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Abstract

Using the nationwide automatic enrollment policy implemented in Türkiye in 2017, this paper examines how much of the contribution flowing into the new automatic pension account represents additional retirement contributions rather than an offsetting of contributions from the pre-existing voluntary IPS account. Using administrative data covering the universe of IPS (Individual Pension System) and AES (Automatic Enrollment System) plans, we track voluntary and automatic contributions at the individual level. To assess how much automatic contributions offset existing voluntary IPS contributions, we focus on individuals who held a voluntary IPS plan before the introduction of AES. Exploiting the age-45 eligibility cutoff and the variation in the timing AES enrollment, we implement an event-time fuzzy difference-in-differences design with imperfect treatment compliance due to the two-month opt-out option after enrollment. This approach estimates both the crowd-out effect of AES on voluntary IPS contributions and its net effect on total retirement contributions. Our findings reveal that AES reduces real monthly voluntary IPS contributions by about 22₺ per participant and roughly 21 percent of the new automatic contributions are offset by lower voluntary retirement contributions. Net of this partial crowding-out, real monthly total retirement contribution increases by about 82₺ per participant. These findings highlight the effectiveness of default-driven saving policies in increasing within-retirement contributions. Automatic enrollment causes a higher crowding-out effect among employees with lower education and lower incomes, but even among employees with these characteristics, automatic enrollment continues to increase total retirement contributions. Finally, the crowding-out effect of automatic enrollment on voluntary contributions weakens and the net effect on total retirement contributions recovers in the medium-term.

Keywords: Automatic enrollment, Crowding-out, Retirement saving, Behavioral public policy

JEL Classifications: H2, D14, H3

ملخص

باستخدام سياسة التسجيل التلقائي الوطنية التي تم تنفيذها في تركيا في عام 2017، تبحث هذه الورقة في مقدار المساهمة المتدفقة إلى حساب التقاعد التلقائي الجديد التي تمثل مساهمات تقاعدية إضافية بدلاً من تعويض المساهمات من حساب IPS الطوعي الموجود مسبقاً. باستخدام البيانات الإدارية التي تغطي عالم خطط IPS (نظام المعاشات التقاعدية الفردية) و AES (نظام التسجيل التلقائي)، نقوم بتتبع المساهمات الطوعية والتلقائية على المستوى الفردي. لتقييم مقدار المساهمات التلقائية التي تعوض مساهمات IPS الطوعية الحالية، فإننا نركز على الأفراد الذين كان لديهم خطة IPS طوعية قبل تقديم AES. من خلال استغلال حد الأهلية للعمر 45 عامًا والاختلاف في توقيت التسجيل في AES، نقوم بتنفيذ تصميم الفرق الغامض في الاختلافات في وقت الحدث مع الامتثال غير الكامل للعلاج بسبب خيار إلغاء الاشتراك لمدة شهرين بعد التسجيل. يقوم هذا النهج بتقدير كل من تأثير الازدحام لـ AES على مساهمات IPS الطوعية وتأثيره الصافي على إجمالي مساهمات التقاعد. تكشف النتائج التي توصلنا إليها أن AES تقلل مساهمات IPS الطوعية الشهرية الحقيقية بحوالي 22₺ لكل مشارك ويتم تعويض ما يقرب من 21 بالمائة من المساهمات التلقائية الجديدة من خلال انخفاض مساهمات التقاعد الطوعية. وبعد خصم هذا الازدحام الجزئي، يزيد إجمالي مساهمة التقاعد الشهرية الحقيقية بنحو 82₺ لكل مشارك. وتسلط هذه النتائج الضوء على فعالية سياسات الادخار القائمة على التخلف عن السداد في زيادة المساهمات أثناء التقاعد. ويؤدي التسجيل التلقائي إلى زيادة تأثير الازدحام بين الموظفين ذوي التعليم المنخفض والدخل المنخفض، ولكن حتى بين الموظفين الذين يتمتعون بهذه الخصائص، يستمر التسجيل التلقائي في زيادة إجمالي مساهمات التقاعد. وأخيراً، يضعف تأثير الازدحام الناجم عن التسجيل التلقائي على المساهمات الطوعية، ويتعافى التأثير الصافي على إجمالي مساهمات التقاعد في الأمد المتوسط.

1. Introduction

Over the past 2 decades, many employees have begun saving for retirement through automatic enrollment (AE) mechanisms. Unlike voluntary participation, eligible employees are automatically enrolled in retirement plans by their employers under the AE, making enrollment the default option. However, enrollment is not mandatory; employees can opt-out if they wish. Therefore, AE leverages inertia and procrastination in favor of saving by requiring participants to actively decide to opt-out of retirement plans, rather than participating them. This significantly reduces the decision costs that hinder the initiation of retirement saving. For example, for employees who intend to save but procrastinate, automatic enrollment in retirement plans acts as a mechanism that narrows the gap between intention and action, altering the architecture of the decision-making environment without eliminating individual preferences. Prior studies show that this seemingly small change in preference architecture significantly increases participation rate and contribution amounts in pension plans (Madrian & Shea, 2001; Thaler & Benartzi, 2004; Choi et al., 2002, 2004). These increases are not dependent on a specific plan, organizational structure, or set of rules; in almost all countries where AE adopted, we find strong evidence documenting an increase in accumulated savings after reform (Choi et al., 2004; Carroll et al., 2009).

While all this evidence suggests that AE policies have been successful, the question of whether automatic contributions are creating new retirement savings remains relevant. If Automatic Enrollment System (AES) contributions crowd-out savings in other pension accounts or alternative financial assets, their impact on saving is overestimated. Therefore, to assess the actual success of AE policies in terms of their impact on total retirement savings, substitution among voluntary retirement savings should be examined. While previous studies have documented that AE significantly increases both participation and contributions in retirement plans (Poterba et al., 1996; Madrian & Shea, 2001; Chetty et al., 2014), reliable causal evidence regarding the extent to which it substitutes voluntary retirement savings is still limited. The challenges we face are simple, but significant. We often cannot observe closely related financial substitutions together in the data. Furthermore, it is difficult to isolate causal effects because policy changes often coincide with unobservable shifts in preferences or common temporal trends.

Therefore, we utilize quasi-experimental variation and detailed administrative records to determine the causal effect of automatic enrollment on total retirement savings (Beshears et al., 2009; Madrian & Shea, 2001). Chetty et al. (2014) provide a leading example of this approach: using Danish pension reform, they estimate how default contribution arrangements affect total savings. Their findings show that default-based policies can significantly increase total savings, especially in individuals with high inactivity. Similarly, when evaluating Thaler and Benartzi's (2004) Save More Tomorrow program, we see that behavioral interventions using default options and commitment mechanisms can permanently change saving behavior in environments where overweighting and procrastination tendencies are evident.

Nonetheless, whether automatic enrollment systems induce real increases in total retirement savings or primarily displace existing voluntary contributions (thereby reallocating retirement savings through a crowding-out effect) remains an open and debated issue in the literature. This study exploits a unique natural experiment that provides a compelling setting to causally examine the extent to which AE policies affect retirement contributions. Türkiye implemented the Automatic Enrollment System at the beginning of 2017. According to this program, all employees under the age of 45 who are employed as an affiliated employer are automatically enrolled in retirement plans by their employers. Enrollment in the program was implemented in staggered manner, depending on the size based on the number of employees and sector of the employer. Initially, employers with 1000 or more employees and the public sector adopted the program. Later, its scope was expanded to include small-scale firms with 5-9 employees. Although enrollment is automatic, it is not mandatory; employees continue to contribute to retirement plans unless they actively choose to opt-out.

