Price

This table reports descriptive statistics for bond prices, computed as mid-prices from transaction records in the Tesouro Direto Program. Panel A presents the mean, 10th percentile, median, 90th percentile, and number of transactions for each bond type. Panel B reports the time-series average share of transaction volume within each daily price quintile, separately by bond type, along with the corresponding number of observations. Price quintiles are constructed cross-sectionally each day across all bonds in the program.

Panel A): Descriptive Statistics of Unit Price

Bond Type	Mean	Pct10	Pct 50	Pct 90	N
Floating-Rate	2.863,23	2.287,92	2.781,10	3.580,13	27.343.082
Inflation-Linked	957,01	773,07	982,05	1.073,76	3.710.842
Inflation-Linked Coupons	520,46	272,58	499,71	761,84	15.890.848
Specials	327,86	42,48	276,09	781,25	1.373.353
Fixed-Rate	248,76	212,23	245,89	291,91	2.143.219
Fixed-Rate Coupons	174,15	123,63	179,98	214,16	10.670.624

Panel B): Share by Price Quantiles

PU Quintile	Share Floating	Share Fixed	Share Infl.-Linked	Share Specials	Mean Unit Price	N
1	0,000	0,908	0,044	0,048	172,1	12.229.655
2	0,000	0,140	0,815	0,044	395,5	12.229.661
3	0,236	0,000	0,744	0,020	1.120,3	12.229.811
4	1,000	0,000	0,000	0,000	2.565,4	12.233.636
5	1,000	0,000	0,000	0,000	3.348,9	12.225.511

Table 6: Price Regression

This table reports estimates from regressions of three bond-level variables, log price, yield-to-maturity, and time-to-maturity, on a buy indicator equal to one for purchase transactions and zero for sales, using transaction-level data from the Tesouro Direto Program. Price is measured as the mid-price at the time of each transaction. Columns (1) through (5) report the same specification under progressively stringent fixed-effect structures: investor fixed effects (1); investor and year-quarter fixed effects (2); investor, year-quarter, and bond-type fixed effects (3); investor and bond-type × year-quarter fixed effects (4); and investor and bond-type × date fixed effects (5). All specifications use standard errors double-clustered at the investor and bond levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:			Buying Indicator		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Log(Price)	-0.031***	-0.017*	-0.039	-0.045	-0.050
	(0.006)	(0.009)	(0.032)	(0.032)	(0.032)
Yield (%)	0.002	0.004	0.010	0.043***	0.086***
	(0.006)	(0.005)	(0.010)	(0.015)	(0.028)
TTM (years)	0.007***	0.008***	0.007***	0.006***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fixed-effects					
Investor	Yes	Yes	Yes	Yes	Yes
YQ	No	Yes	Yes	No	No
Bond Type	No	No	Yes	No	No
Bond Type-YQ	No	No	No	Yes	No
Bond Type-Date	No	No	No	No	Yes
Fit statistics					
Observations	61,131,968	61,131,968	61,131,968	61,131,968	61,131,968
R^2	0.23205	0.26116	0.26168	0.26680	0.28052
Within R^2	0.01746	0.01686	0.00976	0.01225	0.01429

Table 7: Maturity Persistence Cross-Section Evidence

This table reports coefficients from the cross-sectional regressions $\tau^{\text{cur}}_{i,y+k} = \alpha + \beta\,\tau^{\text{cur}}_{i,y} + \gamma' X_{i,y} + \varepsilon_i$ in panel A. In panel B reports the coefficients from the cross-sectional regression $\tau^{\text{purch}}_{i,y+k} = \alpha + \beta\,\tau^{\text{purch}}_{i,y} + \gamma' X_{i,y} + \varepsilon_i$, estimated separately for each horizon $k \in \{1,\ldots,10\}$ years. The dependent variables $\tau^{\text{cur}}_{i,y+k}$ and $\tau^{\text{purch}}_{i,y+k}$ measure, respectively, the current portfolio maturity and the purchase-weighted maturity of investor i at year $y+k$. Each regression retains only investors present in both the initial year y and the terminal year $y+k$. The control vector $X_{i,y}$ includes the log of portfolio value, an indicator for holding more than one bond, gender, marital status, an indicator for college-level education, and age, all measured at the initial year y. Standard errors use heteroskedasticity robust errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

