PONTIFÍCIA UNIVERSIDADE CATÓLICA
DO RIO DE JANEIRO

Giovanni Martello Panno Machado

Investment Fund Demand and Financial Innovation

Dissertação de Mestrado

Thesis presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor: Prof. Leonardo Bandeira Rezende

Rio de Janeiro
March 2024

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Abstract

Machado , Giovanni Martello Panno; Rezende, Leonardo Bandeira (Advisor). **Investment Fund Demand and Financial Innovation**. Rio de Janeiro, 2024. 56p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

This study aims to analyze investment fund demand within the context of recent financial innovations and the level of bank concentration in Brazil. Traditionally, a limited number of banks have dominated the sector, employing a closed-end architecture for fund distribution. The emergence of financial marketplaces has altered this landscape. Using a dynamic quantitative model inspired by Brown et al. (2023), we analyze the interplay between supply and demand for investment funds, accounting for investors' diverse preferences and inertia and acknowledging the potential for price discrimination by investment fund managers across institutional and retail investors. This concise framework provides insights into the evolving dynamics of the Brazilian investment fund market. Results suggests a significant investor preference for investment funds offered by the same platform. Additionally, our model indicates a significant decline in inertia over time, attributed to the emergence of financial marketplaces and technological advancements.

Keywords

Investment Funds; Demand Estimation; Structural Models; Financial Innovation.

Resumo

Machado , Giovanni Martello Panno; Rezende, Leonardo Bandeira. **Demanda por Fundos de Investimento e Inovação Financeira**. Rio de Janeiro, 2024. 56p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Esta dissertação examina a dinâmica da demanda por fundos de investimento no contexto das recentes inovações financeiras e da concentração bancária no Brasil. Historicamente, um número restrito de bancos dominava o setor, utilizando uma arquitetura de distribuição fechada para seus fundos. No entanto, o surgimento de marketplaces financeiros vem reconfigurando este cenário. O estudo utiliza um modelo quantitativo dinâmico baseado em Brown et al. (2023) para analisar a interação entre oferta e demanda, considerando as preferências dos investidores, a inércia e o potencial de discriminação de preços por parte dos gestores entre investidores institucionais e de varejo. Os resultados sugerem uma preferência significativa dos investidores por fundos ofertados na mesma plataforma. Além disso, nosso modelo indica uma queda significativa na inércia ao longo do tempo, atribuída ao surgimento de mercados financeiros digitais e avanços tecnológicos.

Palavras-chave

Fundos de Investimento; Estimação de Demanda; Modelo Estrutural; Inovação Financeira.

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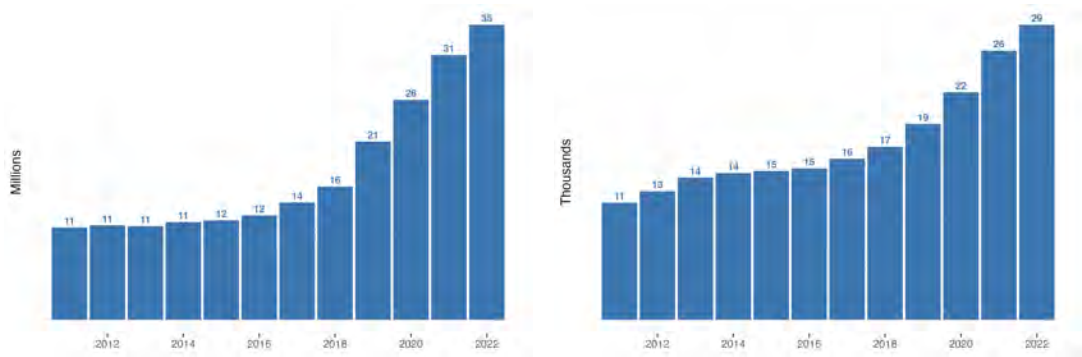
List of Abreviations

AC - Ato de Concentração
AUM - Assets Under Management
CADE - Conselho Administrativo de Defesa Econômica
CPF - Cadastro de Pessoa Física
CNPJ - Cadastro Nacional de Pessoa Jurídica
CVM – Comissão de Valores Mobiliários
FGC - Fundo Garantidor de Crédito
ICVM – Instrução Normativa da Comissão de Valores Mobiliários

1
Introduction

In recent years, Brazil's investment fund sector has undergone significant growth. The number of investment fund accounts has tripled, rising from 12 million in 2016 to 35 million in 2022. Similarly, the number of investment funds offered has increased by almost 80%, growing from 16,000 to 29,000 over the same period (Figure 1.1). This expansion can be largely attributed to the emergence of financial marketplaces, which have significantly transformed the industry. Regulatory adjustments and technological advancements have also played a complementary role in this growth.



(a) Number of Accounts in Investment Funds (b) Number of Investment Funds

Figure 1.1: Growth of the Investment Fund Industry

Historically, some prominent banks have exerted significant influence in the Brazilian market due to their dominance in both deposits and credits. This dominance translated seamlessly into fund management, with the top five banks – Caixa, Banco do Brasil, Itaú, Santander, and Bradesco – controlling roughly 75% of the market share. Taking advantage of their extensive deposit base and a closed-end architecture that restricts investor access to external funds, these banks effectively locked in a sizable portion of the investment fund market.

However, the rise of financial marketplaces has disrupted this long-standing dominance in the investment fund industry. Open-ended platforms have emerged, empowering investors seeking diversification with access to a wider array of financial product providers. These include not just traditional big banks, but also smaller and medium-sized banks, independent fund managers, and even companies issuing private securities. This increased competition has resulted in a significant expansion of investment options available to investors.

Figure 1.2 offers a compelling glimpse into the intensifying competition within the investment industry. The graph reveals a dramatic decline in fees charged by bank-managed funds, a trend that has significantly narrowed the gap between them and independent funds. Most notably, the year 2022 witnessed a convergence in average administrative fees across both categories. This alignment hints at a potential paradigm shift, suggesting a future where fee structures resemble those prevalent in open-ended platforms.

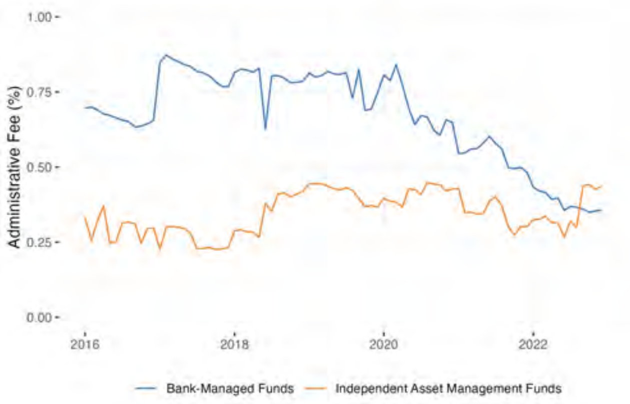


Figure 1.2: Evolution of Asset-weighted fees for Bank-Managed and Independent Funds

These market shifts highlight the importance of understanding the role of major banks and financial innovation in the investment fund industry. Our research specifically aims to analyze the demand for investment funds in the context of recent financial innovations and the level of bank concentration. To shed light on these complex market dynamics, we will begin by examining the impact of major banks on the industry. This will involve a close look at indicators of their market power and the factors that influence it. To achieve this, we have constructed a comprehensive data set using data from the Brazilian Securities and Exchange Commission (CVM) that includes all investment funds operating from 2015 to 2023.

Motivated by these initial findings, we have developed and estimated a dynamic quantitative model that captures the complex interplay between the supply and demand for investment funds. Our model extends the work of Brown et al. (2023) by incorporating in their model the nuances of the Brazilian industry. Specifically, we extend their framework by incorporating the additional dimension of investor preferences for the distribution platform. This allows us to quantify the specific impact of major banks on investment fund demand.

Building on the concept of investor preferences, our dynamic model incorporates a key dimension: investor preference for the distribution platforms.

This results in investors showing a consistent preference for funds distributed through a particular platform, regardless of the specific fund itself. Our findings reveal a statistically significant and positive impact on investor choice, suggesting that investors are more likely to select investment funds offered by their primary bank. This influence is evident when examining cross-elasticities, which measure the impact on demand for one fund when the price of another fund changes. Notably, our analysis reveals that cross-elasticities between funds from the same bank are, on average, 13 times higher for the five largest Brazilian banks. This indicates a significant level of substitutability within these institutions, meaning that investors are more likely to switch between funds offered by the same bank.

Following Brown et al. (2023), investors display inertia, reflecting the tendency of investors to not actively adjust their portfolios every period. This aligns with real-world behavior, in which investors can only reassess their holdings at specific intervals. Interestingly, our findings reveal a significant decrease in investor inertia over time. In the first half of our sample period, only 35.6% of investors made annual portfolio adjustments. This figure grew to 53% in the latter half, representing a nearly 50% increase. This increase in investor activity coincides with the broader changes observed in the Brazilian investment fund industry. Furthermore, our results highlight a clear contrast in investor behavior: institutional investors exhibit greater inertia compared to retail investors. Only 13.5% of institutional investors adjusted their portfolios annually. This difference in behavior may be attributed to variations in financial literacy and risk tolerance between the two investor groups.

As in Brown et al. (2023), investment fund managers practice price discrimination between institutional and retail investors. This means that fund managers may offer different prices to these two investor groups. Our analysis, based on the first-order condition for the investment fund manager, reveals that major banks' affiliated funds tend to have lower average marginal costs. In simpler terms, it appears to be less expensive for these banks to manage their investment funds, potentially allowing them to offer more competitive pricing.

The remainder of the paper follows the structure: Chapter 2 explores the relevant academic literature, while Chapter 3 provides background information on investment funds in Brazil. Chapter 4 offers a detailed description of the data set used to estimate the model described in Chapter 5. The methodology employed for estimating our model is explained in detail in Chapter 6, and the resulting findings are presented in Chapter 7. Finally, Chapter 8 serves as the concluding section.

2
Related Literature

This paper contributes to the growing body of research that utilizes structural models to analyze imperfect competition in financial markets. Our demand model is based on the foundational work of Berry (1994) and Cardell (1997). Specifically, we aim to analyze investment fund demand within the context of recent financial innovations.

Our research closely aligns with the work of Brown et al. (2023), who investigate the sources of market power for index funds. They develop a novel quantitative dynamic model that incorporates investor inertia, search costs, and heterogeneous preferences on the demand side. These frictions enable index fund managers to exert market power through strategies such as price discrimination and higher expense ratios for retail investors. Building upon this framework, we extend their model to capture the unique characteristics of the Brazilian investment fund market, with a particular focus on the role of large banks.

Another highly relevant study is Hortaçsu e Syverson (2004), which examines the impact of non-portfolio fund characteristics and information asymmetry on the proliferation of S&P index funds and the observed dispersion in fees. Their research suggests that non-portfolio attributes, such as fund age, the number of funds within a family, and tax implications, significantly influence investor choice within the S&P index fund market.

