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Abstract

This paper investigates the unintended cognitive consequences of a major retirement savings policy and their implications for intervention design. While previous studies recognize that various heuristics and biases hinder optimal retirement decisions, policy efforts have largely focused on increasing savings rather than addressing the cognitive processes behind them. We take a step in this direction by examining how a nationwide matching contributions policy introduced in Türkiye's Individual Pension System affected the reinforcement learning (RL) heuristic—individuals' tendency to over-extrapolate from past returns. Analyzing a large administrative dataset spanning both pre- and post-policy periods, we find that participants' responsiveness to contemporaneous and lagged returns increases dramatically—by more than five-fold—after the policy is implemented. These results persist after testing alternative explanations. Rather than curbing cognitive distortions, the policy unintentionally amplifies them. These findings highlight the importance of evaluating interventions not just by their impact on overall savings but also by their influence on the cognitive foundations of decision-making.

Keywords: Reinforcement learning, heuristics, decision-making, retirement policies, household saving.
JEL Classifications: D80, G41, D70, J26, G51.

1. Introduction

In recent decades, the interplay of slowing population growth and increasing longevity has heightened concerns about the adequacy of retirement savings worldwide. More than 25 years ago, the World Bank (1994) characterized these demographic shifts and their financial implications as a looming "old age crisis" and began proposing remedial policy measures. Since then, a rich literature in psychology and behavioral economics has identified a variety of cognitive biases and heuristics—among them present bias, limited attention, reinforcement learning (RL), and inertia—that systematically deter individuals from making optimal saving and investment decisions (Tversky and Kahneman, 1974; Barber and Odean, 2001).

In response to these findings, a growing body of work has turned from diagnosing biases to designing policies and interventions—ranging from automatic enrollment to matching contributions—that guide individuals toward better outcomes. These strategies have improved welfare by nudging people to accumulate more savings, thus partly alleviating the burdens of under-prepared retirements. Yet, an important and largely unexplored question remains: While these policies often improve observed behaviors in the short run, do they also address the underlying cognitive distortions that give rise to such problematic behavior in the first place?

A key theoretical concern is that some interventions may effectively mask or even exacerbate cognitive shortcuts. By shielding individuals from the natural consequences of their errors, these policies could diminish the "tough love" learning process through which decision-makers normally refine their judgments. In other words, interventions that provide immediate relief might prevent individuals from ever confronting their suboptimal choices and adjusting their mental models accordingly. Analogously, List (2003, 2011) shows that experienced traders are less prone to certain biases like the endowment effect than inexperienced ones, suggesting that exposure and learning can erode biases over time. If well-intentioned policies insulate individuals from negative feedback, they might inadvertently weaken these natural corrective mechanisms, thereby amplifying rather than diminishing reliance on cognitive heuristics.

Against this backdrop, one bias of particular interest is the RL heuristic. RL, in this context, refers to the over-extrapolation of past experiences when shaping future decisions (Choi et al., 2009). Investors who follow this heuristic tend to infer future outcomes solely from recently realized returns, adopting a "win-stay" strategy (Erev and Roth, 1998). Although some degree of responsiveness to past performance is rational, a systematic overweighting of recent experience can lead to distorted beliefs, risk-taking, and asset allocation decisions over time.

Public interventions that increase perceived returns—such as matching contributions to retirement accounts—present a prime opportunity for examining the interplay between policy design and cognitive heuristics. On the one hand, matching contributions aim to increase savings rates and encourage financial security. On the other hand, by magnifying positive signals, these policies may amplify the RL heuristic. When participants receive additional state-provided returns on top of market gains, they may come to interpret recent successes as indicative of future profitability, reinforcing their propensity to follow the RL pattern even more strongly.

This paper takes a step toward addressing this issue by focusing on a natural experiment in Türkiye, where a nationwide matching contributions policy was introduced in 2013. Under this policy, participants in the Individual Pension System (IPS) receive a 25% state subsidy on their contributions, up to a certain limit. While previous research has established that such policies often succeed in boosting overall savings and participation rates, we ask a different question: Do these matching contributions amplify the RL heuristic, thereby potentially undermining rationality and perpetuating cognitive shortcuts?

We leverage a comprehensive administrative dataset from the Pension Monitoring Center in Türkiye, covering around 39 million contracts from 2008 through 2016. This dataset provides annual contributions, detailed demographic and financial information, and complete investment account histories. Crucially, we identify a group of participants who joined the IPS before 2008 and contributed regularly for at least eight years—four years before and four years after the 2013 policy introduction. This balanced sample allows us to compare behavior before and after the policy change in a symmetric manner, isolating the impact of matching contributions on adherence to the RL heuristic.

Our empirical strategy involves estimating a linear savings model using panel data methods to determine how individuals respond to both contemporaneous and one-year-lagged returns. Consistent with the RL heuristic, we find that participants are highly sensitive to past performance: they tend to increase their contributions after experiencing positive returns, extrapolating recent gains into the future.

We then re-estimate our model separately for the pre- and post-policy periods. The results reveal a striking pattern: after the introduction of the matching contributions policy, the responsiveness of participants to both contemporaneous and lagged returns increases by more than five-fold. In other words, the policy—designed to enhance savings—appears to have amplified the RL heuristic, encouraging participants to rely even more on past performance when making current contribution decisions. We explore several alternative explanations for these findings, including the possibility that observed patterns reflect increased inertia, improved investment skills, rebalancing between IPS accounts and non-IPS assets, or pre-existing trends in RL. None of these factors, however, accounts for the substantial post-policy amplification of RL responsiveness. The results remain robust across various demographic and financial subgroups, indicating that the effect is both widespread and substantial.