AES differs from other country examples by building upon the already existing IPS. While participation in Individual Pension System (IPS) is voluntary, in AES, employers enroll employees, removing key barriers associated with participation in voluntary retirement plans. Employees previously enrolled in IPS are expected to re-enroll in AES, adding to their existing voluntary IPS contributions. This institutional structure provides a unique setting for examining the effects of automatic enrollment on voluntary retirement plans. Previous studies have highlighted potential substitution relationships by tracking AE with other non-retirement accounts such as loans and borrowing (see Chetty et al., 2014; Beshears et al., 2022; Choukhmane & Palmer, 2025). Although we cannot observe borrowing or liquid savings accounts due to data constraints, IPS is a very close alternative to AE as a retirement plan that goes beyond non-retirement accounts. In this sense, we evaluate the causal effect of automatic enrollment on voluntary IPS contributions by tracking both retirement plans, rather than its effect on net retirement savings, and provide evidence on the magnitude of the within-retirement crowding-out effect and whether AES generates new retirement savings.

Our analysis utilizes an unbalanced panel dataset encompassing both voluntary IPS and AES plans and is based on administrative records. Focusing on employees just below and just above the 45-year age cutoff (± 1 age) required for AES, the empirical strategy estimates the extent to which automatic enrollment excludes voluntary contributions to IPS and its net impact on total retirement contributions. The non-mandatory nature of AES and the right to opt-out within 2 months allow employees to demonstrate imperfect compliance with the policy. Simultaneously, the staggered nature of AES enrollment and the examination of medium-term effects throughout the analysis period provides a setting for the use of a event-time fuzzy DiD method using an instrumental-variable framework to reveal causal effects.

The empirical analysis shows that the AES induces a statistically and economically meaningful decline in monthly average real voluntary IPS contributions of about 22₺ per participant. Combined with the estimated increase in total IPS contributions, this implies that monthly average automatic contributions rise by roughly 104₺, so that about 21 percent of the new retirement contribution is offset by lower monthly average real voluntary IPS contributions. Net of this partial crowding-out, total retirement contributions still increase by around 82₺ per participant. We have pegged these amounts to 2017 prices in Türkiye to mitigate inflationary effects. To put it more simply, the AE generated new retirement contributions of approximately 6% of the gross minimum wage, but this was offset by a 1.2% decrease in monthly average real voluntary IPS contributions. These amounts are reasonable, especially considering that in the initial stages, employees of more established firms were included in the AE.

In addition to these results, we document two important heterogeneities. Although AE policies are fundamentally based on including relatively low-educated and low-income employees in the pension system, we show that the largest retirement contributions increase comes from highly educated and high-income employees. We address the role of liquidity constraints as an explanation for this phenomenon, because for low-educated and low-income employees who already have voluntary IPS plan, AE as a second pension plan is highly likely to cause them to exceed the share of their budget allocated to retirement contributions. Despite this, AE still functions to increase total contributions. Finally, although AE substitutes voluntary IPS contributions in the short-term, the crowding-out effect weakens in the medium term. Thus, AE generates an immediate increase in total retirement contributions and preserves much of this gain over the medium term.

This study adds to the literature in several related ways. First, it provides direct causal evidence on how individuals who were already actively saving for retirement respond to automatic enrollment. Much of the existing literature asks whether defaults raise participation and contribution rates, especially among workers unlikely to join or contribute on their own (Madrian and Shea, 2001; Choi et al., 2002, 2004; Beshears et al., 2009). A related but distinct question is whether the additional contributions generated by automatic enrollment represent genuinely new contribution or simply displace voluntary contributions that individuals would have made anyway. Measuring this margin is difficult because the two channels are rarely observed simultaneously. In our setting, existing voluntary IPS participants are automatically enrolled in the AES, and administrative records track both contribution streams for the same individuals. We can therefore decompose the gross AES contribution into the portion offset by reductions in IPS contributions and the portion that constitutes a net addition to retirement accounts, measuring crowd-out within the system directly rather than inferring it from participation rates or account balances.

Second, we show that the net effect of automatic enrollment varies substantially with the characteristics of pre-reform voluntary savers. Prior work finds stronger responses to defaults

among lower-income and less-educated workers and typically links them to inertia or limited attention. Our results uncover an additional margin: among those already saving voluntarily, lower-income and less-educated participants offset a larger share of AES contributions by reducing IPS contributions, while higher-income and more-educated participants retain more of the automatic contribution as net new contribution. A strong gross response therefore need not produce an equally large increase in total retirement contributions. These findings complement the defaults literature by showing that groups that respond strongly to automatic enrollment may also engage in substantial substitution when they already have an adjustable voluntary margin.

Third, the paper provides new evidence on how this substitution evolves after automatic enrollment. Most existing findings examine participation and contribution responses over relatively short horizons and offer limited insight into the persistence of crowd-out. Tracking contribution flows for the earliest enrollment cohort for up to four years and seven months, we document a clearly non-linear adjustment. Crowd-out of voluntary BES contributions deepens over the first three years, peaks around the third year, and then attenuates, while OKS contributions remain relatively stable. As a result, the effect on total retirement contributions follows a U-shaped path rather than converging monotonically toward zero. This pattern complements recent work on gradual adjustment to defaults (Choi et al., 2024; Choukhmane, 2025) and allows us to observe, within the same individuals, how the displaced voluntary contribution and the automatic contribution that triggers it evolve jointly.

Fourth, Turkey's institutional design supplies particularly useful quasi-experimental variation. Legal eligibility changes sharply at the age-45 threshold, permitting comparison of otherwise similar groups around the cutoff. Workers above the threshold remain outside the OKS and form a stable never-treated control group. The two-month opt-out window generates incomplete compliance, which we address by instrumenting continuous participation with legal eligibility. The combination of a sharp assignment rule, a never-treated comparison group, and explicit modeling of incomplete compliance identifies the local causal effect of OKS participation for individuals whose enrollment status is shifted by the eligibility rule.

Although these features are specific to Türkiye, the underlying question is more general. Much of the existing evidence comes from high-income countries where occupational pension coverage is already widespread. Türkiye combines an established voluntary defined-contribution system with a newer automatic-enrollment scheme, so eligible workers can hold two closely substitutable retirement-saving vehicles at the same time. This structure offers a transparent setting in which to examine how much of the contribution generated by layering an automatic mechanism on a voluntary system is genuinely additional, how much is offset through substitution, which groups substitute more heavily, and how the adjustment evolves over time.

The paper is organized as follows: section 2 presents the institutional background to both IPS and AES in Türkiye. Section 3 introduces the dataset and methodology. Section 4 presents the baseline findings, robustness checks, demographic heterogeneities, and medium-term dynamic effects. Finally, section 5 concludes by discussing the results.