Our research contributes to the growing field of industrial organization within consumer finance, a topic that is gaining significant traction in financial market analysis. Several studies have explored competition in the face of disruption: Jiang, Yu e Zhang (2022) examine how banks compete with digital players and the impact on financial inclusion. Similarly, Allen, Clark e Houde (2019) quantify the influence of search costs and brand loyalty on market power in the Canadian market. Others have applied structural models to specific markets: Benetton (2021) analyzes the effect of bank regulation on UK mortgages. Buchak et al. (2018b) and Buchak et al. (2018a) explore the interaction of "shadow banks" with traditional banks on regulation and policy. Examining financial stability and competition, Egan, Hortaçsu e Matvos (2017) constructed a structural model of the US banking sector. Similarly, Egan, Lewellen e Sunderam (2021) decompose the productivity banks to understand the creation of value in the US.

Our research differentiates itself by focusing on the demand-side characteristics of the Brazilian mutual fund industry. While these prior works provide valuable insights into various aspects of financial market competition, they don't specifically address the influence of major banks on investor behavior in the context of a rapidly evolving Brazilian market characterized by platform diversification.

This study also aligns with a growing body of financial literature that uses data from portfolio holdings to model and test theories related to asset demand. This approach, originating in the 1960s and 1970s with the work of Tobin e Brainard (1968), has seen a recent resurgence. Koijen e Yogo (2019) developed a novel asset pricing model that incorporates investor heterogeneity, reflecting the diverse investment strategies of both institutions and households. Their findings suggest that when returns exhibit a factor structure, a portfolio choice model translates into characteristics-based demand. This strengthens the link between finance and industrial organization. Based on this framework, Koijen, Richmond e Yogo (2020) quantify the impact of market trends and regulations on asset prices, informativeness, and wealth distribution. Similarly, Koijen e Yogo (2020) estimate a demand system for financial assets in 36 countries using data from international holdings. This comprehensive framework allows for the analysis of exchange rate variations, long-term yields, and stock prices. It sheds light on major economic events like the European sovereign debt crisis and facilitates the estimation of the convenience yield on US assets.

Our research extends this line of inquiry by focusing on the specific context of the Brazilian mutual fund industry. This will not only contribute to the financial literature on portfolio holdings data, but also offer valuable insights for policymakers and industry participants seeking to navigate this dynamic landscape.

3
Institutional Background

The Brazilian investment fund industry presents a distinct characteristic compared to the United States. Unlike the U.S. market, dominated by independent fund managers, Brazil's landscape is heavily influenced by major banks. These banks have traditionally employed a closed-end architecture for fund distribution and marketing, restricting clients' access and offering only their own funds or affiliated products. This closed system has been the norm for several decades in Brazil. However, recent years have witnessed a significant transformation.

Brazil's investment fund industry has undergone a significant transformation. Before 2017, the Brazilian Federal Trade Commission (CADE) classified investment funds production and commercialization as a single market. This categorization reflected the integrated operations of product providers, mainly banks. However, a landmark change occurred in 2017 with the Concentration Act AC nº 08700.001642/2017-05. This act, prompted by the rise of open-ended platforms (marketplaces), technological advancements, and regulatory changes, redefined the market structure. CADE delineated separate markets for the management/administration of third-party funds and the distribution of investment products.

Open platforms represent a significant departure from the traditional closed-end architecture dominated by major banks. These platforms act as intermediaries connecting a wide range of financial product providers with investors seeking a wider range of investment options. This ecosystem includes small and medium-sized banks, independent fund managers, and even companies issuing private securities. On the contrary, traditional banks have historically operated in a siloed manner, offering only their own internal products or those of affiliated entities.

This modern distribution model for financial products and services fosters a more competitive landscape. It facilitates competition on two key levels: platform competition, where different providers vie for investor attention on the same platform, and competition between open platforms and traditional banks. This open ecosystem also reduces entry barriers for new investment product providers. Unlike the traditional model, newcomers are not burdened with establishing expensive and extensive customer service networks. The benefits are twofold: providers can reduce their product distribution costs, and investors gain from a more vibrant and competitive market.

Regulatory changes and technological advancements further propel the growth of the open platform market, not only for the distribution of investment funds but for the whole spectrum of financial products. Digital registration streamlines the account opening process for clients, eliminating the need for physical visits. Furthermore, the increased limit of the Credit Guarantee Fund (FGC) - from R$70,000 to R$250,000 per institution and CPF – enhances security for small investors. This incentivizes them to explore products offered by smaller, lesser-known institutions that may potentially offer higher returns (although with commensurate risks). Furthermore, the rise of digital platforms, mobile technology, and social networks reduces costs for institutions in customer acquisition, maintenance, and service, eliminating the need for extensive physical branch networks.

These factors have contributed to a shift in investor behavior, with some clients migrating from traditional banks to open-ended platforms such as XP (as illustrated in Figure 3.1).

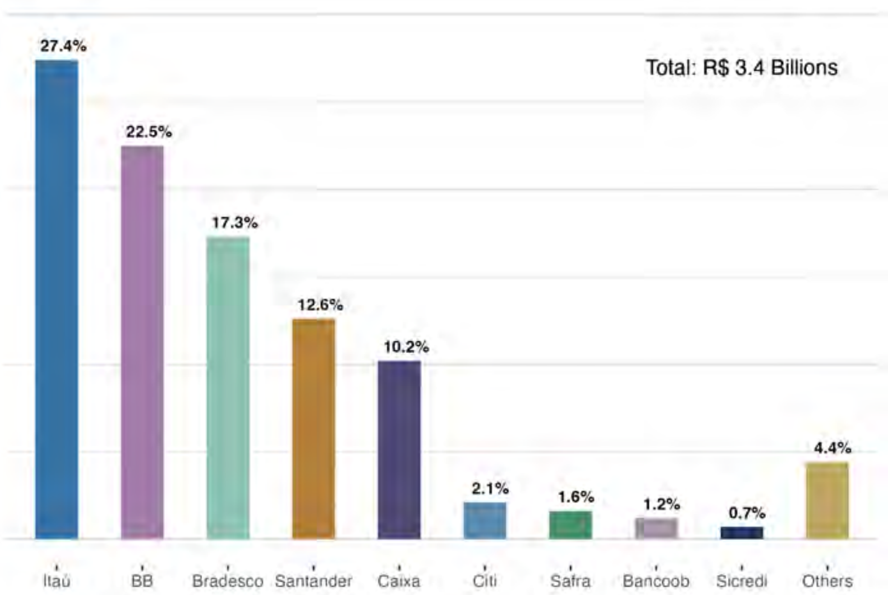


Figure 3.1: Percentage of Net Inflows to XP Brokerage by Bank of Origin (January, 2017) - Source: Banco Central do Brasil and XP Corretora

This paper analyzes the demand for investment funds in the Brazilian context, particularly in light of recent financial innovations. We examine investor behavior both before and after the emergence of open platforms, a significant shift in the industry.

4
Data

Our analysis of investment fund demand in Brazil uses a comprehensive dataset constructed from information provided by the Brazilian Securities and Exchange Commission (CVM). This data set covers all investment funds operating from January 2015 to February 2023. This specific time frame allows us to examine investor behavior before and after the emergence of open platforms, a significant recent innovation in the Brazilian financial market.

CVM data adhere to Instruction No. 555, covering a broad spectrum of fund categories. This includes fixed-income, equity, multi-market, and currency funds. Specialized funds such as funds of funds, those restricted to qualified or professional investors, and private pension funds are also incorporated. It's important to note that Real Estate Investment Funds (ICVM 472) and Investment Funds in Credit Receivables (ICVM 356) are not included in this analysis. The following table summarizes the categories covered in the data set.

Table 4.1: Number of Funds by Asset Class

Equity	Foreign Exchange	Multimarket	Fixed Income
1001	46	1517	1404

To gain a comprehensive view of Brazilian investment funds, we merged three distinct CVM datasets: the "Essential Information Sheet" (*Lâmina de Informações Essênciais*) the "Daily Report" (*Informe Diário*) and the "Information Statement" (*Extrato das Informações*). The "Essential Information Sheet" (available monthly since 2014) provides details on management and performance fees, operational costs, non-portfolio attributes, and other fund characteristics. The "Daily Report" (available monthly since 2000) offers daily data on fund net asset value, share prices, investor flows (inflows and outflows), and shareholder numbers. The "Information Statement" (available since 2015) includes metadata on each fund, such as target audience and portfolio composition restrictions. These datasets can be successfully merged using the National Tax Identification Number (CNPJ) assigned to each individual fund. In addition to this process, we have removed incorrect and missing data points. The final data set covers 3960 funds and has more than 100,000 observations. There are no additional filters.

To capture past performance, a crucial factor influencing investor decisions, we calculated monthly returns for each fund in our dataset using daily data from the CVM's "Daily Report" for the period 2015 to 2023. We employed various return metrics in our structural model, including cumulative returns for 3, 6, and 12-month periods, year-to-date returns, and the standard deviation of returns over a year. These metrics provide a comprehensive picture of a fund's historical performance. Importantly, we incorporated these returns as lagged fund characteristics in our demand estimation model. This ensures that the characteristic space reflects the information available to investors when they make investment decisions.

The following sections of this chapter will delve deeper into the data used to construct our structural model. We will dissect the Brazilian investment fund landscape, focusing on the historical influence of major banks and how it has interacted with the recent rise of open platforms. Furthermore, we will analyze the temporal evolution of fund prices and returns, aiming to identify any trends or potential shifts in investor behavior. Finally, we examine the dispersion of prices and returns across the data set.

4.1 Summary Statistics

This section presents summary statistics for the key variables used in our investment fund demand model. Table 4.2 offers an overview of these statistics, encompassing the entire fund sample and further broken down by target audience (institutional vs. retail investors). The data reveal both diversity in the characteristics and behaviors of funds and substantial differences in investment patterns between these two investor groups.

The data highlight significant disparities in investment patterns between institutional and retail investors. Retail investors, on average, face higher administrative fees compared to their institutional counterparts, suggesting potential price discrimination by fund managers. Furthermore, institutional investors usually chose funds with longer redemption processing times. Finally, the analysis reveals a difference in the scale of financial activities between the two groups. Funds targeting retail investors tend to have lower net asset values and experience higher fluctuations in investor flows (inflows and outflows) compared to those targeting institutional investors. Additionally, the number of investors is typically higher for retail-focused funds.

Table 4.2: Summary Statistics by Type of Investor

	Whole Sample		Institutional		Retail	
	Mean	Sd	Mean	Sd	Mean	Sd
Administrative Fee	0.78	1.00	0.33	0.59	0.79	1.01
Performance Fee	4.64	10.16	4.89	10.30	4.64	10.16
Fund Expenditure	1.36	1.79	0.83	1.58	1.38	1.79
Effective Fee	0.86	1.09	0.42	0.72	0.87	1.09
Redemption Period	6.94	12.99	15.26	19.80	6.69	12.65
Age	8.88	6.65	5.21	4.16	8.99	6.68
Number of Investors	6.00	38.61	0.36	1.34	6.17	39.17
Active Management	0.51	0.50	0.47	0.50	0.52	0.50
Net Worth	1.02	3.77	0.27	0.67	1.04	3.82
Inflows	0.24	2.02	0.04	0.16	0.24	2.05
Outflows	0.23	1.94	0.03	0.15	0.24	1.97

Note: The variables 'Net Worth', 'Inflows' and 'Outflows' are expressed in Billions of R$ and the variable 'Number of Investors' is expressed in thousands of investors. The redemption processing time is expressed in days.