Our findings contribute to the literature in two important ways. First, our analysis bridges a gap in the existing literature on RL heuristics in financial decisions. Previous research has examined RL either in short-run contexts (Choi et al., 2009; Kaustia and Knupfer, 2008; Chiang et al., 2011) or across different cohorts over the long run (Malmendier and Nagel, 2011, 2016). By observing the same individuals across multiple years, we capture the dynamics of RL within individuals' own lifetimes rather than inferring its long-run impact across different cohorts, thus complementing earlier findings.

Second, we show that a retirement savings policy intended to improve financial outcomes can also amplify the RL heuristic. While prior work has documented increases in participation and contributions following policy interventions (Duflo et al., 2006; Chetty et al., 2014; Engelhart and Kumar, 2007), our evidence suggests that such policies may shape not only how much individuals save, but also how they process information and form expectations. These results indicate that effective policy design requires close attention to the cognitive dynamics underlying financial decisions.

The remainder of the paper proceeds as follows. Section 2 provides institutional background on the Türkiye's IPS. Section 3 outlines our data and empirical methodology. Section 4 presents the estimation results. Section 5 examines a range of alternative scenarios. Finally, Section 6 concludes.

2. Institutional Background

The IPS was introduced in Türkiye in October 2003 as a complementary scheme to the existing social security system. Designed to provide individuals with additional income during retirement, the IPS operates on a voluntary basis, granting participants flexibility in determining their contribution levels and allocating their savings among up to 230 different funds by the end of 2013 (PMC, 2014). Participants can transfer their savings across funds up to six times per year without incurring any fees.[4]

There are three distinct ways to participate in the IPS. First, individuals can open a pension account through individual contracts by selecting a pension company offering customized pension schemes. Eligibility is open to all Turkish citizens aged 18 and above, regardless of employment status. Second, institutional groups—such as professional associations, non-governmental organizations, and unions—can participate via group pension contracts. Third, employers can establish employer group contracts to enroll their employees, contributing a percentage of wages on their behalf. Participants may hold multiple contracts of any type simultaneously, paying contributions concurrently without legal restrictions. Unlike systems in countries such as the United States, Canada, and the United Kingdom, the IPS in Türkiye is not employer-sponsored. Individual contracts dominate the system, representing 74% of all contracts in terms of both fund size and the number of contracts by the end of 2013 (PMC, 2014).

Since its inception, the IPS has undergone two significant reforms. The first occurred in 2013, when the state introduced a matching contributions program, providing a 25% match on annual contributions, up to a threshold equivalent to the gross annual minimum wage for that year. This match, later increased to 30% in 2022, applies across all contracts held by a participant, regardless of type. Matching contributions are invested in state contribution funds, which offer an additional layer of returns independent of participants' fund preferences. Participants are entitled to a proportion of their accrued matching contributions if they leave the system before retirement. Specifically, they can withdraw 15% of the match if they exit within 3–6 years, 35% for 6–10 years, and 60% for over 10 years. Full access to matching contributions is granted only

[4] As of the second half of 2021, these allowable number of fund changes was increased 12 per a year.

upon meeting the retirement age and contributing to the IPS for at least 10 years. In the case of a participant has multiple contracts independent of contract type, the matching contributions is calculated from the total contributions in all contracts. At the same time, these matching contributions are assessed in "state contribution funds" regardless of the preferences of individuals and it offers an additional return.

The second reform came in 2017 with the introduction of the Automatic Enrollment System (AES), aimed at increasing participation in the IPS. Under AES, employees under the age of 45 are automatically enrolled by their employers, contributing a minimum of 3% of their gross wage. Participants can opt out without penalty within the first two months; however, withdrawals after this period incur a 15% income tax on returns. For retirees, the tax rate is reduced to 10%. Importantly, enrollment in the AES does not affect existing individual contracts, and participants can continue contributing to or opening new individual accounts while participating in AES.

3. Data and Methodology

3.1. Data

This study utilizes a unique administrative dataset from the Pension Monitoring Centre, the central authority responsible for managing the IPS in Türkiye. This extensive dataset includes information from over 39 million pension contracts, capturing a wide array of financial, occupational, and demographic variables. For our analysis, we focus on the period from 2009 to 2016, isolating potential effects AES policy, which is introduced in 2017, on saving behaviors of individuals (Yanıkkaya et al., 2023). The period chioce also enables us to investigate RL in saving behaviors both before and after the introduction of the matching contributions policy in 2013.

The dataset provides detailed information on participants' annual contributions, cumulative total assets, and portfolio allocations across 12 distinct fund groups. Additionally, it includes demographic data such as age, gender, and education level, alongside financial details such as contract types (individual, pension group, or employer group), pension company affiliations, and number of portfolio rebalancing. Income data, though available for individual contracts, is self-reported and therefore prone to potential biases. Given that income information is only available for 24% of the sample, we use education level as a proxy to control for income effects in our analysis. [5]

To ensure a balanced evaluation of saving behavior over medium- and long-term horizons, we restrict the sample to participants with at least eight consecutive years of contributions. In the first stage of the analysis, we use data from 2009 to 2016 to explore general patterns RL heuristics in saving behavior. In the second stage, we divide the sample into pre-policy (2009–

[5] Numerous studies show a strong relationship between income and education level (Ashenfelter and Krueger, 1994; Harmon et al., 2003, etc.).

2012) and post-policy (2013–2016) periods to examine the impact of the matching contributions policy on RL heuristics.

Our analysis focuses exclusively on individual pension contracts. Group and employer-sponsored contracts are excluded, as their creation often depends on institutional or employer preferences, which may not reflect participants' independent saving choices. Approximately 30% of participants maintain multiple individual contracts; for these cases, we aggregate contributions and returns, weighting them proportionally.