2. Institutional Background

2.1. An overview of the Türkiye's pensions policy environment

Türkiye's retirement income system is organized around a three-pillar architecture. The first pillar, administered by the social security institution, is the mandatory public pension system, where statutory social security contributions are collected through payroll deductions and operates as a defined-benefit (DB) scheme financed on a pay-as-you-go (PAYG) basis. Pension benefits are calculated according to a predetermined formula that takes into account factors such as age, years of service, total contribution days, and average insurable earnings.

The second pillar consists of occupational retirement arrangements, in which employers may provide retirement benefits or voluntary matching contributions. Although Türkiye has similar occupational and institutional supplementary pension schemes, they are not sufficiently widespread to ensure coverage of the entire population. At the end of 2003, the state introduced the IPS, which provides an institutional framework for long-term retirement savings and allows to have an additional retirement income.

The IPS is a standard supplementary retirement system operating under a voluntary opt-in regime. The system is administered through private pension companies, and enables all individuals to participate without any age, employment requirements or citizenship status. Unlike the public mandatory system, the IPS operates as a defined contributions (DC) system since financing structure is based on funding principles. The funds chosen within pension plan aim to generate returns by investing participants' contributions in various investment instruments over the long term.

The key feature of IPS is the matching contributions introduced in 2013, which makes it state-sponsored. Accordingly, the state match contributions at a 25% on contributions up to the amount of annual minimum wage in that year.⁴ Furthermore, this matching contribution is placed in "state contribution funds" that primarily hold relatively low-risk fixed-income assets, offering an additional return, regardless of the participants' preference. Participants are eligible to retire and receive the full amount of their matching contributions if they have contributed for a minimum of 10 years and reached the age of 56 and cannot be withdrawn earlier. Those who opt-out early

⁴ The state has modified this match rate, increasing 30% in 2022, then reducing to 20% in 2026.

before retirement only receive a certain percentage of matching contributions based on their duration of participation, do not benefit from tax advantages, and are subject to deductions (Citci & Yanikkaya, 2024).

Although the number of participants and the accumulated fund balance in the retirement accounts have reached a significant level since the IPS's introduction, Türkiye has occupied a structurally weak position in the second and third pillar of the OECD three-pillar framework, with retirement income security continuing to rely predominantly on the public social security system (Brook & Whitehouse, 2006). In order to change this landscape, the state started to implement the AES, which came into force on 1 January 2017.

2.2. Introduction of the automatic enrollment system

The AES is grounded in a same default participation mechanism observed in the AE framework of countries such as US, UK, New Zealand, despite significant institutional differences. All employees under the age of 45 who are employed by a given employer in the public or private sector are mandatorily enrolled in retirement plans by their employers.⁵ Under the AES program, 3% of gross salaries are automatically contributed to the pension account. Similar to IPS, the AES operates as a defined contributions (DC) system since financing structure is based on funding principles, with contributions invested in AE pension funds by portfolio management companies affiliated with private pension companies. AE plans share the same basic legal and financial architecture as IPS plans, including eligibility for the state match.

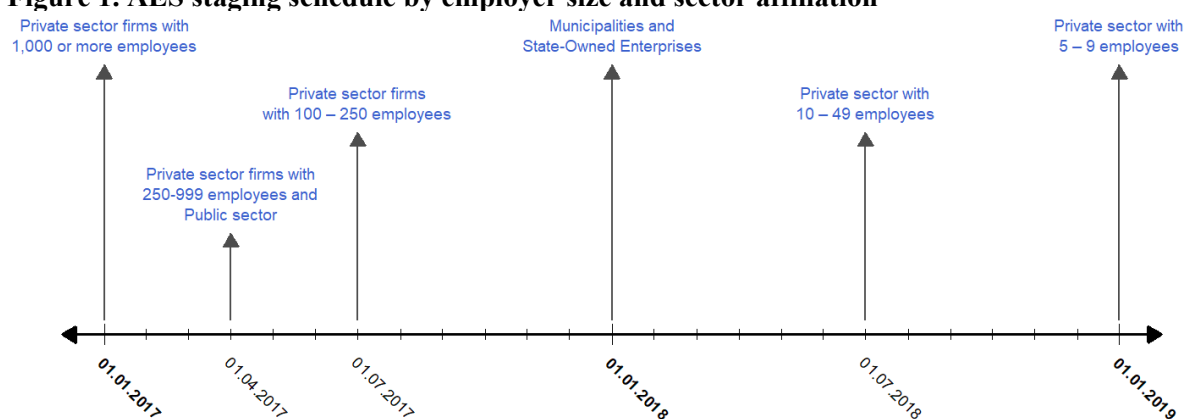
Participants retain the right to opt-out of the system for 2 months defined as statutory cooling-off period, if they choose to opt-out, contributions and after withholding tax investment returns are refunded and they treated as never opted-in. At the same time, opted-out participants are not be able to benefit from the state match in any form. For opt-outs occurring after the second month, investment returns are still subject to withholding tax, and only a portion of the state match is vested based on the duration held.

While the two opt-out decisions are similar in terms of financial penalties, there is a marked behavioral difference between them. Participants who opt-out within 2 months actively reject the default option. They do not adjust saving behavior under the default contribution rate, consistent with high level of financial awareness. However, participants who opt-out after the second month passively accept the default option at the outset of the policy, but later actively leave the program.

⁵ However, a regulation made in 2022 allowed employees who had reached the age of 45 to also participate AE plans if they choose to do so.

The AES was rolled-out in a staggered manner for employees, based on the employer size measured by the number of employees and public or private sector affiliation. Although employers had a designated start date for enrolling their employees in retirement plans, there is no mandatory final enrollment date. Accordingly, as of January 1, 2017, almost all employees affiliated with an employer have been automatically enrolled AE plans, starting with private sector employers with 1,000 or more employees, and subsequently expanded to the medium-sized employers, public sector institutions, and private sector firms with 5-9 employees. Figure 1 illustrates the staging schedule of AES enrollment, based on the employer size measured by the number of employees and public or private sector affiliation.

Figure 1. AES staging schedule by employer size and sector affiliation



Source: Authors' illustrations based on PMC (2018), table titled "Transition Schedule for the Inclusion of Private Sector and Public Sector Employees in Automatic Enrollment".

The statutory 45-year age rule, a central institutional feature of AES, exhibits partial variation for staggered enrollment. For employees whose enrollment falls before 27 December 2018, the relevant benchmark is 1 January 2017: an employee is eligible for AES if they had not yet turned 45 as of 1 January 2017, and ineligible otherwise. For employees whose enrollment falls on or after 27 December 2018, the benchmark shifts to the first day of the calendar year in which the employee is to be enrolled: the employee is eligible if they have not yet turned 45 on that date. In both cases the legal criterion is framed in terms of being under 45 years of age at the relevant reference date; those who have not turned 45 are automatically enrolled, while those who have are excluded from automatic enrollment and may only participate in the IPS via voluntary channels.

At the enrollment, the AES also includes a default investment strategy. Contributions are invested in the "initial" or "standard" pension funds that largely allocate assets in conservative instruments such as deposits and debt securities. At the end of the 2-month statutory cooling-off period, participants may adjust their portfolios by switching to

“flexible” pension funds with a higher risk-return profile (PMC, 2026). Within this framework, AES aims to minimize decision-making costs by isolating employees from the complexity of the financial decision world, not only in terms of contribution decisions but also in terms of fund allocations.