Dependent Variable:	Avg TTM									
Cohort	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Time	(10)	(9)	(8)	(7)	(6)	(5)	(4)	(3)	(2)	(1)
Variables										
Constant	9.072***	6.430***	5.991***	5.293***	4.621***	3.042***	2.950***	1.958***	1.302***	0.6729***
	(1.364)	(0.7235)	(0.5121)	(0.4320)	(0.3169)	(0.2364)	(0.1876)	(0.1409)	(0.1120)	(0.0698)
Avg TTM	0.3189***	0.3846***	0.3836***	0.3774***	0.4092***	0.4917***	0.5571***	0.6706***	0.8082***	0.9234***
	(0.0316)	(0.0233)	(0.0170)	(0.0144)	(0.0112)	(0.0087)	(0.0072)	(0.0059)	(0.0047)	(0.0034)
# > 2 Bonds	0.9185***	1.042***	0.6398***	0.5467***	0.4884***	0.6084***	0.4735***	0.4033***	0.5559***	0.4051***
	(0.3322)	(0.2087)	(0.1547)	(0.1382)	(0.1085)	(0.0866)	(0.0663)	(0.0514)	(0.0373)	(0.0251)
Log Portfolio Value	-0.0887	0.0497	0.0839***	0.0883***	0.0672***	0.0466***	-0.0199	-0.0284***	-0.0425***	-0.0411***
	(0.0964)	(0.0475)	(0.0321)	(0.0279)	(0.0210)	(0.0162)	(0.0125)	(0.0097)	(0.0079)	(0.0050)
Age	-0.0955***	-0.0950***	-0.0917***	-0.0858***	-0.0722***	-0.0594***	-0.0439***	-0.0305***	-0.0187***	-0.0080***
	(0.0140)	(0.0081)	(0.0055)	(0.0046)	(0.0037)	(0.0030)	(0.0025)	(0.0018)	(0.0013)	(0.0008)
Man	0.8928**	0.9240***	0.7273***	0.8118***	0.7653***	0.8100***	0.6388***	0.4966***	0.3978***	0.1595***
	(0.3674)	(0.2042)	(0.1425)	(0.1153)	(0.0936)	(0.0715)	(0.0581)	(0.0440)	(0.0327)	(0.0204)
Single	-0.0290	-0.0467	-0.2043	-0.0332	-0.0300	-0.0257	-0.0674	-0.0555	-0.0542	-0.0353
	(0.3932)	(0.2265)	(0.1576)	(0.1297)	(0.1050)	(0.0808)	(0.0668)	(0.0513)	(0.0377)	(0.0238)
College Degree	-0.2468	-0.0445	-0.0561	-0.1173	0.0290	0.0756	0.1199**	0.0909**	0.0200	-0.0202
	(0.3346)	(0.1925)	(0.1369)	(0.1125)	(0.0934)	(0.0729)	(0.0598)	(0.0460)	(0.0335)	(0.0204)
Fit statistics										
Spearman Cor.	0.265	0.216	0.274	0.291	0.326	0.389	0.490	0.616	0.733	0.901
R^2	0.10948	0.09089	0.08592	0.08287	0.09437	0.11737	0.17222	0.26072	0.38514	0.66648
Observations	1,806	5,566	10,717	16,652	23,760	39,835	51,530	70,583	92,648	126,789