Tables 4.3 and 4.4 provide a more granular examination of our data set. Table 4.3 explores the data through a chronological lens, dividing the sample into two periods at April 2019. This split point might be relevant to significant events impacting the Brazilian investment fund industry, such as the emergence of open platforms. Table 4.4 investigates the data based on fund management, differentiating between bank-managed and non-bank-managed funds. This distinction is achieved by identifying regular expressions associated with bank names within the investment fund names.

Table 4.3 offers compelling evidence of the transformative shifts driven by the evolution of financial marketplaces. The data reveals an expanding market, as indicated by the increase in the average number of investors and the decrease in the average age of investment funds, suggesting the establishment of new entrants. Notably, this period also witnessed a significant decrease in administrative fees by over 10 basis points, potentially reflecting increased competition among fund providers. However, the table also shows an increase in the redemption processing period and the proportion of actively managed funds.

Table 4.3: Summary Statistics over Time

	First Half		Second Half	
	Mean	Sd	Mean	Sd
Administrative Fee	0.85	1.10	0.71	0.90
Performance Fee	3.66	9.14	5.63	11.01
Fund Expenditure	1.34	1.69	1.38	1.88
Effective Fee	0.91	1.15	0.81	1.01
Redemption Period	4.82	10.41	9.07	14.85
Age	9.12	6.28	8.64	7.00
Number of Investors	5.51	32.17	6.49	44.11
Active Management	0.45	0.50	0.58	0.49
Net Worth	1.01	3.85	1.03	3.69
Inflows	0.23	1.88	0.24	2.15
Outflows	0.23	1.85	0.24	2.03

Note: The variables 'Net Worth', 'Inflows' and 'Outflows' are expressed in Billions of R$ and the variable 'Number of Investors' is expressed in thousands of investors. The redemption processing time is expressed in days.

Table 4.4 delves into the differences between Bank-Managed and Independent Funds. A key finding is the higher average administrative fees associated with Bank-Managed Funds, while their average performance fees are lower compared to Independent Funds. This suggests a potential trade-off between these two types of fees based on the fund's management structure. Additionally, Independent Funds exhibit higher average fund expenditures, which could indicate greater operational costs or distinct spending patterns compared to Bank-Managed Funds.

The data also reveals intriguing disparities in investor base and liquidity profiles between Bank-Managed and Independent Funds. Bank-Managed Funds likely benefit from established distribution channels and brand recognition, leading to a higher average number of investors compared to Independent Funds. This difference in market penetration is further reflected in the differences between asset sizes, with Bank-Managed Funds typically having a substantially higher mean net asset value. Finally, the considerable contrast in redemption periods suggests that Bank-Managed and Independent Funds cater to investors with different liquidity needs.

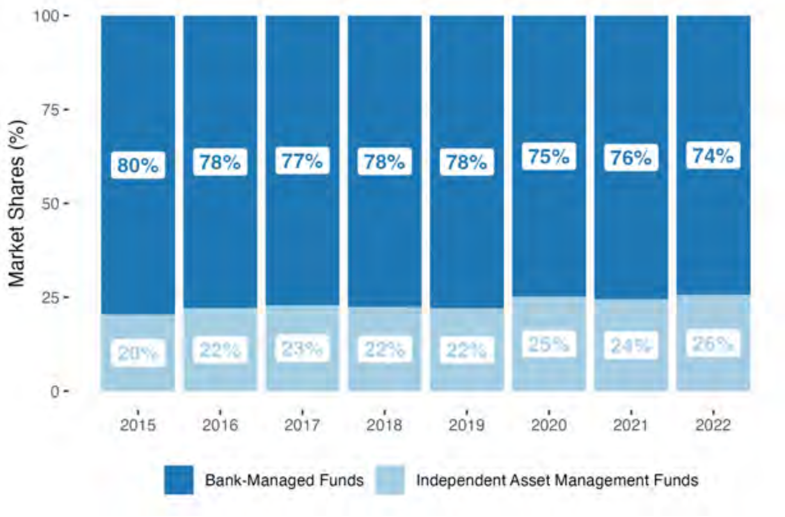
Table 4.4: Summary Statistics for Bank-Managed and Independent Funds

	Bank-Managed		Independent	
	Mean	Sd	Mean	Sd
Administrative Fee	0.88	1.00	0.69	1.00
Performance Fee	2.22	8.60	6.69	10.91
Fund Expenditure	1.08	1.34	1.60	2.06
Effective Fee	0.91	1.03	0.81	1.13
Redemption Period	2.62	6.52	10.59	15.69
Age	10.34	6.52	7.66	6.51
Number of Investors	10.86	55.07	1.90	12.40
Active Management	0.51	0.50	0.52	0.50
Net Worth	1.68	4.57	0.46	2.81
Inflows	0.44	2.90	0.07	0.58
Outflows	0.43	2.79	0.06	0.56

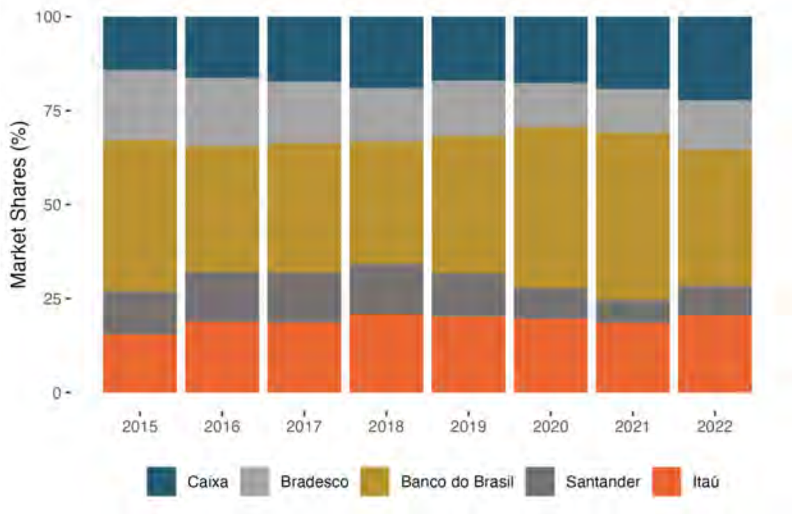
Note: The variables 'Net Worth', 'Inflows' and 'Outflows' are expressed in Billions of R$ and the variable 'Number of Investors' is expressed in thousands of investors. The redemption processing time is expressed in days.

4.2 Market shares

One unique characteristic of the Brazilian investment fund industry is the substantial influence of major banks. As illustrated in Figure 4.1, bank-managed funds hold a dominant position in terms of total assets under management (AUM). While Figure 4.1a reveals a discernible but gradual decline in their market share, falling from 80% in 2015 to 74% in 2022, bank-managed funds still represent a significant portion of the market. This trend suggests that despite ongoing transformations within the industry, major banks remain a formidable force shaping the Brazilian investment fund landscape.



(a) Market Share by Type of Asset Manager



(b) Market Share of Bank-Managed Funds

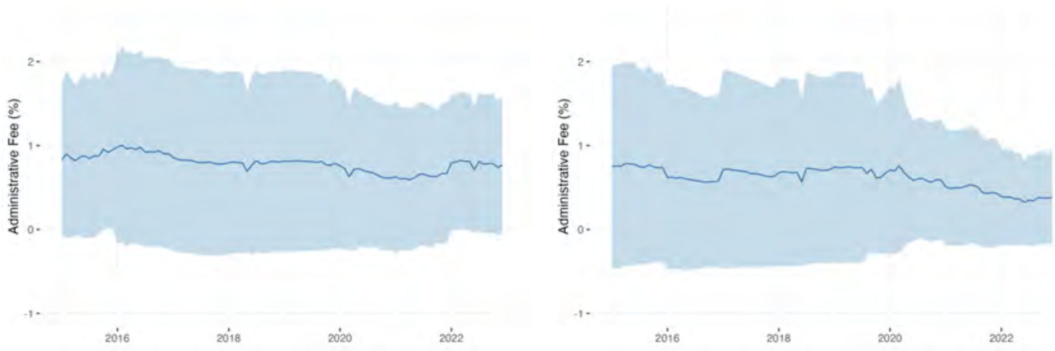
Figure 4.1: Evolution of Market Shares: (a) divides funds as bank-managed or independent; (b) describes the share composition of bank-managed funds

Figure 4.1b provides a breakdown of the market share distribution among bank-managed funds. The data reveals a relatively stable composition over time, with Banco do Brasil, a state-owned bank, consistently leading the pack as the largest asset manager in the country. This dominance is further complemented by the substantial shares held by other major banks, highlighting the enduring influence and presence of these established financial institutions within the Brazilian investment fund market.

4.3 Price Evolution and Dispersion

This subsection explores the dynamics of fees within the Brazilian investment fund industry, focusing on their distribution and how they've changed over time. As shown in Table 4.3, the industry has witnessed a significant decrease in the average administrative fee. This trend is further confirmed by examining the asset-weighted distribution of fees in Figure 4.2b. The figure reveals a clear decline in both the mean and standard deviation of fees over time. This suggests that a larger portion of recently invested assets are subject to lower administrative fees compared to historical averages.

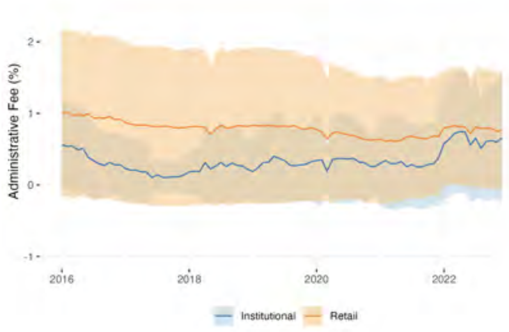
The asset-weighted mean being lower than the equal-weighted mean offers another interesting insight. It indicates a preference among investors for funds with lower fees. This finding underscores a growing emphasis on cost-effective investment options within the Brazilian market.



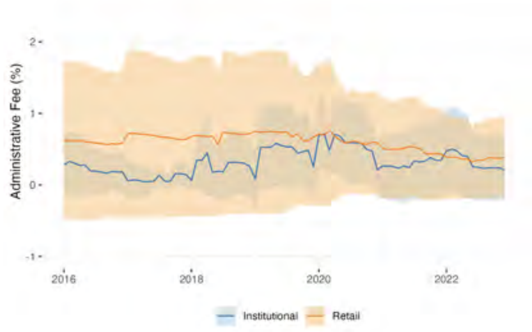
(a) Administrative Fee (b) Administrative Fee (Weighted)

Figure 4.2: Distribution of Fees Over Time: (a) display the equal weighted distribution and (b) the asset-weighted distribution. Upper and Lower bounds are defined by one standard deviation

Figure 4.3 sheds light on the distribution of fees and its evolution over time, categorized by investor type. The data reveals that the average administrative fee for retail investors follows a similar trend as the overall market average observed in Table 4.3. This suggests that retail investors are likely benefiting from the industry-wide decrease in fees. In contrast, the mean fee for institutional investors appears to have a distinct and irregular pattern, deviating from the trend observed for retail investors and the market as a whole. This difference warrants further investigation to understand the factors driving fee structures for institutional investors.