3. Data and empirical strategy

3.1. Data description

The dataset was obtained from the Pension Monitoring Center, a public authority responsible for regulating and ensuring the operation of both the Individual Pension System and the Automatic Enrollment System in Türkiye. Our data allow us to track IPS accounts from 2003 and AES accounts from 2017 to mid-2021. It provides year-end snapshots of more than 17 million participants and over 39 million pension contracts on annual basis. Although the analysis period covers post-2003, the introduction of matching contributions policy in 2013 represents an institutional shift that significantly altered contribution decisions. To ensure a consistent definition and minimize deviations arising from regime differences, the dataset focuses on the period post-2013 and covers the years between 2013-2021.

The anonymized data represents an unbalanced panel and includes financial and demographic details of participants as well as characteristics of their pension contracts. Financially, it presents participants' voluntary and automatic contributions, accumulated state matching contributions, pension account balances, asset class level fund group portfolio allocations, and the total number of fund switches for the relevant year. Demographically, it provides a range of details about individuals, including date of birth, age, gender, education level, and income group. In addition, it details the pension contract types (IPS or AES), number of pension accounts, their start and termination dates, and the reasons for termination. We observe both IPS and AES contracts simultaneously, as well as multiple IPS contracts. We define the individual retirement contributions as the sum of their contributions across all contracts, and we collapse these contributions on an individual basis over the relevant years. Thus, we aggregate the pension contract level dataset to participant level and evaluate participants' saving behavior not based on a single contract, but on their contributions to all the contracts.

To determine the causal effect of AES on retirement contributions with our universe-wide dataset, we are implementing a series of data constraints and cleaning processes. First, we exclude participants who have only an employer-sponsored IPS contract. These types of contracts are those where employers open pension accounts and contribute on behalf of their employees, but they are not structured with the employees' willingness to save and do not reflect their individual preferences. Secondly, we exclude participants outside the labor market, such as housewives, retirees, students, and the unemployed. Because AES includes only “employees,” this exclusion

rule strengthens comparability and consistency between participants in the control and treatment groups that we define in detail later in the empirical strategy section.

Although AES enrollment covers all employees under the age of 45 across all sectors and firm sizes, the reference date for the age rule is not the same for each enrollment period due to a staging rollout. For example, enrollment up to December 27, 2018, the age on January 1, 2017 is used as a reference, while enrollment after that date the participants' age as of January 1 of that year is considered. To preserve the age rule and eliminate the confounding effects of age-related heterogeneities on causal outcomes, we pay attention to the ages in reference dates to which they are subject as of the enrollment date. We exclude individuals who should have been enrolled but were not. These represent individuals who, despite being below the age cutoff, are self-employed, unemployed, or outside the employee population subject to the AES. There is also a very small group of participants who were mistakenly enrolled in AES when they should not have been, considering the reference date and age. Participants with these characteristics are also excluded because they do not belong to the target population of AES. In this way, we maintain clarity regarding the 45-age rule for both control and treatment groups.

An IPS contract can remain open even when the participant makes no contributions, so contract ownership alone does not necessarily indicate active voluntary saving. This distinction is important because financial products are frequently distributed through existing intermediary relationships. The banking literature documents substantial cross-selling across products and shows that credit and customer relationships can facilitate the sale of additional financial services (Lepetit et al., 2008; Basten and Juelsrud, 2026). Related evidence from private-pension and retirement-product markets further shows that subscription decisions can be materially influenced by sales-force and intermediary incentives rather than solely by households' underlying saving preferences (Marotta, 2020; Egan et al., 2022). This issue is particularly relevant in Türkiye, where banks constituted an important distribution channel for voluntary IPS contracts prior to AES (Aktaş Koral, 2025). We therefore require individuals to have made a positive IPS contribution in the year immediately preceding AES enrollment. The restriction defines our target population as active incumbent voluntary savers and prevents dormant or nominal IPS accounts from being treated as evidence of pre-existing voluntary saving.

After all this data filtering, to minimize age-related heterogeneities in our sample and to obtain reliable estimates of causal effects of AES, we focus on observations very close to the 45-year age cutoff, the intuition behind Regression Discontinuity Design (RDD). For this purpose, we select the MSE-optimal bandwidth by estimating bias-corrected local polynomial regression for the reference period of 2016 (Calonico et al., 2014). Here, we use participants' entry age around the 45-year cutoff as the running variable and their monthly average real voluntary IPS contributions as the outcome variable. Our results establish a quasi-experimental assignment that individuals

within a ± 0.886 neighborhood of the age of 45 cutoff are highly similar to one another. This bandwidth enables us to estimate accurately the local causal effect of AES by optimizing the bias-variance trade-off. To ensure ease of application and interpretability, we assign ± 1 year as bandwidth. This preserves observations close to the optimal bandwidth without leading to significant information loss. In the final stage, to reduce the distorting effects of extreme values on the estimations, we trim participants whose observations are less than the bottom 1% or greater than the top 1% of the total contribution distributions. This leaves us with a final sample of an unbalanced panel dataset consisting of 755,421 observations from 101,362 participants.

3.2. Empirical strategy

We utilize an event-time fuzzy differences-in-differences (DiD) estimation strategy using an instrumental-variable framework to identify both the causal effect of AES on monthly average real total contributions (IPS + AES) and the potential crowding-out effect on monthly average real voluntary IPS contributions, following De Chaisemartin and d'Haultfoeuille (2018). There are several important reasons why we use this estimation strategy. First, the enrollment dates assigned to each employer (see figure 1) are the statutory start dates for enrollment, so actual enrollment may occur after the start date, and there may be transitions between employer enrollment cohorts. This prevents us from seeing exactly which cohort the employees belong to, thus not allowing us to use the Sun and Abraham (2021) method, which accounts for cohort-specific effects. Second, the staging rollout of AES leads to the existing event-time specific effects of standard DiD models to be compressed into a single ATE. However, event-time fuzzy DiD takes event-time specific effects into account separately and prevents the effects from conflation. Third, participants adjust their target contributions over time after being enrolled in AES; the impact is large in the first year and decreases over time. Event-time fuzzy DiD focuses on event time rather than calendar time, allowing for observing throughout the event time by isolating dynamic treatment effects. In addition to this, IV framework estimates the local average treatment effect (LATE) for participants whose behavior is altered (compliers) by using eligibility for treatment as an instrumental variable and abstracts the actual causal effect from participants whose behavior is not altered by treatment (never-takers).

First, we define eligibility for treatment. Here, E_i takes a value of 0 if the participants aged [45-46] on January 1, 2017 and only have a voluntary retirement plan during the analysis period, and 1 if the participants aged [44-45] on the reference date for the relevant enrollment period and enrolled in AES during the analysis period.

⁶ To avoid masspoint detecting, we calculate individuals' ages as decimals based on their birth dates. For participants born on December 31, 1971, we assign as exactly 45 years old on January 1, 2017. For those born before and after December 31, 1971, we use that date as the base and assign decimal ages so that they are exactly 44 and 46 years old one year before and one year after, and we continue this process for all birth dates. The 0.88 calculated here corresponds to approximately 10.5 months.