To address potential distortions caused by extreme values, we exclude participants falling in the top and bottom 1% of the distributions for annual contributions and portfolio returns. This ensures that the empirical results are not unduly influenced by outliers.

3.2. Methodology

The primary objective of this study is to investigate the role of past investment experiences in shaping participants' later saving decisions, with particular focus on whether these decisions align with RL heuristics. Specifically, we examine the sensitivity of annual contributions to both contemporaneous and lagged returns, testing whether participants over-extrapolate return experiences in their savings behavior. Our approach aligns with the empirical frameworks of prior RL studies (Kaustia and Knüpfer, 2008; Choi et al., 2009; Chiang et al., 2011).

To model these relationships, we estimate the following baseline equation:

$$CP_{i,t} = \alpha + \beta_1 R_{i,t} + \beta_2 R_{i,t-1} + \gamma D_{i,t} + \delta F_{i,t} + \phi P_{i,t} + \theta M_t + \varepsilon_{i,t} \tag{1}$$

$CP_{i,t}$ is the natural logarithm of annual contributions for participant i end-of-year t. $R_{i,t}$ and $R_{i,t-1}$ are contemporaneous and lagged real returns, respectively (monthly arithmetic average of the annual percentage real return)[6]. $D_{i,t}$ is demographic control vector, including age, gender, and education. $F_{i,t}$ is the financial control vector that includes pension company x year dummies and portfolio allocation shares by fund groups x year. $P_{i,t}$ is number of portfolio rebalancing x year controls and shows portfolio re-optimizing behavior in that year (change in portfolio allocation shares)[7]. M_t is a binary variable indicating the matching contributions policy, which equals 1 for years 2013 onward and 0 otherwise.

To account for potential non-linear effects of age, we include both linear and quadratic terms for age in the demographic control vector $D_{i,t}$. Portfolio allocation shares are modeled as interaction terms with year dummies to account for temporal variations in fund performance.

[6] We utilize monthly contributions, reflecting the predominant preference among individuals for the "monthly payment" option.

[7] Participants may choose to re-optimize and rebalance their portfolios in response to various factors, including shifts in risk tolerance, evolving future expectations, and changes in investment time horizons. However, pension accounts exhibit significant inertia compared to other types of financial accounts (Choi et al., 2002; Agnew et al., 2003; Ameriks and Zeldes, 2011). This tendency toward passivity is evident in our sample, where approximately 70% of participants never changed their portfolio allocation shares, and only about 15% made more than one change throughout their tenure.

Additionally, the proportions of assets allocated to equity and flexible funds are used as proxies for participants' risk tolerance (Malmendier and Nagel, 2011).

In some years and companies, financial advisors at pension companies may enable superior portfolio returns compared to market averages. Fisch et al. (2016) and Marsden et al. (2011) highlight that engaging with a financial advisor is associated with enhanced financial planning activities and outcomes. To account for the influence of differences in pension companies on investment performance—and consequently on savings behavior—our empirical framework incorporates pension company fixed effects as interaction terms with year dummies.

The second objective of this study is to evaluate the impact of the matching contributions policy on participants' RL heuristics. Using a balanced and symmetric dataset, we re-estimate the baseline model separately for the pre-policy (2009–2012) and post-policy (2013–2016) periods. This before-and-after analysis examines whether participants' responsiveness to contemporaneous and lagged returns amplifies following the introduction of the policy. Data from 2013 is excluded from the post-policy period, as returns from this year reflect pre-policy experiences and could confound the analysis.

To eliminate alternative explanations, we extend the analysis in four ways. First, we turn our attention to participants who make portfolio rebalancing, believing that the RL heuristic may reflect an existing inertia in retirement accounts. Second, we assess the profitability of RL-driven portfolio adjustments by analyzing the persistence of individual portfolio alphas. Third, we investigate potential rebalancing effects between IPS accounts and non-IPS assets by interacting RL heuristics with participants' age and education levels. Fourth, we employ a two-year rolling window approach to capture temporal changes in RL tendencies. This robustness analysis further explores the role of portfolio inertia in moderating RL effects.

4. Estimation Results

4.1. Summary statistics

Table 1. Summary statistics

	Mean	Median	Std. Deviation	Minimum	Maksimum	Observations
Annual Contributions (2013=100)	2,753	2,161	1,983	430	19,706	782,936
Average Monthly Real Return (%)	0.07	0.01	0.57	-1.64	2.42	782,936
Lagged Average Monthly Real Return (%)	0.02	-0.01	0.59	-1.64	2.42	685,069

Gender (%)	
Male	Female
46.27	53.73

Age (%)				
≤ 25	26 - 35	36 - 45	46 - 55	55 >
6.83	37.5	38.56	14.8	2.31

Education Level (%)		
Less than High Sch.	High Sch. – Undergrad	Undergrad and over
19.93	31.47	48.6

Average Portfolio Allocation Shares (%)						
Domestic Bonds	Foreign Bonds	Equity	Balanced	Money Market	Standard	Flexible
46.67	3.73	3.41	1.36	12.68	3.44	24.58

Portfolio Rebalancers (%)		
None	1	> 1
68.31	17.00	14.68

Number of Individual Contracts per Individual (%)		
1	2	≥ 3
69.69	17.99	12.32

Having at Least One Pension Group or Employer Group Contract (%)	
Yes	No
8.8	91.2

Source: Pension Monitoring Centre (2024)
Note: We categorize participants' age based on Pension Monitoring Centre classification and education level based on Barro and Lee (2013).