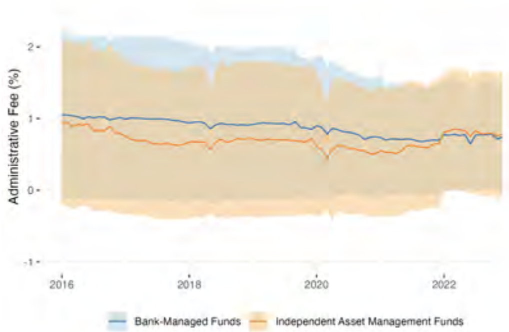
(a) Administrative Fee



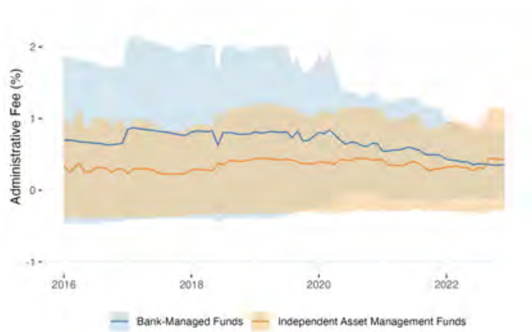
(b) Administrative Fee (Weighted)

Figure 4.3: Distribution of Fees Over Time by Type of Investor

Figure 4.4 categorizes the average fees between Bank-Managed and Independent Funds. Consistent with the overall market trend, the average administrative fee for bank-managed funds exhibits a declining trend over time. This suggests that even established players like banks are adapting to the evolving market by lowering fees. In contrast, the average fee for independent funds remains relatively stable, albeit at a consistently lower level. Interestingly, the asset-weighted mean administrative fee for both bank-managed and independent funds appears to converge in 2022. This convergence suggests a potential alignment with the fee structures prevalent in the open-ended platform space, possibly driven by increased competition within the industry.



(a) Administrative Fee



(b) Administrative Fee (Weighted)

Figure 4.4: Distribution of Fees Over Time for Bank-Managed and Independent Funds

4.4 Returns

This subsection focuses on the historical performance of investment funds in the Brazilian market, specifically analyzing annual returns. To capture this performance, we utilized daily share price data to calculate monthly and annual returns for each fund. We also computed the standard deviation of returns to assess risk. However, this section primarily focuses on annual returns, examining their evolution over time and dispersion across the industry. It's important to note that we employ lagged returns in our analysis. This ensures that the information considered reflects what was available to investors at the time they made their investment decisions.

Figure 4.5 presents the evolution of average annual returns for various sub-samples of the data set. Interestingly, the plot reveals a consistent pattern across all sub-samples, with no significant long-term outperformance by any particular group. This observed uniformity in performance trends suggests a high degree of coherence within the Brazilian investment fund market. Different categories of funds may be responding similarly to market conditions and displaying similar risk-return profiles.

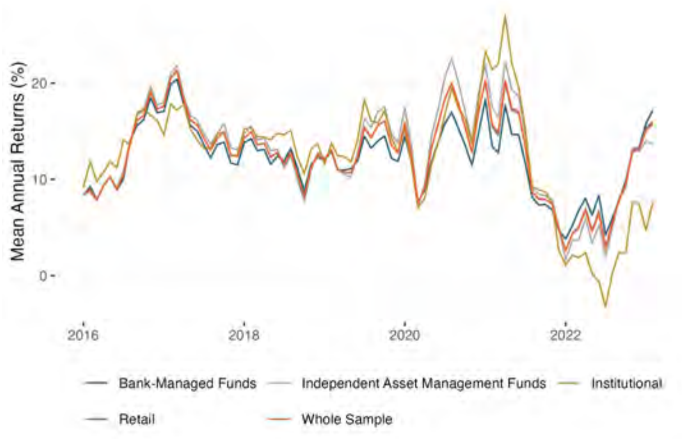
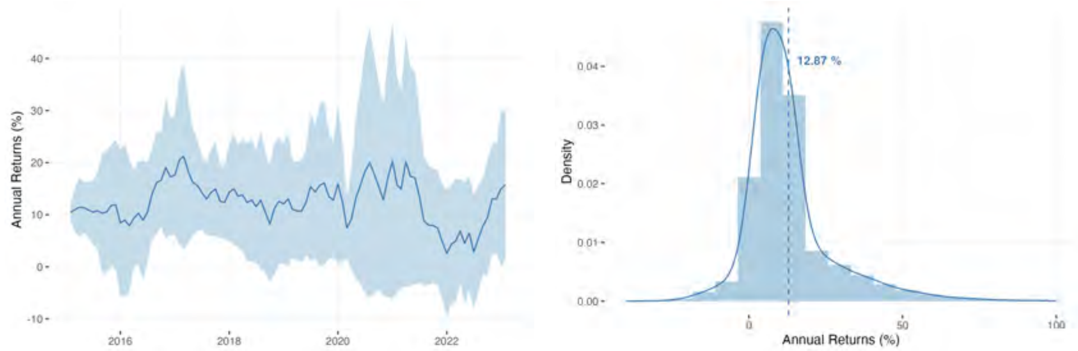


Figure 4.5: Mean Annual Returns over Time

While Figure 4.5 highlighted a general coherence in performance trends across fund categories, a significant variation in returns exists among individual funds within those categories. Figure 4.6 illustrates this dispersion by depicting the distribution of returns across all investment funds over time. The graph reveals clear spikes in volatility coinciding with periods of economic uncertainty, such as the severe economic recession and political turmoil in early 2016, the implementation of economic reforms and global economic uncertainties including trade tensions between the U.S. and China in late 2018, and the substantial impact of the COVID-19 pandemic, including disruptions in global supply chains and government responses, in early 2020.



(a) Dispersion of Returns over Time (b) Histogram of Annual Returns

Figure 4.6: Distribution of Annual Returns: Upper and Lower bounds in (a) are defined by one standard deviation

Figure 4.6b reinforces this point by showcasing a histogram with a pronounced spread of returns and evident fat tails in the distribution. The distribution's skew towards the right suggests a prevalence of funds with higher returns compared to those with lower returns. These observations suggest that individual fund performance can vary significantly, particularly during periods of market volatility, even when broad fund categories exhibit similar overall trends.

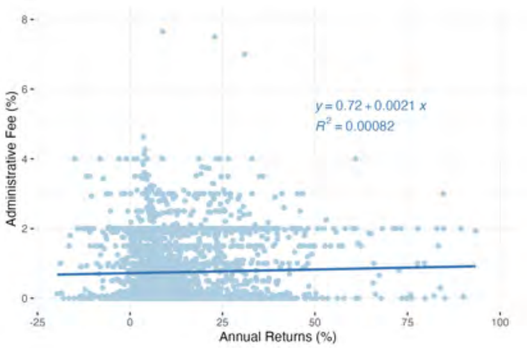


Figure 4.7: Relationship between Fees and Returns

To understand the potential link between fees and performance, we examined the correlation between mean administrative fees and mean annual returns for each fund. Figure 4.7 presents a scatter plot along with a trend line to visualize this relationship. Interestingly, the data reveals no statistically significant correlation between administrative fees and annual returns. This challenges the traditional assumption that higher fees translate to superior fund performance. This finding suggests that factors beyond fund performance, such as the underlying investment strategies, manager skill, and market conditions, likely play a more prominent role in determining fees within the

Brazilian market. Further investigation into these nuanced factors influencing fund pricing and performance dynamics is warranted.

5
Structural Model

This chapter focuses on developing a dynamic quantitative model to explore the interplay between supply and demand for investment funds in the Brazilian context, particularly in light of recent financial innovations. We aim to leverage this model to analyze investment fund demand and how it interacts with these innovations.

Our model extends the work of Brown et al. (2023). We adapt their model to account for the specificities of the Brazilian market. These include the significant influence of large domestic banks on investment funds. Specifically, our model incorporates the additional dimension of investor preferences for the distribution platform. This modification gives a particular focus on the prominent role of Brazilian banks in distribution channels of the investment fund industry.

In our model, investors exhibit a range of preferences for specific investment funds. This horizontal differentiation creates competition among funds with similar characteristics, as investors seek options that best align with their individual goals. Additionally, investors may also favor certain distribution platforms over others, regardless of the specific funds offered. This vertical differentiation creates an additional layer of competition between platforms themselves. Investors might value a platform's reputation, user experience, or the range of investment options available.

Following Brown et al. (2023), investors exhibit inertia, meaning they tend to stick with their existing investment portfolios for a period of time, even when new options become available. This behavior can give established funds a bit of an edge in the market. On the supply side, investment fund managers can offer different prices to institutional and retail investors, a practice known as price discrimination. This can influence investor decisions, as institutional investors with larger investment volumes may be offered more favorable pricing.

5.1
Demand for Investment Funds

We model investor demand for investment funds as a discrete choice problem. Investors considering a hedge fund face a two-stage decision process. First, they select a distribution platform. Then, within the chosen platform, they select a specific investment fund. To analyze this nested decision structure, we employ a nested logit approach.

As in Brown et al. (2023), we concentrate on the investor's selection of a fund within a specific asset class, leaving aside the broader question of portfolio allocation. For example, our model examines an investor's choice of an fixed income fund without considering the initial decision of whether and how much to invest in fixed income.

We also consider two distinct investor categories: institutional and retail. In the Brazilian context, "institutional investor" encompasses not only the standard definition but also investors committing over one million reais. We represent these categories with the variable T, where T can be either I (institutional) or R (retail). Institutional and retail investors differ in their preferences, inertia, and access to specific types of funds. Notably, the pool of investment funds available to retail investors is distinct from that accessible to institutional investors.

5.1.1 Investors preference

At each time period t, investor i must select a single investment fund from a set of available options $j^T = 1, 2, \ldots, J^T$ within a specific fund category. These funds are grouped into G mutually exclusive and exhaustive categories. The categorization is based on the financial institution managing the fund, which also handles its distribution. These institutions include established players like Itaú, Santander, and Bradesco, along with newer entrants such as XP and BTG.

Adding to the evolving landscape of financial institutions, a separate category (nest) is designated for non-bank funds, distinct from those offered by traditional banks. This acknowledges the growing presence of new players like XP and BTG alongside established banking institutions.