Although age rule serves as a sharp cutoff for enrollment in AES, opt-out from AES, leads to a fuzziness of treatment assignment around the 45-year-old cutoff due to imperfect compliance. Therefore, being eligible for AES only determines the likelihood of continuing (not opting-out) treatment, it does not sharply determine the treatment. In this case, reduced-form effect of eligibility leads to misclassification of the treatment, capturing the intention-to-treat effect rather than the actual causal effect of the treatment. Therefore, we use the eligibility based on 45-age cutoff as an instrument for assessing actual treatment effect. The actual treatment effect (R_i) is 0 if participants opt-out within two months, and 1 if they remain enrolled after two months. Let $G_i \in \{2017, 2018, 2019\}$ be the enrollment years of the participants in AES. Thus, event time as follows: $k_{it} = t - G_i$. In this case, the event-time specific endogenous treatment variables are:

$$D_{it}^k = 1(k_{it} = k) \times R_i \#(1)$$

and event-time specific instruments are:

$$Z_{it}^k = 1(k_{it} = k) \times E_i \#(2)$$

Therefore, given $k \geq 0$, there is an event-time eligibility variable corresponding to each event-time treatment variable. Five endogenous variables and five excluded instruments are used together. The first-stage equation estimated for each D^k is as follows:

$$D_{it}^k = \alpha_i^k + \lambda_t^k + \sum_{j=0}^4 \pi_{kj} Z_{it}^j + u_{it}^k \#(3)$$

In the second stage, we estimate the following equation:

$$C_{it} = \alpha_i + \lambda_t + \sum_{k=0}^4 \beta_k \hat{D}_{it}^k + \varepsilon_{it} \#(4)$$

In equation (4), C_{it} denotes the dependent variable, capturing either individual i 's monthly average real voluntary IPS contributions in year t , or the combined total of monthly average real voluntary IPS and real AES contributions.⁷ α_i represents unobservable individual-specific fixed effects, while λ_t represents time-specific fixed effects. $\hat{D}_{it}^k$ is the value of the instrumented actual treatment, i.e., the value of remaining enrolled at k event time obtained from first stage equation (3). Considering that the standard IV assumptions are validated, β_k is the main parameter we focus on, representing the local average treatment effect of remaining enrolled on the contributions of complying individuals at each event time (Angrist & Imbens, 1995). Finally, to calculate the

⁷ Because the year-end snapshots in our dataset show the end of July for 2021, and irregularities in the recording dates differentiate the timeframe for year-end contributions, we use monthly average real contributions. This allows us to standardize contributions and prevents late-enrolled participants' contributions from appearing mechanically lower than they actually are.

overall effect of AES on both voluntary and total retirement contributions, we aggregate the estimated event-time specific LATE to a single coefficient:

$$LATE^{Agg} = \sum_{k=0}^4 w_k \hat{\beta}_k \quad (5)$$

Where, w_k is the weight of the number of complier observations in each event time, among the total number of complier observations across all event times. The calculated $LATE^{Agg}$ takes into account the unbalanced event time distribution caused by staggered rollout of AES by not giving equal weight to small and large event time groups. In all specifications, we cluster standard errors at the participant and workplace levels to allow for serial correlation within both unobservable participant-specific saving trends and shocks, as well as potential peer effects (Duflo & Saez, 2003).

4. Empirical findings

4.1. Summary statistics

Table 1 summarizes the main demographic characteristics of the individuals used in analysis including categories gender, education and income deciles. Overall, when considering all demographic characteristics, there is no significant difference between participants in the treatment group who are enrolled in AES and those in the control group who are not enrolled. An important observation is that 61.4% of entrants prefer to opt-out decision within the first two months. This is consistent with the high opt-out rates (or low participation rates) in AES relative to other countries' experiences, as documented in previous reports and studies (Kocabıyık & Küçükçakal, 2018; Adaman et al., 2021; Meral & Şener, 2021; OECD, 2023).

The number of men is slightly higher than women because, as predicted, their higher labor force participation and earnings lead to a greater capacity to save and participation in the pension system. Similarly, university graduates are more likely to participate in the pension system due to factors such as higher financial literacy and greater awareness of saving. Regarding gross salaries, the majority of participants are concentrated at the range between gross minimum wage and three times that amount. This range represents employees who are in relatively more corporate firms and have a greater capacity to save.

Table 1. Demographic characteristics of participants

	(I)	(II)	(III)
	Control	All Entrants	
		Opted-Out	Remained Enrolled
Number of observations	491,259	158,616	105,546
Number of unique individuals	65,918	21,778	13,666
Percentage	65.03	21.49	13.48
Gender (%)			
Male	57.26	56.16	60.54
Female	42.74	43.84	39.46
Education (%)			
Less than High school	18.65	14.30	13.99
Highschool - Less than College	35.13	32.05	31.02
College or Higher	46.22	53.65	54.99
Income (%)			
Net Income $\leq$ GMW	33.94	33.93	33.81
GMW < Net Income $\leq$ GMW x 3	40.67	44.27	44.37
Net Income > GMW x 3	25.39	21.80	21.82

Note: This table presents summary statistics on participant's demographic characteristics separately. Column (I) reports for the control group, consisting of participants in the age interval [45-46], who hold only voluntary IPS contract, while Columns (II)-(III) report treatment group consists of participants in the age interval [44-45], who hold both a voluntary IPS and an automatic AES contract. Participants in Column (II) represent those who opted-out within 2 months (i.e. never-takers), whereas participants in column (III) represent those who remain enrolled (i.e. compliers). We base our categorization of demographic characteristics on the PMC (2018) classification. GMW is Gross Minimum Wage.

After summarizing demographic characteristics, we next turn to contribution behaviors of same participants. Table 2 displays the mean, median, and percentage change of participants' contributions pre- and post-AES. The columns respectively detail contributions for participants who only have voluntary IPS and are not eligible for AES (column I), who were eligible and enrolled in AES but opted-out within 2 months (column II), and who are eligible and remained enrolled. First, it is noteworthy that mean and median monthly contributions decreased across all participants following the implementation of the AES. This downward trend is explained by the increase in inflation in Türkiye during the implementation of the AES, which eroded the real value of contributions, despite nominal contributions increase.

Table 2. Summary statistics of contributions

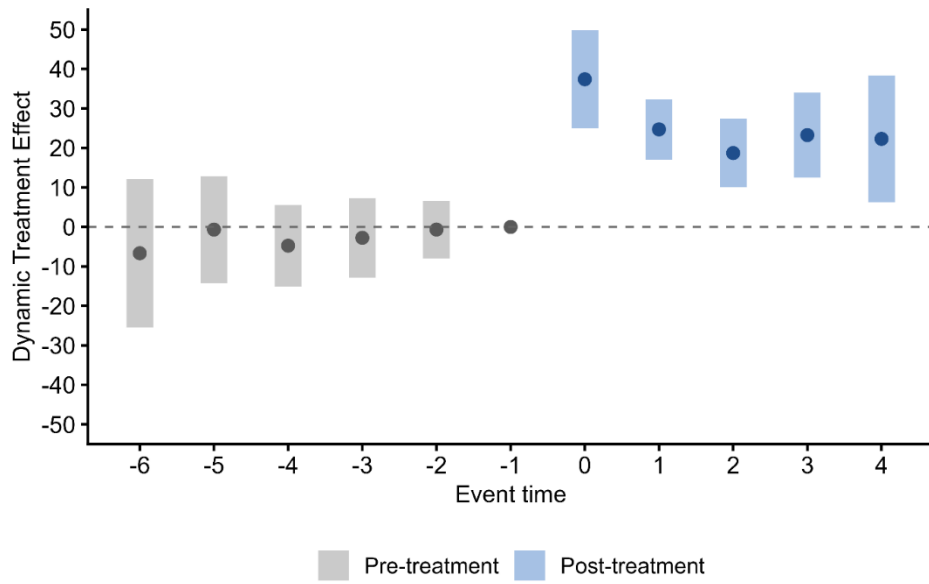
	(I)	(II)	(III)
	Control	All Entrants	
		Opted-Out	Remained Enrolled
Panel A. Means			
Pre-AES IPS Contributions	326	318	312
Post-AES IPS Contributions	293	298	258
Post-AES Total Contributions	293	298	343
% Change — IPS (Post-Pre)	-9.91	-6.16	-17.22
% Change — Total (Post-Pre)	-9.91	-6.16	9.81
Panel B. Medians			
Pre-AES IPS Contributions	214	216	210
Post-AES IPS Contributions	190	200	165
Post-AES Total Contributions	190	200	240
% Change — IPS (Post-Pre)	-11.07	-7.59	-21.57
% Change — Total (Post-Pre)	-11.07	-7.59	14.49
Panel C. Distributions			
Standard Deviations	333	316	334
Minimum	0	0	0
Maximum	2303	2301	2302