Table 1 provides summary statistics for the dataset, encompassing contributions, returns, demographic profiles, and portfolio characteristics. The average annual contributions by participants during the sample period (2009–2016) are approximately 2,753 ₺ in 2013 prices, representing roughly 26% of the net minimum wage in that year. This ratio aligns with the total domestic savings-to-GDP ratio of 23.2%, as reported by the Ministry of Development (2024).

On average, participants' real portfolio returns approach zero, consistent with findings from prior studies (Peker, 2016) that attribute near-zero returns to high fund management fees and administrative expenses. Similar underperformance of IPS funds has been highlighted in other research (Ayaydın, 2013; Açıkgöz et al., 2015).

Demographically, women slightly outnumber men in the sample, with females representing 53.7% of participants. The average age of participants is 35, with age distributions concentrated in the 26–35 and 36–45 age ranges. Approximately 48.6% of participants have attained an undergraduate degree or higher, indicating a strong preference for IPS participation among more educated individuals. Notably, 30% of participants maintain multiple individual contracts, while 8.8% hold both individual and employer-sponsored or group contracts.

Participants demonstrate a risk-averse portfolio allocation strategy. Domestic bond funds dominate portfolios, accounting for 50% of total assets on average, while allocations to equity funds remain low. However, flexible funds, which provide strategic diversification, compensate for the underrepresentation of equities, contributing 25% to overall allocations. This balance reflects participants' cautious approach to risk management within the IPS framework.

4.2. Baseline model

The baseline regression results, presented in Table 2, examine the relationship between portfolio returns and participants' annual contributions, progressively incorporating controls to isolate the effects of return experiences. The dependent variable is the annual contribution, while the key independent variables—contemporaneous and lagged monthly portfolio returns—capture the influence of return experiences on saving decisions.

Table 2. Regression of contributions on returns (2009 - 2016)

	(I)	(II)	(III)	(IV)	(V)	(VI)
Return	0.126***	0.122***	0.174***	0.208***	0.223***	0.222***
	(0.0015)	(0.0015)	(0.0025)	(0.0041)	(0.0041)	(0.0050)
Lagged Return	0.072***	0.0707***	0.135***	0.0915***	0.117***	0.109***
	(0.0012)	(0.0013)	(0.0018)	(0.0025)	(0.0025)	(0.0031)
Age		0.0341***	0.0304***	0.0297***	0.0291***	0.0335***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Age^2		-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Gender		0.114***	0.0909***	0.0835***	0.0802***	0.0777***
		(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0015)
High Sch. - Undergrad						0.0774***
						(0.0020)
Undergrad and over						0.200***
						(0.0019)
Matching contributions dummy	0.139***	0.140***	0.209***	0.632***	0.511***	0.655***
	(0.0014)	(0.0014)	(0.0067)	(0.0361)	(0.0364)	(0.0619)
Constant	7.692***	6.834***	5.775***	5.604***	5.572***	6.344***
	(0.0010)	(0.0088)	(0.0695)	(0.0835)	(0.0814)	(0.0548)
Company x Year dummies	No	No	Yes	Yes	Yes	Yes
Portf. Alloc. Shares x Year Controls	No	No	No	Yes	Yes	Yes
Portf. Rebalancing x Year Controls	No	No	No	No	Yes	Yes
Observations	685,069	685,069	685,069	685,069	685,069	469,763

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In the simplest specification (column I), a one-unit increase in contemporaneous average monthly returns is associated with a 12% increase in contributions, while lagged returns contribute an additional 7%. Including year fixed effects in column II slightly reduces these coefficients, reflecting the influence of broader time-specific factors. Columns III and IV add demographic controls (age and gender) and pension company fixed effects, and account for participant heterogeneity and provider-level differences. Finally, the fully specified model in column V incorporates number of portfolio rebalancing as interaction terms with year dummies, producing the most precise estimates. In this model, the combined effect of contemporaneous and lagged returns results in a 34% increase in contributions.

A one-unit increase in average monthly portfolio returns, together with the lagged effect, leads to a 34% rise in annual contributions. With mean contributions of 2,753 ₺, this translates to an additional 936 ₺ per participant. This result demonstrates the significant influence of return experiences on saving behavior.

Choi et al. (2009), demonstrates that individual investors determine their contributions rate response to contemporaneous returns, not lagged returns. Our findings support their findings regarding contemporaneous returns but differ from them by revealing that participants also responsive to lagged returns. Evidences also corroborate Kaustia and Knüpfer (2008), Song et al. (2021) and Chiang et al. (2011)'s findings by showing that lagged returns are a strong determinant of future contributions such.

RL provides a compelling framework for interpreting these findings. Participants tend to anticipate that investments yielding past rewards (or losses) will continue to be profitable (or unprofitable) in the future. Instead of adopting fully forward-looking optimization, participants appear to rely on RL heuristics, adjusting their contributions upward following positive returns. This behavior likely serves as a cognitive shortcut, helping individuals navigate the uncertainty and complexity of investment choices.

While Choi et al. (2009) emphasize the short-term responsiveness of contributions to contemporaneous returns within the same cohort, and Malmendier and Nagel (2011) document the enduring impact of macroeconomic experiences across cohorts, our results bridge this gap by presenting evidence of medium-to-long-term RL effects within the same cohort. These results expand the understanding of RL heuristics, illustrating how individuals integrate past return experiences over time and form a reinforcement stock that persistently guides their savings decisions.

Demographic variables provide additional context for variations in saving behavior. Older participants and those with higher education levels contribute more on average, consistent with life-cycle saving theories and income effects. Gender differences also persist, with male participants contributing more than females, reflecting broader labor market trends. While these demographic factors account for heterogeneity, they do not alter the primary findings regarding RL.