Panel B

Dependent Variable:	Avg TTM at Purchase									
Cohort	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Time	(10)	(9)	(8)	(7)	(6)	(5)	(4)	(3)	(2)	(1)
Variables										
Constant	10.67***	7.795***	7.092***	6.066***	5.894***	4.943***	4.682***	3.625***	2.586***	1.166***
	(1.377)	(0.7340)	(0.5146)	(0.4295)	(0.3113)	(0.2264)	(0.1797)	(0.1351)	(0.1080)	(0.0684)
Avg TTM at Purchase	0.4416***	0.5411***	0.5311***	0.5225***	0.5383***	0.5956***	0.6316***	0.7188***	0.8373***	0.9271***
	(0.0341)	(0.0246)	(0.0185)	(0.0157)	(0.0122)	(0.0092)	(0.0076)	(0.0059)	(0.0045)	(0.0032)
# > 2 Bonds	1.251***	1.501***	1.131***	0.9038***	0.8483***	0.7310***	0.5282***	0.3226***	0.4233***	0.2851***
	(0.3482)	(0.2137)	(0.1577)	(0.1390)	(0.1084)	(0.0842)	(0.0648)	(0.0501)	(0.0363)	(0.0247)
Log Portfolio Value	0.0303	0.1226**	0.1401***	0.1511***	0.0913***	0.0370**	-0.0098	-0.0204**	-0.0418***	-0.0177***
	(0.0979)	(0.0486)	(0.0328)	(0.0281)	(0.0211)	(0.0159)	(0.0123)	(0.0096)	(0.0078)	(0.0050)
Age	-0.0925***	-0.0902***	-0.0832***	-0.0769***	-0.0637***	-0.0483***	-0.0368***	-0.0259***	-0.0154***	-0.0078***
	(0.0146)	(0.0083)	(0.0057)	(0.0047)	(0.0038)	(0.0030)	(0.0024)	(0.0018)	(0.0013)	(0.0008)
Man	0.2387	0.3426	0.1952	0.2829**	0.2585***	0.2961***	0.2275***	0.2370***	0.2397***	0.0891***
	(0.3844)	(0.2119)	(0.1477)	(0.1187)	(0.0953)	(0.0707)	(0.0572)	(0.0430)	(0.0318)	(0.0200)
Single	0.1855	0.1476	0.0064	0.1381	0.1245	0.0651	0.0080	-0.0225	-0.0382	-0.0374
	(0.4101)	(0.2336)	(0.1630)	(0.1331)	(0.1066)	(0.0800)	(0.0658)	(0.0502)	(0.0367)	(0.0234)
College Degree	-0.2888	-0.0252	-0.0611	-0.1178	-0.0066	0.0043	0.0405	0.0380	-0.0091	-0.0275
	(0.3508)	(0.1999)	(0.1417)	(0.1157)	(0.0949)	(0.0723)	(0.0591)	(0.0452)	(0.0327)	(0.0201)
Fit statistics										
Spearman Cor.	0.345	0.281	0.320	0.344	0.396	0.463	0.545	0.672	0.780	0.910
R^2	0.14479	0.13118	0.12427	0.11862	0.13594	0.15882	0.21616	0.31331	0.44317	0.69165
Observations	1,806	5,566	10,717	16,652	23,760	39,835	51,530	70,583	92,648	126,789

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1 Internet Appendix

1.1 Orthogonalization

Specifically, in the k-th iteration, we identify the k characteristics with the largest $c(k-1)'\Omega^{vh}c(k-1)$, where $c(k-1)$ denotes the characteristics resulting from the $(k-1)$-th iteration and $c(0) = c$. Using this set of k selected characteristics as predictors, the remaining characteristics are projected out via a multivariate kernel regression. This local linear regression employs a Euclidean distance metric over the k predictor characteristics and applies a truncated Gaussian kernel with a bandwidth chosen such that 10% of all other bonds fall within twice the bandwidth parameter, with zero weight assigned beyond this threshold. The orthogonalized characteristic $c(k)$ is then defined as the ranks of the regression residuals, normalized to the interval $[-0.5, 0.5]$, with $c(k) = c(k-1)$ for the k strongest selected characteristics. After $C-1$ iterations, where C denotes the total number of characteristics, the procedure yields the sequentially orthogonalized characteristic set $c^o = c(C-1)$.