Note: This table presents summary statistics on participant's monthly real contributions separately including both voluntary IPS and total (IPS with AES) contributions. Column (I) reports for the control group, consisting of participants in the age interval [45-46], who hold only voluntary IPS contract, while Columns (II)-(III) report treatment group consist of those in the age interval [44-45], who hold both a voluntary IPS and an automatic AES contract. Participants in Column (II) represent participants who opted-out within 2 months (i.e. never takers), whereas participants in column (III) represent participants who remained enrolled (i.e. compliers). Contributions are in Turkish Lira monthly basis and deflated to year-end 2017 Türkiye's Consumer Price Index (CPI).

On average, voluntary IPS contributions of participants across all groups exhibit a declining trend. This trend is likely attributable to the increase in inflation in Türkiye during the implementation of the AES, which eroded contribution values in real terms. Considering that participants who are ineligible for AES or opted out from AES, total retirement contributions are equal to voluntary IPS contributions alone. In the relevant period, only participants who remain enrolled in AES increase total retirement contributions by approximately %9.81. However, it is precisely these participants who most remarkably decrease monthly average real voluntary IPS contributions amounting to 17.22%, thereby partially offsetting the increase in total contributions consistent with a possible crowd-out effect. Similarly, the same pattern is observed in median contributions. This preliminary evidence motivates our empirical analysis to estimate crowd-out across voluntary IPS contributions and identify the effect of the total retirement contribution.

Figure 2 presents the difference between total real contributions of ineligible individuals for AES and real contributions of AES enrollers over time. The gray colored dots indicate the differences between real contributions paid of two groups before the policy and the blue colored dots plot the differences between real contributions paid of two groups after the policy. The figure shows that there is almost no systematic difference in contribution behavior between eligible and ineligible participants before the AES comes into effect. Following Beck et al. (2010), we also check the existence of a systematic difference by estimating pre- and post-treatment average treatment effect with binary time-varying treatment. The pre-treatment coefficients (Wald F-statistics 0.613, $p = 0.689$) are statistically indistinguishable from zero and provide no evidence against parallel trends.

Figure 2. The dynamic effect of AES on coefficient of real total contributions



Note: This figure visualizes event study plots, focusing on the difference in real total contributions of participants who are eligible and ineligible for AES. It shows dynamic average treatment effects for each period with bars at 95% confidence intervals. Standard errors are clustered at the individual and workplace level. Source: Authors' calculations.

4.2. Baseline findings

Before interpreting the baseline estimates, we first examine the first stage results. There is a strong positive correlation between remaining enrolled in the AES that is endogenous variable and being eligible that is instrumental variable, as those who are not eligible do not have the option of remaining enrolled. Looking at the diagnostic tests in Table 3, the first-stage F-test is estimated to be 2,049. This is well above the conventional threshold and is statistically significant, confirming that the instrumental variable strongly predicts the endogenous treatment status. In addition, the first-stage statistics indicate that eligibility strongly predicts AES participation. We therefore find no evidence of a weak-instrument concern. Having established the validity of the identification strategy, we present the baseline findings of impact of the AES on retirement saving behaviors employing the event-time fuzzy DiD approach outlined in the methodology section.

Table 3. Baseline results

	(I)	(II)	(III)
Dependent variable:	Total Retirement Contributions	Voluntary IPS Contributions	AES Contributions
Aggregate LATE	82.318*** (2.488)	-22.079*** (2.434)	104.397*** (0.467)
Constant	276.1*** (1.043)	277.1*** (1.039)	-0.935*** (0.0781)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	755,421	755,421	755,421
# of Individuals	101,362	101,362	101,362
Diagnostic tests			
First stage F-stat		2,049.51	
p-values		(0.000)	
Endogeneity test: chi2(4)	75.115	61.835	-
p-values	(0.000)	(0.000)	-

*Note: This table presents local average treatment effect estimates weighted by observations. In column (I), the dependent variable is combined of both monthly average real voluntary retirement and AES contributions, while in columns (II) and (III) the dependent variables are only monthly average real voluntary IPS contributions and only monthly average real AES contributions, respectively. The last rows of the table present the diagnostic tests for our two-stage model. We report a single F-stat because the same first stage is run across all specifications. Contributions are in Turkish Lira monthly basis and deflated to year-end 2017 Türkiye's Consumer Price Index (CPI). Standard errors, clustered at the individual and workplace level, are in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.*

The results reported in table 3, indicate that event-time fuzzy DiD estimates of the impact of AES on three outcome variables: i) total retirement contributions which is combined of both voluntary IPS and AES contributions (column I), ii) only voluntary IPS contributions (column II) and iii) only AES contributions (column III). Treated x event time interaction terms weighted by the number of observations at each event time, captures the aggregate local average treatment effect (LATE) of the AES policy for complier participants who remained enrolled in AES. In all specifications, this estimate is statistically significant and economically noteworthy. As shown in column (I), AES leads to increase the total retirement contributions for compliers by approximately 82₺ per month on average. The magnitude of the coefficient is economically substantial, corresponding to approximately 26% of the pre-AES sample mean for compliers.

Turning to voluntary IPS contributions, in contrast, the estimated aggregate LATE becomes negative, indicating that the AES reform leads to a relative decline in voluntary IPS contributions among individuals in the treatment group. On average, AES reduces monthly average real voluntary IPS contributions for compliers by 22₺ per month, representing approximately 7% of the pre-AES sample mean and 1.2% of the average monthly gross minimum wage in 2017.

To quantify the extent to which AES crowds out voluntary IPS contributions, we exploit the accounting identity that, in our data, total pension contributions equal the sum of voluntary IPS contributions and AES contributions in each individual–year observation, $C_{i,t}^{tot} = C_{i,t}^{vol} + C_{i,t}^{AES}$. Let $\hat{\delta}^{vol}$ denote the coefficient on LATE in the voluntary IPS regression (Table 3, Column II), and $\hat{\delta}^{tot}$ the corresponding coefficient in the total-contributions regression (Column I). Although we can measure the increase in AES contributions for compliers through this equation,

we parametrically estimate it in column (III) by assigning zero to each individual's voluntary contributions. The magnitude of $\hat{\delta}^{AES}$ is 104.39₺. We define the crowding-out share of voluntary IPS by AES as, $\phi = \frac{-\hat{\delta}^{vol}}{\hat{\delta}^{AES}}$.