The utility obtained by investor i^T from choosing investment fund j^T from the class of investment g at time t is given by:

$$u_{ijt}^T = \delta_{ijt}^T + \zeta_{igt}^T + (1 - \sigma^T)\varepsilon_{ijt}^T$$

where the mean utility level is written as:

$$\delta_{jt}^T = -\alpha^T p_{jt} + x'_{jt}\beta^T + \xi_{jt}^T$$

The term $-\alpha^T p_{jt}$ captures the dissatisfaction investors experience due to administrative and performance fees associated with fund j at time t (denoted by p_{jt}). The variable x_{jt} represents a matrix containing various fund characteristics. The vector β^T captures the preferences of investor type T regarding these characteristics. Essentially, $x_{jt}\beta^T$ calculates the utility derived from these observed features. The superscript T designates parameters that can vary based on the investor type.

In addition to the observable characteristics, the indirect utility function incorporates three unobserved factors: ξ_{jt}^T, ε_{ijt}^T, and ζ_{igt}^T. The first term, ξ_{jt}^T, captures unobserved product features that are generally appealing to all investors of type T. This term follows a normal distribution.

The remaining two terms, ε_{ijt}^T, and ζ_{igt}^T,capture variations in investor preferences across individuals. Both terms adhere to an Extreme Values Type I (EVTI) distribution. ε_{ijt}^T represents an individual-specific preference shock specific to a particular investment fund j at time t. On the other hand, ζ_{igt}^T reflects a preference shock related to the distribution platform i where the fund is offered. This shock applies uniformly to all funds offered through that platform. This structure implies horizontal differentiation among investment funds. In other words, two investors of the same type T may have different preferences for the "best" fund or distribution platform, even when considering unobserved factors.

Our framework incorporates a parameter, σ^T, that captures the within-platform correlation of utility levels for investors of type T. This value ranges from 0 to 1. At the lower end (0), it signifies no correlation between funds offered by the same distributor, essentially reverting to a standard logit model. Conversely, a value approaching 1 indicates perfect correlation, where investors only compare options within a platform and base their decisions solely on the specific characteristics of each fund. It's important to remember that horizontal differentiation is a broader concept also influenced by the parameters α^T and β^T. These parameters reflect how different investor types weigh the importance of fees and other fund characteristics. Even when considering unobserved factors, investors of different types may have varying preferences for the "best" fund or platform, highlighting the multifaceted nature of horizontal differentiation in this context.

5.1.2 Fund Choice

The market share of a specific fund j among active investors of type T at a given time t depends on the likelihood that this particular fund offers a higher level of satisfaction compared to other options. Formally, considering that $\zeta_{igt}^T + (1 - \sigma^T)\varepsilon_{ijt}^T$ follows a EVTI distribution, we can mathematically express this probability as:

$$s_{jt}^{T} = \frac{e^{\delta_{jt}^{T}/(1-\sigma^{T})}}{D_{gt}^{\sigma^{T}}\left[\sum_{g'} D_{gt}^{(1-\sigma^{T})}\right]}$$

where:

$$D_g = \sum_{l \in G \cap \mathcal{J}_{m(j),t}^{t}} e^{\delta_{lt}^{T}/(1-\sigma^{T})}$$

In this setting, investors choose investment funds within a specific market - $\mathcal{J}_{m(l),t}^{t}$ Importantly, we consider the specific set of investment options available to each investor type T at a given time t within that market. This ensures our analysis focuses on realistic choices investors face when deciding which fund to purchase.

5.1.3 Inertia

Following Brown et al. (2023), we acknowledge that investors may not actively change their holdings every period. Each period there's a chance an investor will remain inactive and a chance they'll become active. Inactive investors stick with their current investments, while active investors rebalance their portfolios to maximize their objective function. We assume the likelihood of an investor being inactive varies between investor types (institutional vs. retail) but remains consistent for each specific type. Formally, ϕ^{T} represents the probability of a type T investor being inactive in a given period, with $1-\phi^{T}$ representing the probability of being active.

Equation 5.1.2 is used to determine market shares when active investors choose a fund. This implies investors either base their decisions on a short-term view, assuming their preferences and available options remain unchanged over time, or they exhibit true short-sightedness. Since a proportion ϕ^{T} of type T investors remains inactive each period, the total value of assets under management (AUM) of fund j held by type T investors at time t, denoted as $AUM_{j,t}^{T}$, can be expressed as:

$$AuM_{j,t}^{T} = \underbrace{\phi^{T} AuM_{j,t-1}^{T}(1+r_{m(j),t-1})}_{AuM_{j,t}^{T,\text{Inactive}}} + \underbrace{(1-\phi^{T})M_{m(j),t}^{T} s_{j,t}^{T}}_{AuM_{j,t}^{T,\text{Active}}}$$

The total AuM for fund j by type T investors $AuM_{j,t}^{T}$ can be broken down into two parts. The first part, $AuM^{T,\text{Inactive}}$, reflects the demand from investors who choose to stick with their current holdings. This demand grows based on the return of fund j over the period from $t-1$ to t, denoted as $r_{j,t-1}$. The second part, $AuM^{T,\text{Active}}$, captures the demand from investors who actively rebalance their portfolios. The term $M^T_{m(j),t}$ represents the total amount invested in market $m(j)$ by investors of type T at time t.

5.2 Supply of Investment Funds

The supply side of the model follows the same structure of Brown et al. (2023). Each firm, denoted by k, create and manage two main categories of investment vehicles: retail mutual funds and institutional mutual funds. Although both types of funds serve a similar function, they cater to distinct investor groups. Retail mutual funds are designed specifically for individual investors, while institutional mutual funds are geared towards institutional investors such as pension funds, insurance companies and high net worth individuals.

The per-period profits of investment fund managers in a market m are defined by:

$$\Pi_{k,m,t} = \sum_{j \in \mathcal{J}_{k,m}} (AuM^R_{j,t} + AuM^I_{j,t})(p_{j,t} - c_j)$$

Here, $\mathcal{J}_{k,m}$ represents the set of investment funds offered by investment fund manager k in market m. The terms $AuM^I_{j,t}$ and $AuM^R_{j,t}$ denote the demand for fund j from institutional and retail investors, respectively. Funds earn a markup of $p_{j,t} - c_j$ for each dollar of assets collected, where c_j signifies the marginal cost of operating the fund.

Investment fund managers engage in a differentiated, multi-product, dynamic, Nash-Bertrand, administrative fee-setting game. Let $\mathbf{p}_{k,t}$ be the vector of prices for funds managed by k in period t. The key challenge for each fund manager is to determine the series of prices (fees) to set over time, $\mathbf{p}_{k,t}\mathbf{p}_{k,t+1}, \cdots$. Their goal is to maximize the total value of their future profits, discounted by β.

$$\max_{\mathbf{p}_{k,t},\mathbf{p}_{k,t+1},\cdots|\mathbf{p}_{-k,t},\mathbf{p}_{-k,t+1},\cdots} \sum_{\tau=t}^{\infty} \beta^{\tau-t} \sum_{j \in \mathcal{J}_{k,m}} (AuM^R_{j,\tau} + AuM^I_{j,\tau})(p_{j,\tau} - c_j)$$

To simplify the analysis, is assumed that fund managers have complete knowledge of their competitors' pricing strategies over all future periods. This simplifies the decision-making process for fund managers by excluding the complexities of strategically adjusting prices today to influence competitor pricing decisions in the future.

The changes on the demand side of our model do not alter the interpretation of the first order conditions of the investment manager problem described by Brown et al. (2023). In their model, inertia creates a trade-off for fund managers when setting prices. On the one hand, inertia can incentivize lower prices to attract new investors who are likely to stay invested due to inertia. This is because these new investors become a more predictable source of future revenue. However, inertia also has another effect: it makes demand less elastic. Elasticity refers to how sensitive demand is to price changes. In other words, when inertia is high, even if a fund increases its price, investors might be less likely to switch to a competitor due to the hassle of inertia. This reduced sensitivity to price changes allows fund managers to potentially set higher prices without a significant drop in demand. This can be seen in the first-order condition for the problem of a single product retail mutual fund manager:

$$0 = \frac{\partial AuM_{j,t}^R}{\partial p_{j,t}} \left[\underbrace{p_{j,t} - c_j}_{\text{Static Profits}} + \underbrace{\sum_{\tau=T+1}^{\infty} (\beta(1 + \tilde{r}_{m(j),\tau})\phi^R)^{\tau-t}(p_{j,\tau} - c_j)}_{\text{Present Value of Future Profits}} \right] + AuM_{j,t}^R$$

The first-order condition is quite standard, except for the term $\sum_{\tau=T+1}^{\infty}(\beta(1 + \tilde{r}_{m(j),\tau})\phi^R)^{\tau-t}(p_{j,\tau} - c_j)$, which captures the influence of inertia. When a new investor chooses the fund today, there's a chance ϕ^R they'll remain invested in the next period. This probability increases as an exponent for each future period, meaning there's a smaller chance $(\phi^R)^2$ of them staying for two periods, an even smaller chance for three periods, and so on. Fund managers consider this when setting prices, as their decisions affect not only current demand but also how future demand is influenced by inertia.

However, our model implies significant changes to demand elasticity, which plays a important role in the supply side of the model as we have seen.

5.3 Substitution Patterns

We compute the own-price and cross elasticities for the funds in the model described above. The elasticities for active investor implied by the nested logit model can be expressed by:

$$\epsilon^D_{jkt} = \begin{cases} -\frac{\alpha}{1-\sigma} p_{jt} \left[1 - \sigma s_{jt|g} - (1-\sigma) s_{jt}\right] & \text{if} \quad k = j \\ \alpha s_{kt} p_{kt} \left(1 + \frac{1}{1-\sigma} \frac{1}{s_{gt}}\right) & \text{if} \quad k \neq j \text{ and } \quad k \in G^j \\ \alpha s_{kt} p_{kt} & \text{if} \quad k \neq j \text{ and } \quad k \notin G^j \end{cases}$$

where $s_{jt|g}$ is there share of the investment fund within its group at time t and s_{gt} is the share of the group within the whole industry at time t. Formally:

$$s_{jt|g} = \frac{e^{\delta^T_{jt}/(1-\sigma^T)}}{\sum_{k \in g} e^{\delta^T_{kt}/(1-\sigma^T)}}$$

$$s_{gt} = \frac{\left(\sum_{j \in g} e^{\delta^T_{jt}/(1-\sigma^T)}\right)^{(1-\sigma^T)}}{\sum_{g'} \left[\sum_{k \in g'} e^{\delta^T_{kt}/(1-\sigma^T)}\right]^{(1-\sigma^T)}}$$

Elasticity tells us how sensitive investor demand is to changes in the price of the fund p_{jt}. The elasticities implied by the model differentiate between three cases depending on the relationship between funds j and k. First, we consider the own-price elasticity. This applies when we're considering the elasticity of demand for a specific fund j with respect to its own price p_{jt}. Here, σ plays a crucial role. A higher σ (stronger within-group correlation) leads to a larger negative elasticity. In simpler terms, when funds within a group are highly correlated, a price increase for fund j will make investors more likely to switch to other funds within the same group $s_{jt|g}$ due to their similarity. This substitution effect strengthens the negative impact on demand for fund j. Additionally, a higher σ reduces the impact of the overall market share s_{jt} of fund j on elasticity.