4.3. Impact of matching contributions policy on RL

The introduction of a 25% matching contributions policy in 2013 represents a significant structural change in Türkiye's IPS, and it offers a unique opportunity to assess how guaranteed returns shape investor behavior. In principle, if participants exhibit RL heuristics—adjusting their contributions upward in response to positive past returns—then an additional state-provided return that magnifies these signals may further amplify such behavior. By ensuring a supplemental reward beyond market gains alone, the policy can amplify investors' propensity to interpret recent success as indicative of future profitability, reinforcing their tendency to follow a win-stay pattern (Erev and Roth, 1998).

To evaluate this logic, we compare the responsiveness of participants' annual contributions to contemporaneous and lagged returns before (2010 – 2012) and after (2014 – 2016) the policy's introduction.

Table 4. Regression results of before and after matching contributions policy

Panel A: Before (2010-2012)					
	(I)	(II)	(III)	(IV)	(V)
Return	0.0525***	0.0529***	0.0749***	0.0280***	0.0354***
	(0.0019)	(0.0019)	(0.0029)	(0.0051)	(0.0051)
Lagged Return	0.0016	0.00244*	0.0799***	0.0565***	0.0725***
	(0.0014)	(0.0014)	(0.0021)	(0.0029)	(0.0029)
Age		0.0330***	0.0287***	0.0281***	0.0275***
		(0.0006)	(0.0006)	(0.0006)	(0.0006)
Age^2		-0.00031***	-0.00026***	-0.00025***	-0.00024***
		(0.00008)	(0.00008)	(0.00008)	(0.00008)
Gender (Male = 1)		0.107***	0.0856***	0.0813***	0.0788***
		(0.0018)	(0.0017)	(0.0017)	(0.0017)
Constant	7.674***	6.871***	6.793***	6.609***	6.590***
	(0.00103)	(0.0123)	(0.0119)	(0.0303)	(0.0302)
Panel B: After (2014-2016)					
	(VI)	(VII)	(VIII)	(IX)	(X)
Return	0.316***	0.296***	0.337***	0.348***	0.368***
	(0.0039)	(0.0038)	(0.0050)	(0.0075)	(0.0075)
Lagged Return	0.272***	0.256***	0.184***	0.196***	0.216***
	(0.0033)	(0.0032)	(0.0046)	(0.0062)	(0.0062)
Age		0.0355***	0.0329***	0.0322***	0.0319***
		(0.0007)	(0.0007)	(0.0007)	(0.0007)
Age^2		-0.00030***	-0.00027***	-0.00025***	-0.00025***
		(0.00001)	(0.00001)	(0.00001)	(0.00001)
Gender (Male = 1)		0.105***	0.0925***	0.0832***	0.0795***
		(0.0021)	(0.0021)	(0.0021)	(0.0020)
Constant	7.782***	6.879***	5.813***	6.057***	5.950***
	(0.0015)	(0.0144)	(0.0598)	(0.0830)	(0.0858)
Company x Year dummies	No	No	Yes	Yes	Yes
Portf. Alloc. Share x Year dummies	No	No	No	Yes	Yes
Portf. Rebalancing x Year dummies	No	No	No	No	Yes
Observations	293,601	293,601	293,601	293,601	293,601

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 presents the regression results for the pre-policy period (2010–2012) and the post-policy period (2014 – 2016). Prior to 2013, a one-unit increase in monthly returns is associated with approximately a 10.8% rise in annual contributions (Panel A) consistent with RL heuristics.

After the implementation of the matching contributions, the sensitivity amplifies considerably, with the same increase in monthly returns linked to roughly a 58.4% elevation in annual contributions (Panel B), a nearly fivefold amplification compared to the pre-policy period. This sharp, policy-aligned increase suggests that the matching scheme did not merely boost average saving levels, as shown by previous studies (Çitçi and Yanıkkaya, 2024; Yanıkkaya et al., 2024), but also altered the behavioral underpinnings of how participants interpret past return experiences.

It is important to acknowledge the potential influence of unobserved contemporaneous shifts. To address this, we included year fixed effects, extensive demographic and portfolio controls, and pension company-by-year interactions in our models. The results remain consistent across specifications, reinforcing the conclusion that the matching contributions policy was the key driver of the observed behavioral shift. The substantial and discrete "jump" in RL sensitivity following the policy is difficult to reconcile with alternative explanations.

The findings highlight the complex behavioral dynamics introduced by matching contributions policies. On the one hand, these policies are effective in increasing savings, as demonstrated by the dramatic rise in contribution sensitivity to returns post-policy. On the other hand, they also amplify behavioral biases such as RL heuristics, raising concerns about participants' ability to make fully rational financial decisions.

5. Alternative Scenarios

In this section, we examine alternative scenarios that may explain positive impact of return on contributions.

5.1. Inertia

There is substantial evidence in the literature that fund trading in pension accounts is characterized by significant inertia (Choi et al., 2002; Agnew et al., 2003; Ameriks and Zeldes, 2011). Most participants adhere to the default portfolio allocation set at enrollment and rarely make changes or rebalance (Choi et al., 2004). In our sample, participants changed their portfolio allocations an average of 0.1 times per year, with 68% never making a single change during the 8-year period.

A plausible alternative explanation for our findings is that participants may increase contributions following positive returns not due to RL heuristics but because they tend to follow a default behavior of maintaining or modestly increasing contributions when returns are favorable. The observed behavioral pattern could mimic RL heuristics (e.g., maintaining or increasing contributions following positive returns) while being driven by inertia and a reluctance to actively re-optimize portfolios.

To examine this explanation, we categorize participants based on the total number of portfolio allocation changes made over the 8-year period and re-estimate our model for each group separately. Table 5 reports the results.