1.2 Decomposing time-to-maturity

The analysis in the main text uses time-to-maturity as a continuous characteristic. This section demonstrates that replacing it with three dummy indicators for short-term (below 3 years), medium-term (3 to 5 years), and long-term (above 5 years) bonds yields the same economic interpretation. Specifically, the first clientele remains driven by floating-rate exposure, and the second clientele continues to reflect duration preferences, now evidenced by large absolute loadings on both the short- and long-term maturity indicators. Figure IA.1 reports the principal component loadings under this alternative specification, and Table IA.1 reports the corresponding clientele strength for each bond characteristic.

[Figure IA.1 about here]

[Table IA.1 about here]

1.3 Retail Programs around the world

The Tesouro Direto program is one of at least 22 retail government bond programs operating worldwide. While these programs share the common objective of broadening household access to sovereign debt, they differ substantially in their design, including the range of bonds offered, pricing mechanisms, available maturities, transaction procedures, and distribution platforms. Table IA.2 provides a comparative overview of these 22 programs, reporting for each the program name, year of launch, transaction costs, price-setting mechanism, bond types offered, maturity range, trading procedure, and platform.

[Table IA.2 about here]

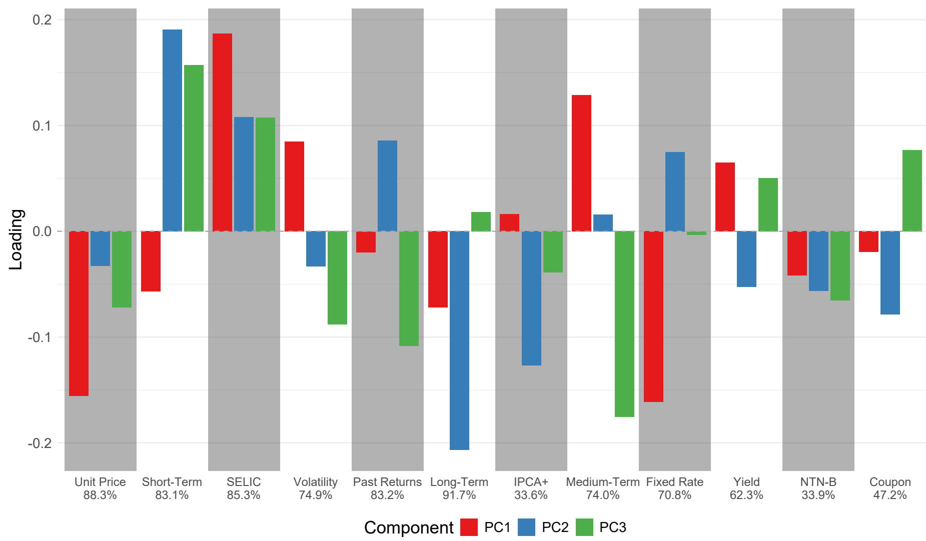
1.4 Descriptive Bonds characteristics Tilts

[Table IA.3 about here]

Figures

Figure IA.1: Characteristics Loading

This figure presents the loadings of investor characteristic tilts on the first three principal components (PCs) extracted from a matrix of bond characteristic tilts of dimension $156{,}000 \times 12$. Characteristic tilts are constructed using orthogonalized investor characteristics. Time-to-maturity is decomposed into three dummy indicators for short-, medium-, and long-term bonds. The ten bond characteristics considered are: low price, short-term maturity, yield, floating rate, past 3-month volatility, past 3-month return, long-term maturity, inflation-linked, medium-term maturity, fixed rate, special bonds, and coupon payment. The x-axis reports each bond characteristic alongside the R^2 from a univariate regression of the respective PC loading on that characteristic.



Tables

Table IA.1: Clientele Strength: Raw and Orthogonalized Characteristic Tilts

This table reports clientele strength measured as the variance of characteristic tilts across investors in December 2024 using both orthogonalized and raw characteristics tilts following the procedure explained in section 4 the same used by Balasubramaniam, Campbell, Ramadorai, and Ranish (2023). The bonds characteristics are order from the highest orthogonality variance. The second column transform the variance into the standard deviations. The third column "Off-Diagonal" column presents the percentage of the variance of the variance that can be attributed to off-diagonal elements of the co-holding matrix. All statistics equally weight investors.