Additionally, we consider substitute funds within the group. This case applies when we consider a different fund k offered by the same group as fund j. Here, a higher σ (stronger correlation) leads to a higher positive elasticity. This is because when a price increase occurs for fund k, investors are more likely to be attracted to the substitute fund j within the same group due to their similarity. The term $(1+1/(1-\sigma)*1/s_{gt})$ amplifies this effect. A stronger correlation (higher σ) and a smaller market share for the group (lower s_{gt}) will further increase the positive elasticity, indicating greater demand for substitute funds within the group when the price of fund k increases.

Finally, we consider substitute funds outside the group. This case considers substitute funds k offered by different groups altogether. Here, σ has no direct impact because these funds are not considered close substitutes by investors due to their lack of association with fund j's group. The elasticity depends mainly on the market share of the substitute fund k and the price p_{kt}.

In conclusion, the within-group correlation σ significantly influences the elasticity of demand within a group of correlated funds. A higher σ strengthens the substitution effect between these funds, making them more responsive to price changes within the group.

6
Empirical Strategy

This chapter outlines the empirical strategy employed to estimate the structural model. We utilize the dataset described in Chapter 4 and adopt a two-stage approach similar to Brown et al. (2023). The first stage focuses on investor demand. We utilize an instrumental variable strategy to estimate the degree of inertia exhibited by investors. Following this, we estimate their preference parameters. With these demand-side parameters in hand, we then shift our focus to the supply side, where we estimate the marginal costs faced by investment fund managers.

6.1
Demand Side

6.1.1
Inertia

The inertia estimation follows exactly the methodology of Brown et al. (2023). Total assets under management held by investor type T in fund j at time t evolve as:

$$AuM_{j,t}^{T} = \phi^{T} AuM_{j,t-1}^{T}(1 + r_{j,t}) + AuM_{j,t}^{T,\text{Active}}$$

While estimating a simple regression of current assets under management on lagged assets scaled by returns, there might be an endogeneity problem. That is, lagged assets under management might be correlated with an unobserved variable, the assets held by active investors $AuM_{j,t}^{T,\text{Active}}$. If investor preferences for specific funds tend to persist over time, lagged assets and actively managed assets would likely be positively correlated. This endogeneity bias could lead to an overestimation of inactive investors. To address this issue, an instrumental variable is required – a factor that influences lagged assets but has no direct impact on the current demand of active investors.

Brown et al. (2023) suggest past returns as a potential instrumental variable for lagged assets under management. Its validity hinges on the assumption that a portion of investors remain inactive each period, forgoing portfolio rebalancing. For the instrument to be exogenous, past returns must be uncorrelated with the current investment decisions of active investors. In simpler terms, the instrument is effective only if active investors do not engage in "return chasing," where they adjust their portfolios based on recent performance. While a theoretical model might assume rational investors who avoid return chasing, empirical evidence suggests that some investors exhibit this behavior.

To accommodate return chasing, we posit that investors pursuing returns base their decisions on cumulative returns over different time horizons, specifically, 1-month, 3-month, 6-month, 12-month, and year-to-date cumulative returns, which are commonly reported by funds. We instrument for lagged assets using the past twelve monthly returns. The underlying concept is that, conditioned on reported returns, the choice of active investors remains unaffected by past monthly returns. Additionally, we consider specifications that include market-by-time fixed effects. This captures the possibility that investors chase returns at the asset class level, rather than solely focusing on individual fund performance.

We conduct the estimation of the fraction of inactive consumers through the following empirical analogue of the preceding equation:

$$\ln AuM_{j,t}^{T} = \phi^{T}(i) \ln AuM_{j,t-1}^{T}(1 + r_{j,t}) + x'_{j,t-1}\Gamma + \iota_{j,t}^{T}$$

Our analysis utilizes data at the fund-month-investor type level. We employ the past twelve months' return as an instrument for lagged assets under management, while also controlling for shorter-term cumulative returns (one-month, three-month, six-month, and year-to-date) as well as the standard deviation of fund returns over the past year and the redemption processing period. The estimated value of ϕ^T captures the causal effect of a change in lagged assets under management on current assets, specifically the portion attributable to investor inertia. In simpler terms, a one-percent increase in lagged assets due to factors outside the model (e.g., initial investment) would lead to an estimated ϕ^T percent increase in current assets, reflecting the persistence of investor holdings.

6.1.2 Active Investor Demand

The estimated inertia coefficient plays a crucial role in distinguishing between active and inactive investor behavior. By focusing on the revealed choices of active investors, we can estimate demand for both retail and institutional investors within the framework outlined above. As mentioned previously, the first step in this process involves calculating market shares among active investors.

Utilizing our inertia estimates, we determine the total assets held by active investors of type T in fund j at time t through the formula:

$$AuM_{j,t}^{T,\text{Active}} = \exp\left(\frac{\ln AuM_{j,t}^{T} - \hat{\phi}^{T}\ln(AuM_{j,t-1}^{T}(1+r_{j,t}))}{1-\hat{\phi}^{T}}\right)$$

Subsequently, we compute the market share among active type T investors for each fund j at time t as:

$$s_{j,t}^{T} = \frac{AuM_{j,t}^{T,\text{Active}}}{\sum_{l\in\mathcal{J}_t^T} AuM_{l,t}^{T,\text{Active}}}$$

This computation yields our estimate of active market shares, serving as the dependent variable in our main demand specifications.

6.1.3 Preferences

Within our demand framework, we derive a simplified expression for mean utility levels by taking logs of market shares. This formulation allows us to estimate investor demand parameters using linear methods:

$$\begin{aligned}\ln(s_{jt}^{T}) - \ln(s_{kt}^{T}) = {} & \alpha^{T}\left(p_{jt}-p_{kt}\right) + \left(x'_{jt}-x'_{kt}\right)\beta^{T} \\ & + \sigma\left[\ln(\bar{s}_{jt|g}^{T}) - \ln(\bar{s}_{kt|\tilde{g}}^{T})\right] \\ & + \mu_{m(j),\tau}^{T} + \xi_{jt}^{T}\end{aligned}$$

Our analysis uses data at the fund-month level and incorporates market-by-time fixed effects. This controls for unobserved factors that affect all funds within a particular asset class over a specific time period. By doing so, we focus on the investor's decision regarding which fund to choose within an asset class, rather than their broader portfolio allocation decisions.

A key parameter of interest is α which captures the degree to which investors are responsive to administrative fees charged by funds. However, fees may be correlated with unobserved characteristics of the fund - ξ_{jt} - that also influence investor choices. To address this potential bias, we require instrumental variables, z_{jt}, that are correlated with fees but not with these unobserved factors or the unexplained variation in investors' choices within a specific market-time group (represented by the error term).

Drawing on established practices within industrial organization research, we propose instrumental variables to address potential bias in the fee coefficient. The assumption is that fees are determined by underlying costs, captured by fund expenses, and do not directly influence investor decisions. Regarding the within-group share, we follow a common approach by using the number of investment funds within the same market-time group (the nest) as an instrument.

Our current approach focuses solely on administrative fees, which may limit its comprehensiveness. Performance fees can also significantly influence investor decisions and should ideally be incorporated into the analysis. However, finding suitable instrumental variables for both fees might be challenging with the data available. One potential solution involves creating a new metric, the 'effective fee.' This would combine the administrative fee with a performance-based component. The performance fee would only be applied when the fund outperforms a benchmark, and the magnitude of the fee would be tied to the degree of outperformance.

6.2 Supply Side

As in Brown et al. (2023), we invert the investment fund manager's first-order condition to derive the marginal cost that rationalizes the manager's chosen administrative fee. Given our demand specifications, we express the first-order condition of the investment fund manager in matrix form as:

$$M_t^R \mathbf{s}_t^R + M_t^I \mathbf{s}_t^I = \left(M_t^R \Omega_t^R + M_t^I \Omega_t^I \right) \times (\mathbf{p}_t - \mathbf{c}_t)$$

Here, the elements of the matrix $\Omega_t^T(\mathbf{p})$ are given by:

$$\Omega_{(l,m)}(\mathbf{p}) = \begin{cases} -\frac{\left(1-\phi^T\right)}{1-\beta\left(1+\tilde{r}_{m(j)}\right)\phi^T} \frac{\partial s_l}{p_m}(\mathbf{p}_t) & \text{, if } l, m \in \mathcal{J}_{l,m} \\ 0 & \text{, else} \end{cases}$$

In the data, we directly observe the scalars M_t^R and M_t^I, and the vectors $\mathbf{s}^R$, $\mathbf{s}^I$, and $\mathbf{p}$. Given $\beta(1+\tilde{r})$, we utilize our inertia and demand estimates to compute the matrices Ω_t^R and Ω_t^I. We assume the managers' annualized growth-adjusted discount rate is 5%, implying that on a monthly basis, $\beta(1+\tilde{r}) = 0.996$. For each period t, we then directly solve for implied costs as:

$$\mathbf{c}_t = \mathbf{p}_t - \left(M_t^R \hat{\Omega}_t^R + M_t^I \hat{\Omega}_t^I \right)^{-1} \left(M_t^R \mathbf{s}_t^R + M_t^I \mathbf{s}_t^I \right)$$

7
Results

This chapter explores the findings from our structural model, shedding light on the dynamics of demand for and supply of investment funds in the Brazilian context, especially considering the impact of recent financial innovations.

7.1
Inertia

The estimates of inertia discussed in Subsection 6.1.1 are presented in Tables 7.1 and 7.2. Specifically, these tables report the estimates for ϕ^T, measuring the causal impact of an exogenous change in lagged AUM on current AUM, which is attributed to inertia. To put it differently, a 1% exogenous increase in AUM during the previous period results in a ϕ^t percent increase in AUM during the current period.

Table 7.1: Investor Inertia - Evolution over Time

	Whole Sample	First Half	Second Half
Lag AuM	0.954***	0.964***	0.939***
	(0.009)	(0.016)	(0.014)
Updating at least once a year	43.2%	35.6%	53.0%
Num.Obs.	103975	51987	51988
R2 Adj.	0.993	0.994	0.992

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 7.1 explores how inertia has evolved over time. Column (2) presents estimates for the first half of the sample period (January 2015 to April 2019), while column (3) shows estimates for the second half (up to February 2023). Based on the baseline results in the first column, a 1% increase in lagged assets under management (AUM) translates to a 0.954% increase in current AUM. This suggests that approximately 95.4% of investors are inactive each month. In other words, our model estimates that 43.2% ($= 1 - .954^{12}$) of investors rebalance their portfolios at least once a year.

Table 7.1 reveals a noteworthy decline in investor inertia over the sample period. As shown in column (2), the estimated percentage of investors updating their portfolios at least annually in the first half of the sample (2015-2019) is 35.6%. This figure increases to 53%,in the second half (up to 2023), reflecting a growth of around 49% in investor portfolio rebalancing activity. This trend coincides with the transformations within the Brazilian investment fund industry, potentially driven by factors like heightened market competition and technological advancements that have reshaped how investors interact with their investments.

Table 7.2 delves deeper, providing estimates of the inertia coefficient stratified by investor type.