Table 5. Regression results by total number of portfolio rebalancing

	= 0	= 1	= 2	> 2
	(I)	(II)	(III)	(IV)
Return	0.256***	0.201***	0.153***	0.131***
	(0.0057)	(0.0097)	(0.0140)	(0.0088)
Lagged Return	0.111***	0.118***	0.104***	0.0788***
	(0.0034)	(0.0060)	(0.0090)	(0.0063)
Age	0.0241***	0.0310***	0.0331***	0.0507***
	(0.0004)	(0.0012)	(0.0023)	(0.0023)
Age^2	-0.0002***	-0.0003***	-0.0002***	-0.0004***
	(0.00000)	(0.00001)	(0.00003)	(0.00003)
Gender (Male = 1)	0.0712***	0.0594***	0.0795***	0.100***
	(0.00142)	(0.00314)	(0.00549)	(0.00495)
Matching contributions dummy	0.877***	0.246***	0.401***	0.697***
	(0.0519)	(0.0874)	(0.139)	(0.111)
Constant	5.625***	5.636***	5.591***	6.111***
	(0.1020)	(0.1310)	(0.2430)	(0.1080)
Company x Year dummies	Yes	Yes	Yes	Yes
Portf. Alloc. Share x Year controls	Yes	Yes	Yes	Yes
Portf. Rebalancing x Year dummies	Yes	Yes	Yes	Yes
Observations	467,992	116,494	42,791	57,792

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The regression results reveal that RL heuristics persist across participants with varying levels of portfolio activity. Among participants who never changed their portfolio allocations (column I), the positive and significant coefficients on contemporaneous (β_1 return = 0.256) and lagged returns (β_2 lagged return = 0.111) indicate that RL heuristics align with their contribution behavior, even in the presence of substantial inertia. This suggests that inertia alone cannot explain their saving decisions, as participants still exhibit sensitivity to past returns.

Participants who made one, two changes or more frequent optimizer participants over the 8-year period also demonstrate RL heuristics, with slightly lower sensitivity to contemporaneous and lagged returns. This indicates that RL heuristics are not limited to passive savers but extend to those who engage in moderate portfolio adjustments.

The findings effectively challenge the hypothesis that the observed behavior is driven solely by inertia. The persistence of RL heuristics across all subgroups, including those making one or more portfolio changes, demonstrates that RL operates independently of default-driven inertia.

5.2. Investment skills

One explanation for our finding that participants increase contributions in response to positive returns is that they may view high returns as evidence of superior investment skill. Over time, such participants might perceive themselves as more capable than average, leading them to devote additional resources to their IPS accounts. If this explanation holds, we would expect persistence in individual portfolio alphas over time, as consistently high-performing participants maintain better-than-average results.

To test this hypothesis, we examine the persistence of participants' portfolio alphas between year *t* and year $t-1$, following the approach of Choi et al. (2009). Portfolio alphas measure risk-adjusted excess returns, calculated using portfolio betas derived from return variations. Given the annual nature of our dataset, we approximate portfolio alphas using deviations of individual annual returns from an 8-year average for each year. While this approximation is less precise than standard alpha calculations using monthly data, it provides a practical solution for capturing return deviations over longer horizons. We calculate a market return for each fund group annually and assign it to individuals based on their portfolio allocations. Portfolio alphas are then calculated using the assigned market return, participants' annual returns, and the Türkiye 10-year treasury bond yield as the risk-free rate.

The average alpha across the 8-year period is near zero (0.05), suggesting that, as a group, participants fail to achieve consistent risk-adjusted outperformance. This outcome may reflect inherent challenges in outperforming benchmarks in an efficient market, compounded by administrative fees, suboptimal fund allocation strategies, or limited portfolio optimization. While these factors warrant further exploration, the lack of persistence provides a robust starting point for evaluating individual investment behavior and its implications for the IPS system.

Our empirical analysis is summarized in the following regression model:

$$\alpha_{i,t} = \varphi + \beta_1 \alpha_{i,t-1} + \gamma D_{i,t} + \delta F_{i,t} + \phi P_{i,t} + \theta M_t + \varepsilon_{i,t} \tag{2}$$

where $\alpha_{i,t}$ represents participant *i*'s portfolio alpha in year *t*. The other variables are demographic, financial and number of portfolio rebalancing control vectors, respectively, as in our basic model setup. We again control these vectors as interactions with year fixed effects. To further explore persistence in alphas, we separately test the persistence of positive and negative lagged alphas.

Table 6. Persistence analysis of portfolio alphas

	Full Sample		Before		After	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Lagged Alpha	-0.654***		-0.505***			-0.599***
	(0.0023)		(0.0049)			(0.0009)
Lagged Alpha ≥ 0		-0.613***		-0.086***	-0.742***	
		(0.0039)		(0.0079)	(0.0024)	
Lagged Alpha < 0		-0.692***		-0.848***	-0.509***	
		(0.0028)		(0.0056)	(0.0009)	
Age	0.0320***	0.0040***	-0.0038***	0.0041***	0.0031***	0.0051***
	(0.0006)	(0.0006)	(0.0014)	(0.0013)	(0.0003)	(0.0003)
Age^2	-0.00043***	-0.00005***	-0.00006***	-0.00005***	-0.00004***	-0.00007***
	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)
Gender (Male = 1)	0.00938***	0.00766***	0.0116***	-0.0036	0.0169***	0.0119***
	(0.0018)	(0.0018)	(0.0038)	(0.0036)	(0.0010)	(0.0010)
Matching contributions dummy	0.884***	0.903***				
	(0.1640)	(0.1640)				
Constant	-0.799***	-0.876***	-1.079***	-1.925***	1.263***	0.906***
	(0.1930)	(0.1960)	(0.1440)	(0.1460)	(0.1660)	(0.1590)
Company x Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Portf. Alloc. Share x Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Portf. Rebalancing x Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	685,069	685,069	293,601	293,601	293,601	293,601

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The regression results, reported in Table 6, provide robust evidence that portfolio alphas lack persistence over time. Across all specifications, lagged alpha coefficients are negative and statistically significant at the 1% level, indicating a reversal rather than persistence. Participants with positive alphas in year $t-1$ tend to underperform in year t, while those with negative alphas in year $t-1$ tend to outperform subsequently. This pattern holds for the full sample and in both the pre-policy (2010–2012) and post-policy (2014–2016) periods.