	Orthogonalized			**Raw**		
Characteristic	Variance	Std. Dev.	% Off-Diag.	Variance	Std. Dev.	% Off-Diag.
Unit Price	0.106	0.326	0.083	0.106	0.277	0.083
Short-Term	0.068	0.452	-68.675	0.068	0.401	-68.675
Floating Rate	0.068	0.451	-40.717	0.068	0.408	-40.717
Volatility	0.056	0.236	4.274	0.071	0.228	-40.082
Past Return	0.055	0.235	-26.616	0.081	0.243	-33.855
Long-Term	0.055	0.406	-26.907	0.055	0.360	-26.907
Inflation-Linked	0.053	0.400	-22.591	0.053	0.364	-22.591
Medium-Term	0.051	0.390	-16.993	0.051	0.341	-16.993
Fixed Rate	0.049	0.384	-20.289	0.049	0.329	-20.289
Yield	0.044	0.210	2.879	0.040	0.173	-58.805
Specials	0.023	0.264	-3.491	0.023	0.210	-3.491
Coupon	0.022	0.258	-1.079	0.022	0.236	-1.079

Table IA.2: Retail Debt Programs across Countries

This table presents the characteristics of retail debt programs across 22 countries, including Australia, Austria, Brazil, Mexico, Croatia, Czechia, Estonia, Hungary, Indonesia, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, New Zealand, Poland, Portugal, Romania, the United Kingdom, and the United States. These programs provide individual investors with access to sovereign bonds, offering various structures, interest rates, maturity periods, and trading mechanisms.

Country	**Program Name**	**Launched year**	**Costs**	**Price Formation**	**Type of Bond**	**Maturity Span**	**Trading Procedure**	**Program Platform**	**Source**
Australia	Treasury Bonds and Treasury Indexed Bonds	2013	No direct fees for government-issued bonds, brokerage fees may apply for ASX trades	Set in government auctions and traded on the ASX at market prices	Fixed-rate bonds (coupon payments), Inflation-indexed bonds	Treasury Bonds: 2-30 years; Treasury Indexed Bonds: 5-25 years	Traded on the ASX through licensed brokers	Exchange-traded Australian Government Bonds (eAGBs) on ASX	Link
Austria	Bundesschatz	2003-2019/ 2024-	No fees for purchasing, holding, or selling Bundesschatz securities	Interest rates updated daily based on market conditions, fixed for the chosen term	Fixed-rate bonds (coupon payments)	1 month to 10 years; Green Bundesschatz: 6 months and 4 years	Purchased directly from the Austrian Treasury, not tradable in secondary markets; tradable bonds available on Vienna Stock Exchange	Bundesschatz via Link using ID Austria authentication, offline option available	Link
Brazil	Tesouro Direto	2002	Custody Fee: 0.2% p.a.; Admin Fee: varies (often 0%)	Updated 3x daily based on market rates; fixed, Selic-linked, or inflation-linked	Floating-rate (Selic), Fixed-rate, Inflation-indexed (IPCA+)	Tesouro Selic: 1-7 years, Tesouro Prefixado: 2-6 years, Tesouro IPCA+: 4-30 years	Online purchases via financial institutions or Tesouro Direto; daily buyback by the Treasury	Online platform & app for investment and tracking	Link
Mexico	Cetesdirecto	2010	No purchase fees; interest subject to taxation	Auction-based pricing; yields reflect market conditions	Zero-coupon bonds (Cetes); fixed-rate bonds (Bonos)	Cetes: 28 to 364 days; Bonos: 3 to 30 years	Purchased directly through the Cetesdirecto platform; tradable on the secondary market	Online platform accessible to Mexican residents	Cetesdirecto