Table 7.2: Investor Inertia - by Type of Investor

	Whole Sample	Retail Investors	Institutional Investors
Lag AuM	0.954***	0.952***	0.988***
	(0.009)	(0.010)	(0.029)
Updating at least once a year	43.2%	44.6%	13.5%
Num.Obs.	103975	100889	3086
R2 Adj.	0.993	0.994	0.986

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7.2 breaks down the inertia coefficient estimates by investor type. Similar to the previous table, the first column displays the baseline results. Columns (2) and (3) present estimates for retail and institutional investors, respectively. Our findings regarding inertia differ from those of Brown et al. (2023), as we observe evidence suggesting greater inertia among institutional investors compared to retail investors. Table 7.2 indicates that 13.5% of institutional investors rebalance their portfolios at least annually, compared to retail investors. This aligns with anecdotal observations in Brazil that retail investors tend to engage in more frequent redemptions, whereas institutional investors hold assets within the same fund for longer periods. While a full exploration of these behavioral differences is beyond the scope of this paper, the observed contrast might be attributable to variations in financial expertise and risk tolerance between these investor groups.

7.2 Nested Logit Estimation

Having established the level of investor inertia, we now delve into the analysis of their preference parameters. Table 7.3 provides a comprehensive overview of the key findings from our baseline nested logit model estimations. All regressions include year, month, and market fixed effects, encompassing the entire sample of investment funds. The table showcases the results from different model specifications. Column (1) presents estimates from a model that utilizes only portfolio characteristics to define the funds. Column (2) focuses on non-portfolio attributes, and Column (3) combines both categories of fund characteristics.

Table 7.3: Nested Logit Estimation

	(1)	(2)	(3)
Effective Fee	-0.348***	-0.473***	-0.430***
	(0.020)	(0.024)	(0.023)
Monthly Returns	0.050***		0.053***
	(0.003)		(0.003)
Yearly Returns	0.027***		0.027***
	(0.001)		(0.001)
Deviation of Returns	-0.142***		-0.123***
	(0.008)		(0.008)
First Year	-0.528***	-0.366***	-0.252***
	(0.060)	(0.059)	(0.062)
Fund Age		0.033***	0.032***
		(0.002)	(0.002)
Active Management		0.316***	0.294***
		(0.020)	(0.020)
σ	0.268***	0.240***	0.247***
	(0.008)	(0.008)	(0.008)
Num.Obs.	102720	102720	102720
R2 Adj.	0.720	0.695	0.670

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The parameter σ remains constant across all model specifications. It captures the inherent value investors place on investing in funds offered by the same platform (often major banks), reflecting the potential influence of brand loyalty on investment decisions. A value of σ approaching 1 indicates perfect correlation within the bank platform. Our model estimates for σ are positive and statistically significant, suggesting a preference among investors for funds belonging to the same banking institution. We will delve deeper into these substitution patterns in Section 7.3.

Table 7.3 presents key findings on investor preferences derived from our nested logit model. The results align with expectations, as we observe a negative and statistically significant relationship between expense ratios and investor demand for funds. In other words, investors tend to shy away from funds with higher fees. Conversely, funds with stronger historical returns and lower volatility are associated with greater demand. This aligns with the risk-return preferences of most investors. Interestingly, the table also reveals that funds in their first year attract less investment compared to established funds. Finally, the model suggests a preference for actively managed funds over passively managed ones.

Building on the baseline demand model, we further analyze investor preferences across different time horizons using sub-samples. Table A.1 presents the detailed results. These findings indicate that investor preferences, as reflected by the coefficient magnitudes and signs, exhibit relative stability over time. The key exception is the coefficient for fees, where we observe a noteworthy decrease in price sensitivity among investors in the latter half of the sample period. It's important to note that these results account for the influence of investor inertia.

Table A.2 delves deeper, exploring how investor preferences vary by investor type. The results reveal notable differences between institutional and retail investors. The preferences of retail investors more closely resemble those observed in the baseline model (Table 7.3). For institutional investors, the primary drivers of demand for investment funds appear to be annual returns, fund age, and the distribution platform. Other fund characteristics were not statistically significant for this investor group.

7.3
Elasticities and Substitution Patterns

A key element of our analysis focuses on investor responsiveness to pricing and how investment choices are made across different funds. We explore this aspect by calculating own-price elasticities and cross-price elasticities for retail investors. These results are presented visually in Figures 7.1 and 7.2, respectively.

Figure 7.1 presents the distribution of own-price elasticities for retail investors. The dashed blue line represents the average elasticity, which is -

0.8. This value falls within the range reported by Brown et al. (2023) who document elasticities of -1.3 for retail investors in index funds. Our research focuses primarily on actively managed funds, which may lead to a dampened price sensitivity among investors compared to passively managed options like index funds.

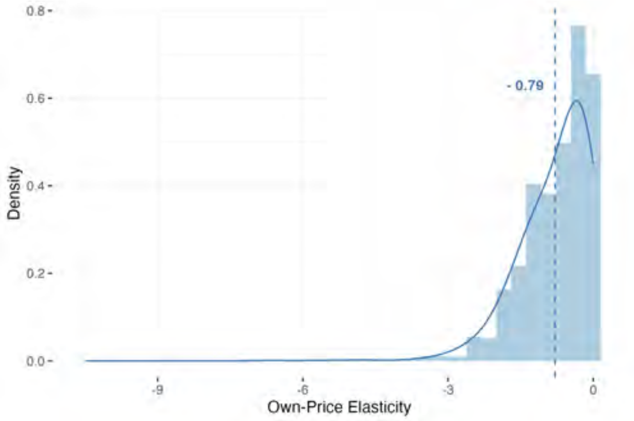
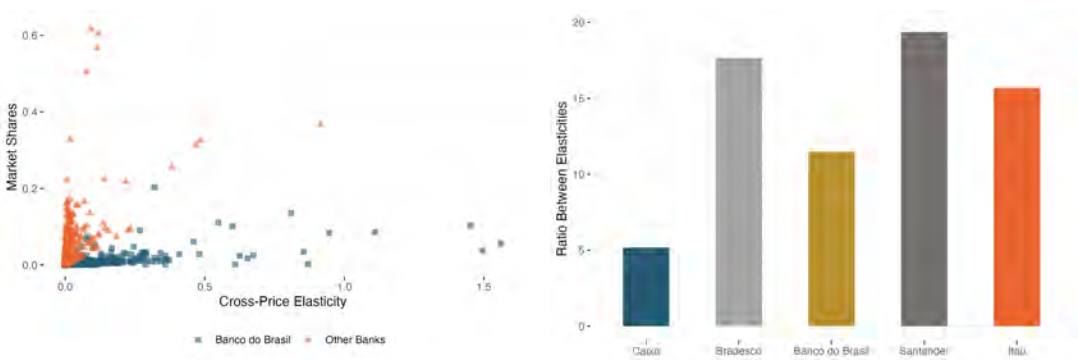


Figure 7.1: Distribution of Own-Price Elasticities of Retail Investors

As previously discussed, the Brazilian investment fund industry is heavily influenced by major banks, which hold a significant share of both deposits and loans. This influence extends to fund management, where banks leverage their large customer bases and often closed-end distribution structures that limit investor options to external funds. This can effectively lock in a substantial portion of the investment fund market for these banks. Our model captures this influence through the parameter σ, which reflects the investor preference for funds belonging to the same platform (typically a bank). Figure 7.2 visually depicts this platform-specific preference.



(a) Cross-Price Elasticity

(b) Ratio between Elasticities

Figure 7.2: Cross-Price Elasticities: Investment Funds within and outside a Bank

Figure 7.2a depicts the cross-price elasticities for retail fixed-income funds. These elasticities measure how a change in the fees charged by fund k affects the market share of fund j, in this case a fixed income retail fund from Banco do Brasil. A higher elasticity indicates a stronger substitution effect, meaning that investors are more likely to switch between funds j and k in response to a fee change. The figure reveals that fixed-income retail funds offered by Banco do Brasil tend to have higher cross-elasticities with each other compared to funds from other investment managers. This suggests a greater degree of substitutability among fixed-income options within the Banco do Brasil platform.

Building on the analysis in Figure 7.2a, Figure 7.2b takes a deeper look at the substitution patterns. Here, we compare the cross-price elasticities of funds offered by the same bank to those of funds from different managers. This comparison is achieved by calculating the ratio between the two sets of elasticities. The results indicate that, on average, the cross-elasticities between fixed-income retail funds offered by the five largest Brazilian banks are roughly 13 times higher than the elasticities between these funds and those from other investment managers. This significant difference highlights the strong degree of substitutability among fixed-income options within these major banks, further emphasizing their influential role in shaping the Brazilian investment fund market.

7.4 Sensibility Analysis

This section explores a hypothetical scenario where we remove investor inertia from the model entirely. This is achieved by setting the inertia coefficient $\phi^I = \phi^R = 0$ In this scenario, all investors are assumed to actively rebalance their portfolios in each period, aiming to maximize their subjective utility. Table 7.4 presents the estimates for the entire sample of funds under this assumption.

The overall results are largely consistent between the scenarios with and without inertia, as the signs and direction of the relationships between variables and investor demand remain unchanged across all fund characteristics. However, two key distinctions emerge. First, in the absence of inertia, investors exhibit a heightened sensitivity to expense ratios, with a difference exceeding 20% compared to the baseline model. This is particularly evident in specification (3) of the table. Second, the preference for investing in funds from the same platform (bank) becomes more pronounced when inertia is removed.

Table 7.4: Nested Logit Estimation - Without Inertia

	(1)	(2)	(3)
Effective Fee	-0.427***	-0.536***	-0.521***
	(0.010)	(0.012)	(0.012)
Monthly Returns	0.011***		0.014***
	(0.002)		(0.002)
Yearly Returns	0.012***		0.012***
	(0.000)		(0.000)
Deviation of Returns	-0.075***		-0.057***
	(0.004)		(0.004)
First Year	-0.828***		-0.567***
	(0.029)		(0.030)
Fund Age		0.037***	0.034***
		(0.001)	(0.001)
Active Management		0.217***	0.199***
		(0.010)	(0.010)
σ	0.355***	0.330***	0.325***
	(0.005)	(0.005)	(0.005)
Num.Obs.	103915	103915	103915
R2 Adj.	0.559	0.508	0.511

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix A examines the counterfactual scenario (no investor inertia) for various investor groups and timeframes. The results for institutional investors, in particular, diverge from those presented in Table A.2 in two key ways.