For the full sample, the lagged alpha coefficient is -0.654, consistent with reversals observed in both sub-periods. When splitting the sample by the sign of lagged alphas, the reversal is more pronounced for participants with positive alphas (−0.742) compared to those with negative alphas (−0.509). These results demonstrate that participants do not achieve consistent risk-adjusted outperformance and that past returns are poor predictors of future results.

The absence of persistence in portfolio alphas undermines the hypothesis that return chasing or variance avoidance is driven by rational learning about one's investment skill. While participants may view positive past returns as evidence of superior knowledge or ability, the observed reversal of alphas suggests that such beliefs are unfounded.

5.3. Rebalancing

Another potential alternative explanation for the observed positive relationship between portfolio returns and contribution changes is the rebalancing hypothesis. This explanation posits that participants might adjust their contributions as part of a broader strategy to maintain a target allocation between IPS and non-IPS financial assets. If a participant holds a significant amount of non-IPS assets, a positive correlation between returns on IPS and non-IPS assets could create the appearance of return chasing due to rebalancing.

For example, consider a household aiming to maintain a stable buffer stock of non-IPS assets. When IPS returns are high, non-IPS returns may also increase (due to correlated market performance). To restore the non-IPS balance to its target level, participants might increase IPS contributions and withdraw or consume from non-IPS accounts. Such behavior could mimic RL heuristics, where increased IPS contributions appear to follow higher returns.

This rebalancing explanation predicts two patterns:

1. **Age and Asset Levels**: Younger participants, who typically hold fewer financial assets, should exhibit weaker return-contribution correlations compared to older participants, who are more likely to hold substantial non-IPS assets.

2. **Financial Sophistication**: More financially sophisticated participants, who tend to diversify investments and hold more non-IPS financial assets, should exhibit stronger return-contribution correlations compared to less financially sophisticated participants.

To evaluate these predictions, we examine participants' responsiveness to returns across different age groups and levels of financial sophistication. While financial sophistication is not directly observable, we use participants' education levels as a proxy. We include interaction terms for age, education level, and returns in our regression models to test whether these factors significantly influence the relationship between returns and contributions.

Table 7. Impact of age and education level on RL

	(I)	(II)	(III)
Return	0.180***	0.177***	0.183***
	(0.0189)	(0.00696)	(0.0231)
Return x Age	-0.0004		-0.0003
	(0.0010)		(0.0011)
Return x Age^2	0.00004***	0.00003***	0.00004***
	(0.00001)	(0.00002)	(0.00001)
Return x High Sch. – Undergrad		-0.00481	-0.00484
		(0.0042)	(0.0042)
Return x Undergrad and over		-0.00622	-0.00628
		(0.0040)	(0.0040)
Lagged Return	0.0896***	0.0714***	0.0780***
	(0.0161)	(0.0051)	(0.0201)
Lagged Return x Age	-0.0006		-0.0003
	(0.000866)		(0.0010)
Lagged Return x Age^2	0.00003***	0.00002***	0.00003***
	(0.00001)	(0.000002)	(0.00001)
Lagged Return x High Sch. – Undergrad		-0.00285	-0.00288
		(0.0036)	(0.0036)
Lagged Return x Undergrad and over		-0.0029	-0.0029
		(0.0034)	(0.0034)
Constant	5.591***	6.343***	6.343***
	(0.0822)	(0.0556)	(0.0556)
Company x Year dummies	Yes	Yes	Yes
Portf. Alloc. Shares x Year controls	Yes	Yes	Yes
Portf. Rebalancing x Year dummies	Yes	Yes	Yes
Observations	685,069	469,763	469,763

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 presents the results of our analysis. In column I, we interact age and age-squared with both contemporaneous and lagged returns. The coefficients on the interaction terms are insignificant, indicating that age does not meaningfully moderate participants' responsiveness to returns. While older participants are marginally less responsive to both contemporaneous and lagged returns, the differences are not statistically significant.

In column II, we include participants' education levels as a proxy for financial sophistication, interacting them with contemporaneous and lagged returns. Again, the interaction terms are insignificant, suggesting no meaningful differences in responsiveness to returns across education levels. Although more educated participants appear slightly less responsive to returns, the effect is not statistically significant.

In column III, we include both age and education level interactions in the same model. The results remain consistent with those from columns I and II: neither age nor education level significantly influences the sensitivity of contributions to returns. Participants' behaviors appear unaffected by these factors, contrary to what the rebalancing explanation would predict.

The results are inconsistent with the key predictions of the rebalancing hypothesis. If rebalancing were driving the observed behavior, we would expect return sensitivity to vary significantly across age and education levels, reflecting differences in non-IPS asset holdings and financial sophistication. However, our findings show no significant interaction effects between returns and age or education. Older participants, who are likely to hold more non-IPS assets, do not exhibit stronger return sensitivity than younger participants. Similarly, participants with higher levels of education, used as a proxy for financial sophistication, are not significantly more responsive to returns than those with lower education levels. These results suggest that rebalancing is not the primary driver of the observed relationship between portfolio returns and contribution changes.