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Country	Program Name	Launched year	Costs	Price Formation	Type of Bond	Maturity Span	Trading Procedure	Program Platform	Source
Croatia	Savings Bonds	2023	Typically no purchase fees; interest subject to taxation	Issued at par with fixed interest rates	Fixed-rate bonds (coupon payments)	1 to 5 years	Purchased directly from the Ministry of Finance or through designated banks; limited secondary market trading	Subscriptions via participating banks or financial institutions	Croatian Ministry of Finance
Czechia	Savings Government Bonds	2011	No purchase fees; interest may be taxable	Fixed interest rates set at issuance	Fixed-rate bonds (coupon payments)	6 years	Purchased directly from the Ministry of Finance; tradable after a holding period	Online platform provided by the Ministry of Finance	Czech Ministry of Finance
Estonia	Government Bonds	2024	Information not readily available	Information not readily available	Information not readily available	Information not readily available	Information not readily available	Information not readily available	Estonian Ministry of Finance
Hungary	Hungarian Government Securities Plus (MÁP Plusz)	2019	No purchase fees; interest income is tax-exempt for residents	Fixed interest rates with step-up structure over time	Fixed-rate bonds (coupon payments)	5 years	Purchased through Hungarian State Treasury, banks, and post offices; tradable with some restrictions	Available via Hungarian State Treasury's online platform and physical branches	Hungarian State Treasury
Indonesia	Retail Sukuk and Retail Government Bonds	2006	No purchase fees; taxes on interest income apply	Fixed profit-sharing rates for Sukuk; fixed interest rates for bonds	Sharia-compliant Sukuk; fixed-rate bonds	2 to 3 years	Purchased through designated selling agents; tradable after a holding period	Online platforms of participating banks and securities companies	Indonesia Ministry of Finance

Country	Program Name	Launched year	Costs	Price Formation	Type of Bond	Maturity Span	Trading Procedure	Program Platform	Source
Ireland	State Savings	1990	No fees; interest subject to Deposit Interest Retention Tax (DIRT)	Fixed interest rates; some products offer tax-free returns	Fixed-rate savings products; prize bonds	3 to 10 years depending on the product	Purchased directly from the State Savings or through An Post offices; non-tradable	Online services and An Post offices nationwide	State Savings
Israel	Galil and Shahar Bonds	Year	No purchase fees; interest subject to taxation	Fixed interest rates set at issuance	Fixed-rate bonds (coupon payments)	2 to 20 years	Purchased through designated banks and brokers; tradable on the Tel Aviv Stock Exchange	Available via participating financial institutions	Israel Ministry of Finance
Italy	Buoni del Tesoro Poliennali (BTP)	2012	No purchase fees; interest subject to withholding tax	Fixed interest rates determined at issuance	Fixed-rate bonds (coupon payments)	3 to 30 years	Purchased through banks and financial intermediaries; tradable on the secondary market	Accessible via banking institutions and online trading platforms	Italian Treasury
Japan	Japanese Government Bonds for Retail Investors	2003	No purchase fees; interest subject to taxation	Fixed and floating interest rates available	Fixed-rate and floating-rate bonds	3, 5, and 10 years	Purchased through banks, post offices, and securities companies; tradable after a holding period	Available via financial institutions and Japan Post offices	Ministry of Finance Japan
Korea	Korea Treasury Bonds	1998	No purchase fees; interest subject to taxation	Auction-based pricing; yields reflect market conditions	Fixed-rate bonds (coupon payments)	3 to 20 years	Purchased through banks and securities firms; actively traded on the Korea Exchange	Accessible via financial institutions and online brokerage services	Korea Treasury Bonds
Latvia	Savings Bonds	Year	No purchase fees; interest subject to taxation	Fixed interest rates set at issuance	Fixed-rate bonds (coupon payments)	1 to 5 years	Purchased through the Treasury or designated banks; limited secondary market	Available via the Treasury's platform and participating banks	Latvian Treasury
Lithuania	Savings Notes	2021	No purchase fees; interest subject to taxation	Fixed interest rates determined at issuance	Fixed-rate bonds (coupon payments)	2 to 10 years	Purchased directly from the Ministry of Finance or through designated agents; non-tradable	Online platform provided by the Ministry of Finance	Lithuanian Ministry of Finance