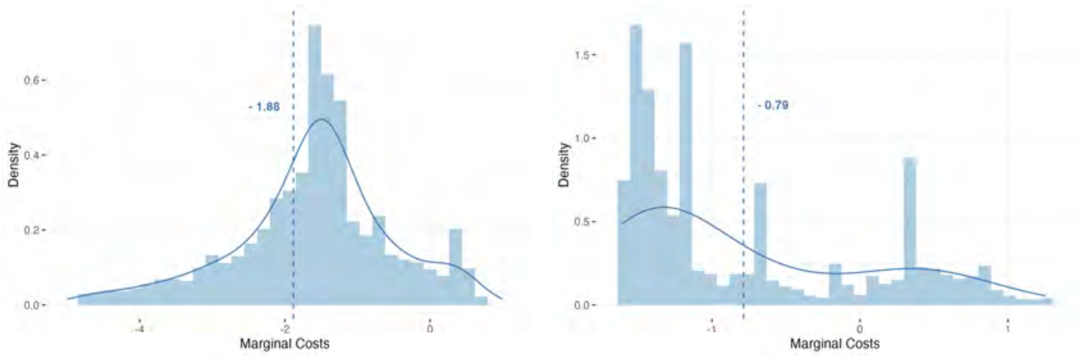
First, Table A.4 suggests that, when inertia is removed, institutional investors become more price-sensitive than retail investors. This aligns with economic expectations and findings from prior research, such as the work by Brown et al. (2023).

Second, the influence of the bank platform (captured by σ) appears to be weaker for institutional investors compared to retail investors in the absence of inertia. As shown in Table A.4, the estimated value of σ is lower for institutional investors. This indicates that institutional investors may be less likely to be swayed by factors related to the bank platform when making investment decisions, potentially reflecting their greater financial sophistication.

7.5 Supply Side

Next, we turn our attention to the supply side of the model and examine the distribution of marginal costs for retail investment funds. To ensure efficient computations, we restrict our analysis to funds where $s_{j,t}^{R} > 1e-4$. Furthermore, to mitigate the influence of outliers, we present a winsorized distribution of marginal costs, where extreme values are replaced with values at the 5th and 95th percentiles.

As in the work of Brown et al. (2023), our findings indicate that certain funds exhibit negative marginal costs. The authors propose a potential explanation for this phenomenon, suggesting that mutual funds may generate revenue by lending the shares they own for a fee, thereby offsetting the costs of running the fund. Additionally, the advantages of having a larger pool of assets under management extend beyond this revenue-generating strategy. Investment funds endowed with greater assets typically enjoy reduced fees from brokers during trading activities. Furthermore, they exhibit resilience in maintaining prolonged positions in short sales and the derivatives market, consequently curbing operational costs.



(a) Whole Sample (b) Without Banks

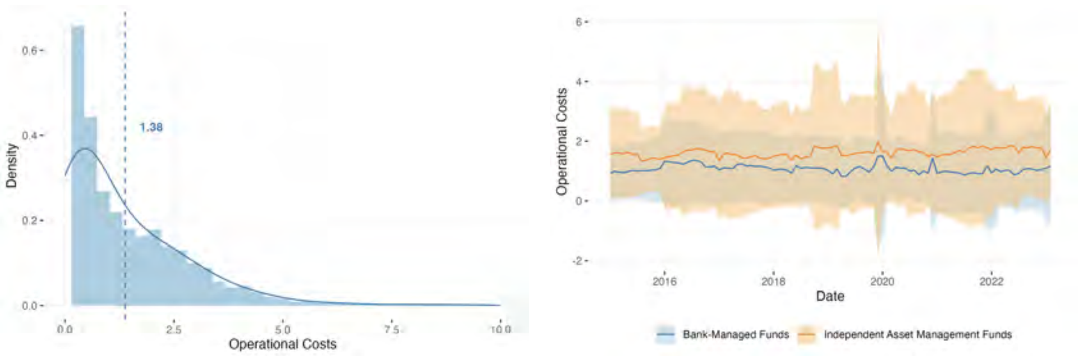
Figure 7.3: Distribution of Marginal Costs for Retail Investment Funds

Figure 7.3 explores the distribution of marginal costs for retail investment funds. Panel (a) of the figure, presented in 7.3a, depicts the marginal costs for the entire sample of retail funds, encompassing those offered by the five largest banks in Brazil. Panel (b) in 7.3b shows the estimates for the same sample, but excluding funds from these five major banks. A visual comparison of these panels reveals that the overall distribution of marginal costs in panel (a) (including the big five banks) exhibits a lower average cost compared to panel (b) (excluding them). This suggests that investment funds associated with these large banks tend to have lower marginal costs.

In addition to our estimates, Figure 7.4 delves into the operational costs of investment funds. The figure presents a histogram (distribution) of these costs as a percentage of a fund's net asset value (NAV) alongside a graph depicting their change over time.

One noteworthy observation is that the average operational cost in our sample appears to be higher than the average administrative fee. This suggests that funds may generate revenue from sources beyond the explicit fees charged to investors. However, it's important to acknowledge that our analysis focuses solely on disclosed operational costs and may not capture all potential cost factors.

The graph also reveals that operational costs exhibit minimal variation over the time period examined. This suggests a pattern of relative stability in these costs.



(a) Distribution (b) Evolution over Time

Figure 7.4: Operational Costs

8
Conclusion

This research examined investor demand for investment funds in Brazil, considering the interplay between recent financial innovations and the high level of bank concentration. Traditionally, a select few banks have dominated the industry, leveraging closed-end distribution structures to limit investor choice. However, the emergence of financial technology platforms has transformed the landscape by lowering distribution costs and introducing greater competition.

To understand the complex dynamics of investor behavior and bank influence in the Brazilian investment fund industry, we developed and estimated a dynamic quantitative model, extending the work of Brown et al. (2023). This model captures the interplay between investor demand and fund supply. As in their work, it acknowledges investor heterogeneity in preferences and inertia, along with the ability of fund managers to price discriminate between institutional and retail investors. Uniquely, our model is tailored to the Brazilian context by incorporating investor preferences for distribution platforms, allowing us to quantify the significant role that banks play in shaping investment fund demand.

Our analysis of investor behavior revealed a trend of decreasing inertia over time. The proportion of investors actively rebalancing their portfolios annually increased from 35.6% in the first half of the sample to 53% in the latter half, coinciding with the transformations in the Brazilian investment fund industry. Furthermore, our results suggest that institutional investors exhibit higher inertia compared to retail investors, with only 13.5% revising their portfolios annually. This behavioral contrast may potentially stem from disparities in financial sophistication and risk aversion, but further research is needed to explore these potential explanations definitively.

On the preference side, our analysis suggests a significant investor preference for investment funds offered by the same platform, as evidenced by a positive and statistically significant estimate for the platform preference parameter σ in our model. This preference is further supported by the finding of higher cross-elasticities for funds within the same bank compared to those from different managers. Specifically, the results indicate that, on average, cross-elasticities within the same bank are 13 times higher for the five largest Brazilian banks. Our examination of marginal costs revealed that, on average, funds associated with these major banks exhibit lower marginal costs.

9
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A
Demand Estimation Results

A.1
With Inertia

A.1.1
Preferences Evolution over Time

Table A.1: Preferences over Time

	First Half		Second Half	
	(1)	(2)	(3)	(4)
Effective Fee	-0.409***	-0.525***	-0.282***	-0.330***
	(0.025)	(0.030)	(0.033)	(0.036)
Monthly Returns	0.053***	0.057***	0.043***	0.046***
	(0.005)	(0.005)	(0.004)	(0.005)
Yearly Returns	0.023***	0.022***	0.029***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
Deviation of Returns	-0.098***	-0.073***	-0.164***	-0.154***
	(0.013)	(0.013)	(0.011)	(0.011)
First Year	-0.704***	-0.313**	-0.485***	-0.311***
	(0.118)	(0.120)	(0.069)	(0.073)
Fund Age		0.045***		0.022***
		(0.003)		(0.002)
Active Management		0.510***		0.082**
		(0.029)		(0.027)
σ	0.248***	0.237***	0.283***	0.265***
	(0.011)	(0.011)	(0.010)	(0.011)
Num.Obs.	51360	51360	51360	51360
R2 Adj.	0.662	0.601	0.767	0.740

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.1.2
Preferences by Type of Investor

Table A.2: Preferences by Type of Investor

	Retail		Institutional	
	(1)	(2)	(3)	(4)
Effective Fee	-0.422***	-0.498***	0.234	-0.302
	(0.019)	(0.022)	(0.728)	(0.735)
Monthly Returns	0.050***	0.054***	0.015	0.034
	(0.003)	(0.003)	(0.059)	(0.058)
Yearly Returns	0.026***	0.026***	0.079***	0.075***
	(0.001)	(0.001)	(0.015)	(0.015)
Deviation of Returns	-0.142***	-0.126***	-0.060	0.019
	(0.008)	(0.008)	(0.124)	(0.124)
First Year	-0.509***	-0.254***	-0.210	0.602
	(0.056)	(0.059)	(0.779)	(0.792)
Fund Age		0.030***		0.176***
		(0.002)		(0.042)
Active Management		0.228***		0.845**
		(0.019)		(0.319)
σ	0.260***	0.240***	0.288***	0.291***
	(0.007)	(0.008)	(0.060)	(0.059)
Num.Obs.	99957	99957	2760	2760
R2 Adj.	0.654	0.605	0.802	0.779

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2
Without Inertia

A.2.1
Preferences Evolution over Time

Table A.3: Preferences over Time - Without Inertia

	First Half		Second Half	
	(1)	(2)	(3)	(4)
Effective Fee	-0.424***	-0.544***	-0.409***	-0.470***
	(0.012)	(0.015)	(0.016)	(0.017)
Monthly Returns	0.011***	0.015***	0.012***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
Yearly Returns	0.009***	0.008***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Deviation of Returns	-0.067***	-0.045***	-0.062***	-0.051***
	(0.006)	(0.006)	(0.005)	(0.005)
First Year	-0.783***	-0.417***	-0.834***	-0.657***
	(0.056)	(0.057)	(0.033)	(0.034)
Fund Age		0.045***		0.026***
		(0.001)		(0.001)
Active Management		0.412***		-0.002
		(0.014)		(0.013)
σ	0.364***	0.347***	0.360***	0.334***
	(0.008)	(0.008)	(0.006)	(0.006)
Num.Obs.	51957	51957	51958	51958
R2 Adj.	0.514	0.475	0.621	0.588

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2.2
Preferences by Type of Investor

Table A.4: Preferences by Type of Investor - Without Inertia

	Retail		Institutional	
	(1)	(2)	(3)	(4)
Effective Fee	-0.441***	-0.531***	-0.605***	-0.701***
	(0.010)	(0.012)	(0.109)	(0.111)
Monthly Returns	0.012***	0.014***	0.012	0.014
	(0.002)	(0.002)	(0.010)	(0.010)
Yearly Returns	0.012***	0.012***	0.025***	0.025***
	(0.000)	(0.000)	(0.002)	(0.002)
Deviation of Returns	-0.075***	-0.058***	-0.071***	-0.059**
	(0.004)	(0.004)	(0.020)	(0.020)
First Year	-0.864***	-0.605***	-0.040	0.176
	(0.030)	(0.031)	(0.124)	(0.127)
Fund Age		0.033***		0.055***
		(0.001)		(0.007)
Active Management		0.194***		-0.111*
		(0.010)		(0.051)
σ	0.357***	0.327***	0.208***	0.214***
	(0.005)	(0.005)	(0.026)	(0.026)
Num.Obs.	100889	100889	3023	3023
R2 Adj.	0.558	0.511	0.258	0.256

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$