5.4. Trend in RL

One possible alternative explanation for the observed post-2013 acceleration in RL heuristics is that it reflects a gradual, pre-existing trend. Participants might have been becoming more attentive to past returns or progressively learning through ongoing market exposure, irrespective of policy changes. To assess this possibility, we employ a rolling-window estimation and examine the trajectory of return sensitivities year-by-year.

If RL heuristics were steadily amplifying due to accumulating experience or other long-run changes, one would expect a progressive increase in the return coefficients over time. Instead, the evidence shows a pronounced discontinuity. Before the introduction of the matching contributions, RL sensitivity appears relatively stable. Immediately after the policy is implemented, both contemporaneous and lagged return coefficients rise sharply and remain at these higher levels thereafter, with no indication of a pre-existing upward trend.

Figure 1. Return coefficients over the years

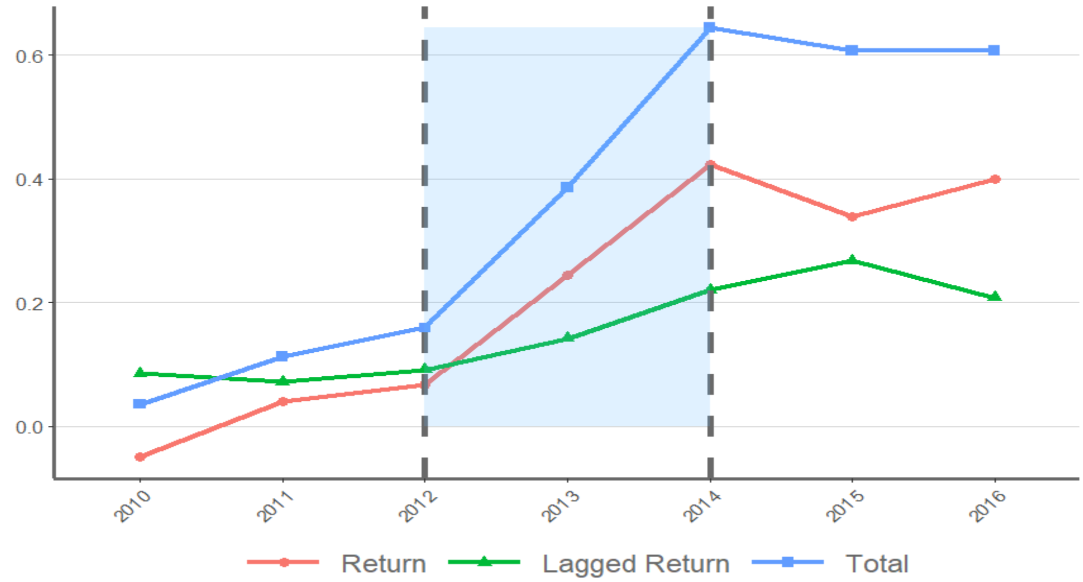

Figure 1 illustrates the trend of contemporaneous and lagged return coefficients over time, based on a 1-year rolling window estimation. The analysis incorporates demographic controls such as gender and age, consistent with our baseline model, as well as additional controls for pension company-by-year interactions, year-by-share effects, and portfolio allocation changes-by-year effects. Across all estimation windows, both contemporaneous and lagged return coefficients remain significant at the 1% level, underscoring the robustness of the observed relationships over time.

The clear temporal alignment of this behavioral shift with the policy intervention reinforces the conclusion that the matching contributions—and the associated guaranteed gains—fundamentally altered the way investors incorporate past returns into their decision-making. Rather than attributing the result to a gradual evolution in investor sophistication or evolving market norms, the evidence points toward a policy-driven "level effect." By enhancing the salience of positive return experiences, the policy appears to have locked participants into more pronounced RL patterns.

6. Conclusion

Saving for retirement is one of the most consequential financial undertakings—and often a sequence of decisions—individuals face in their lifetimes. Poor or biased judgment in this domain can impose significant and enduring welfare costs, which are seldom easily reversed. Policymakers must therefore grapple with a fundamental question: should individuals be left to learn from their own mistakes, or should interventions guide them toward better decision-making? Depending solely on individuals to overcome cognitive distortions may be unrealistic and ultimately costly, both to the individuals themselves and to the broader society.

Interventions designed to improve retirement saving outcomes have the potential to enhance welfare. Yet their efficacy hinges on the extent to which they interact constructively with the cognitive processes that shape financial decisions. Merely alleviating the immediate burdens of insufficient savings—without targeting the underlying biases—risks leaving deep-seated distortions untouched. Consequently, understanding the interplay between policy interventions and behavioral heuristics is critical. Sound policy should not only increase savings quantitatively but also guide individuals toward more grounded, rational decision-making over the long term.

Our findings offer new insights into this interplay. By examining how a well-intentioned matching contributions policy in Türkiye’s IPS influenced RL behavior, we reveal that policies which appear successful on the surface—boosting participation and contributions—can simultaneously reinforce the very heuristics that impede optimal decision-making. Instead of nudging individuals toward more considered financial planning, the policy inadvertently magnified their tendency to extrapolate from recent outcomes, thus underscoring the complexity of shaping not just behavior, but the cognitive foundations behind it.

This evidence highlights the importance of designing interventions that achieve more than short-term numerical targets. To be truly effective, policies should be complemented by tools that encourage reflective judgment, and gradually reduce overreliance on simplistic heuristics. Striking this balance will require innovation and nuanced thinking—efforts that go beyond treating the symptoms of poor saving habits and instead work—to recalibrate the mental frameworks that produce them. Ultimately, reimagining policy in this manner can help ensure that individuals not only save more, but also learn to save more wisely.

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