Country	Program Name	Launched year	Costs	Price Formation	Type of Bond	Maturity Span	Trading Procedure	Program Platform	Source
New Zealand	Kiwi Bonds	Year	No purchase fees; interest subject to taxation	Fixed interest rates set periodically by New Zealand Debt Management	Fixed-rate bonds (coupon payments)	6 months, 1 year, 2 years, and 4 years	Purchased directly from the New Zealand Debt Management; non-tradable	Online application via New Zealand Debt Management's website	New Zealand Debt Management
Poland	Retail Treasury Bonds	Year	No purchase fees; interest subject to taxation	Fixed interest rates set at issuance	Fixed-rate bonds (coupon payments)	2 to 10 years	Purchased through designated banks; tradable on the secondary market	Available via participating banks	Ministry of Finance - Poland
Portugal	Certificados de Aforro and Certificados do Tesouro	1960	No purchase fees; interest subject to taxation	Fixed interest rates set at issuance	Fixed-rate bonds (coupon payments)	Certificados de Aforro: up to 10 years; Certificados do Tesouro: 5 to 7 years	Purchased through CTT (Portuguese Postal Services); non-tradable	Available via CTT offices and online	Agência de Gestão da Tesouraria e da Dívida Pública - IGCP
Romania	FIDELIS Government Bonds	2024	No purchase fees; interest income is tax-exempt for individuals	Fixed interest rates determined at issuance	Fixed-rate bonds (coupon payments)	1 to 5 years	Purchased through participating banks and brokers; tradable on the Bucharest Stock Exchange	Available via participating financial institutions	Bucharest Stock Exchange

Country	Program Name	Launched year	Costs	Price Formation	Type of Bond	Maturity Span	Trading Procedure	Program Platform	Source
United Kingdom	National Savings and Investments (NS&I)	1861	No purchase fees; interest subject to taxation unless specified tax-free	Fixed and variable interest rates depending on the product	Fixed-rate bonds, Premium Bonds (prize-linked), Income Bonds	Varies by product; typically 1 to 5 years	Purchased directly from NS&I; some products are non-tradable	Online platform, phone, and mail services	NS&I
United States	TreasuryDirect	1986	No purchase fees; interest subject to federal taxation	Fixed and inflation-adjusted interest rates	Series EE Bonds (fixed-rate), Series I Bonds (inflation-indexed)	Up to 30 years	Purchased directly through the TreasuryDirect website; non-tradable	Online platform provided by the U.S. Department of the Treasury	TreasuryDirect

Table IA.3: Descriptive Statistics of Account and Bond's Characteristics

This table presents the descriptive statistics of the account and bond's characteristics tilts.

	Mean	Std. Dev.	P10	P25	Median	P75	P90
Account Attributes							
Portfolio Size (USD)	20769.065	73100.195	21.497	148.634	1846.599	12332.765	47094.707
Age (Years)	39.033	12.999	24.000	30.000	38.000	46.000	58.000
Experience (Years)	3.815	2.859	0.392	1.378	3.249	5.803	8.145
No. Bonds (Holding)	3.627	3.376	1.000	1.000	3.000	5.000	8.000
No. Bonds (Traded)	5.835	5.525	1.000	2.000	4.000	8.000	13.000
Characteristic Tilts							
Maturity (TTM)	-0.008	0.231	-0.312	-0.178	-0.010	0.153	0.323
Volatility	-0.251	0.233	-0.460	-0.434	-0.320	-0.141	0.060
Past Returns	0.240	0.247	-0.120	0.120	0.318	0.422	0.480
Yield	0.192	0.173	-0.060	0.132	0.236	0.300	0.362
Unit Price	-0.167	0.277	-0.460	-0.414	-0.240	0.008	0.266
Fixed Rate	0.217	0.329	0.000	0.000	0.010	0.324	0.942
Specials (NTN-B)	0.062	0.210	0.000	0.000	0.000	0.000	0.114
Inflation-Linked	0.311	0.364	0.000	0.000	0.140	0.577	1.000
Floating Rate	0.410	0.408	0.000	0.000	0.301	0.853	1.000
Coupon	0.097	0.236	0.000	0.000	0.000	0.023	0.366