Numerically, these estimates indicate that roughly 21% of the additional AES contributions induced by the reform are offset by lower voluntary IPS contributions ($\phi \approx 0.21$ [0.17, 0.26]), while the remaining 79% represent net new retirement contributions. Equivalently, each 1₺ of AES contributions generated by the reform is associated with an increase of about 0.79₺ in total monthly average real retirement contributions and a reduction of about 0.21₺ in monthly average real voluntary IPS contributions.

These magnitudes place our estimates in a natural position within the broader literature on retirement saving policies. First, the fact that roughly 79% of AES-induced contributions translate into higher total retirement contribution aligns AES with the evidence on automatic and mandatory saving mechanisms, rather than with tax incentives that often generate little net new retirement contribution (e.g., Çitçi & Yanıkkaya, 2024). Chetty et al. (2014) find relatively low crowd-out (on the order of 15–20%) for Danish mandatory and employer pension contributions, while reforms to tax-favored voluntary accounts show much closer to full reallocation across assets. Our within-retirement crowd-out estimate of about 21% is similar to their benchmark for mandatory schemes, but far below the near-complete offset one might expect if AES merely displaced existing voluntary IPS contributions. Second, the pattern is consistent with the 401(k) and auto-enrolment literature (Madrian & Shea, 2001; Choi et al., 2002, 2004; Cribb & Emmerson, 2020), which documents large mechanical increases in plan contributions when defaults are changed, but leaves open how much of this is net of other saving. By observing both the automatic AES channel and the pre-existing voluntary channel in the same administrative system, our estimates make explicit that Türkiye's AES reform generates significant net additional retirement contribution, alongside meaningful but clearly incomplete rebalancing away from voluntary IPS.

4.3. Placebo tests

We conduct two placebo tests to eliminate the possibility that our findings are driven by random chance and to ensure they are not attributable to unobserved spatial-temporal effects or coincidental trends. As the first placebo test, we check whether the empirical model incorrectly identifies treatment effects in periods when the policy had not yet been implemented. For this purpose, we restrict our sample to the pre-AES period (2013-2016) and assign policy beginning in 2014 by retaining the actual treatment and control definitions. Then, we shift the placebo policy timing forward one year at a time in sequence and this procedure estimates a total of 3 different in-time placebo models. The placebo policy timing produces a non-staggered, pseudo-treatment effect in the absence of a real policy, therefore we operate these placebo models using a two-period

fixed effect specification and report the estimation results in table 3. As seen in table 4, in all specifications, insignificant placebo coefficients support the assumption of the baseline model by not producing a placebo treatment effect.

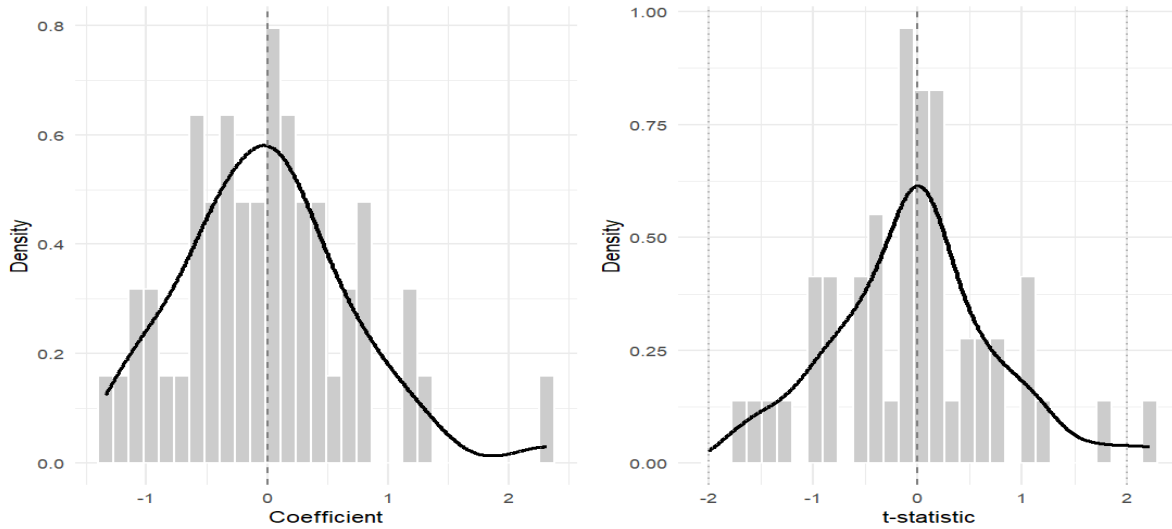
Table 4. In-time placebo models

	(I)	(II)	(III)
Treated * Placebo policy timing	2.283 (3.451)	-0.905 (4.247)	-1.734 (8.398)
Constant	327.5*** (0.988)	328.3*** (0.863)	328.3*** (0.858)
Placebo policy timing start year	2014	2015	2016
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	296,101	296,101	296,101
# of individual	85,562	85,563	85,564

*Note: This table reports on the first placebo test by employing two-period fixed effect Difference-in-Differences method in pre-AES period. The treatment and control groups are the same as in the original model. However, the assigned placebo policy timing in column I is 2014-2016 and pre-placebo period is 2013, in column II are 2015-2016 and pre-placebo period is 2013-2014, and finally in column III it is only 2016 and pre-placebo period is 2013-2015. The dependent variable is the monthly average real voluntary IPS contributions. Robust standard errors, clustered at the individual and workplace level, are in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.*

As a second placebo test, we check whether the empirical model incorrectly identifies treatment effects in groups where the policy had been implemented. While retaining the actual treatment timing, we restrict the sample to participants in the control group aged 45 and assign placebo treatments in decimal age increments of 0.01, sequentially. That is, in the first placebo model, participants aged [45.00-45.01) were the placebo treatment, while those aged [45.01-46.00) remained as the control group. We shift the assignment rule and iterate the placebo models a total of 100 times, by assigning the participants aged [45.00-45.99) as treated and participants aged [45.99-46.00) as control in the final specification. Although actual enrollment in AES is staggered, we start the practice of placebo treatment as of 2017, the first year the policy was implemented. This setting allows us to check for mechanistically spurious treatment effects even without actual treatment, providing a consistent construct since the control group's first event time ($k=0$) is 2017. Again, as with the first placebo, we employ the two-period fixed effect models. Figure 3 visualizes the coefficients obtained from the second placebo difference-in-differences model and the corresponding t-statistics, providing evidence that the placebo treatment effect is indistinguishable from zero.

Figure 3. Density of placebo treatment coefficients and corresponding t-statistics



Note: This figure illustrates the density of the coefficients and corresponding t-statistics of the placebo treatment effect in 100 TWFE models assigned to control group participants aged [44-45] with 0.01 age increments, taking 2017 as the policy timing. Source: Authors' calculations.

4.4. Heterogeneity analysis

At the heart of automatic enrollment policies lies the goal of encouraging low- and middle-income individuals with relatively low saving capacity to save and increase their participation in the pension system by changing their default options. For individuals without saving habits, participation in a pension system may have significant potential impact on individual welfare. Early evidence suggests that AE policies most commonly affect low income and low educated individuals (Madrian & Shea 2001; Choi et al. 2004). However, in countries like Türkiye where there is a high opt-out rate, historically low household savings, limited participation in the pension system, and savings are directed towards predominantly alternative investment instruments rather than financial markets, it is unclear to what extent such behavioral policy mechanisms achieve their intended success.

Approximately 61.25% of new participants enrolled in AES (including those who did not have a voluntary retirement plan beforehand) have less than a high school education, and correspondingly, approximately 62.50% have an income below the gross minimum wage. Furthermore, approximately 65% of those who remain enrolled share the same demographic characteristics in terms of both education level and income group, consistent with previous studies.⁸ Therefore, compared to the counterfactual, these participants achieved the greatest

⁸ The descriptive statistics reported here derived from unrestricted full dataset before implementing the sample restrictions used in the baseline analysis.

positive retirement savings gains relatively, amounting to 3% of their gross wages. However, it remains an open question which participants with specific demographic characteristics in the analysis sample—those who have a voluntary IPS contract and are financially conscious about saving—responded to AES and to what extent.

To shed light on this issue, we are taking our empirical model a step further by analyzing education level-specific heterogeneous effects. While AES enrollment is staggered in terms of company size and sector, participation in each stage includes all employees in a company, thus including no education and wage related heterogeneous effects. To reveal these effects, we first assign each participant to separate cohorts, referencing the education levels and income groups in Table 1. Next, we extend our analysis by incorporating interactions of cohort x event time x treated and estimate cohort-specific LATEs using a cohort-specific event-time fuzzy DiD approach. Thereby, we examine how the interactions of education level and income group alter the treatment effect. Before revealing the estimation results, once again, diagnostic test confirms that the instrumental variable strongly predicts the endogenous treatment status and verifies that the use of the IV estimation strategy is validated for both heterogeneity analysis.

Table 5. Cohort-specific LATE by education levels

	(I)	(II)	(III)
Dependent variable:	Total Retirement Contributions	Voluntary IPS Contributions	AES Contributions
Less than High school	28.259*** (5.368)	-53.636*** (5.203)	81.894*** (1.261)
Highschool – Less than College	45.633*** (4.006)	-35.495*** (3.896)	81.128*** (0.857)
College or Higher	115.031*** (1.776)	-10.027*** (1.732)	125.057*** (0.36)
Constant	279.5*** (1.039)	280.1*** (1.037)	-0.577*** (0.0697)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	727,453	727,453	727,453
# of Individuals	101,362	101,362	101,362
Diagnostic tests			
First stage F-stat		318.345	
p-values		(0.000)	
Endogeneity test: chi2(12)	1,563	1,559	-
p-values	(0.000)	(0.000)	-

*Note: This table presents local average treatment effect estimates weighted by observations by education level. In column (I), the dependent variable is combined of both monthly average real voluntary IPS and AES contributions, while in columns (II) and (III) the dependent variables are only monthly average real voluntary IPS contributions and only monthly average real AES contributions, respectively. The last rows of the table present the diagnostic tests for our two-stage model. We report a single F-stat because the same first stage is run across all specifications. Contributions are in Turkish Lira monthly basis and deflated to year-end 2017 Türkiye's Consumer Price Index (CPI). Standard errors, clustered at the individual and workplace level are in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.*

Table 5 presents heterogeneous effects of AES across education levels on participant's contribution responses. Estimated LATE is statistically significant across all specifications and all education level cohorts. As education level increases, an accelerating increase in total

contributions and accelerating decrease in voluntary IPS contributions indicates a strong relationship between education level and response to AES. In addition, our results for AES contributions (column III) show that AES contributions at a fixed salary percentage of 3% do not differ significantly between less than high school and high school – less than college education levels. It may be explained, in particular, by the participants without a university degree tend to have similar professions and therefore similar salaries. Consistent with this, participants with college degrees pay significantly higher AES contributions than both of these cohorts, reflecting their higher wages.

The calculated within-retirement crowd-out rate is highest in less than high school at 65.5%, followed by high school – less than college at 43.7%, and college or higher at 8%. This finding shows that, compared to new savers, low-educated participants achieve the least retirement savings gains. Higher education levels are positively associated with financial knowledge and literacy, forward-looking financial planning (Lusardi & Mitchell, 2007a, 2007b, 2011), and taking advantage of savings opportunities (Gelber, 2011). As a reflection of these and many other channels, it appears that more highly educated participants are less likely to substitute for voluntary IPS contributions and instead tend to preserve their increased total retirement contributions. In addition, considering that lower education levels are associated with relatively low wages, it is quite likely that a 3% additional contribution at lower education levels would exceed the share allocated to retirement contributions from the budget. It could also be argued that these participants, being financially conscious about saving through voluntary IPS plans, have a stronger incentive to maintain their targeted retirement contribution rate by shifting their voluntary contributions. Thus, the within-retirement crowding-out rate decreases as the education level increases due to the income effect. If this is the case, the same pattern should be expected to arise in income groups. Table 6 shows the heterogeneous effects of income groups.

Table 6. Cohort-specific LATE by income groups

	(I)	(II)	(III)
Dependent variable:	Total Retirement Contributions	Voluntary IPS Contributions	AES Contributions
Net Income $\leq$ GMW	68.022*** (5.354)	-36.812*** (5.205)	104.834*** (1.228)
GMW < Net Income $\leq$ GMW x 3	61.914*** (4.329)	-32.831*** (4.225)	94.745*** (0.85)
Net Income > GMW x 3	104.063*** (4.364)	-37.891*** (4.247)	141.954*** (0.869)
Constant	281.1*** (1.043)	281.6*** (1.040)	-0.527*** (0.0625)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	694,342	694,342	694,342
# of Individuals	101,362	101,362	101,362
Diagnostic tests			
First stage F-stat		175.100	
p-values		(0.000)	
Endogeneity test: $\chi^2(12)$	596	593	-
p-values	(0.000)	(0.000)	-

*Note: This table presents local average treatment effect estimates weighted by observations by net income deciles. In column (I), the dependent variable is combined of both monthly average real voluntary IPS and AES contributions, while in columns (II) and (III) the dependent variables are only monthly average real voluntary IPS contributions and only monthly average real AES contributions, respectively. The last rows of the table present the diagnostic tests for our two-stage model. We report a single F-stat because the same first stage is run across all specifications. Contributions are in Turkish Lira monthly basis and deflated to year-end 2017 Türkiye's Consumer Price Index (CPI). Standard errors, clustered at the individual and workplace level are in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.*

As shown in table 6, Aggregate LATE estimates are statistically significant for all income groups and specifications. Higher income groups, as well as higher education levels, are associated with higher AES contributions. However, it is worth noting that the income is based on individuals' self-reports and does not fully capture the 3% fixed contribution as it includes income components other than wages. Participants with net incomes lower than GMW pay an average of 10₺ more in not economically meaningful smaller contributions compared to participants with net incomes higher than GMW but less than three times that amount. However, participants with incomes more than three times higher than GMW pay significantly higher AES contributions compared to other income groups, indicating higher wages (column III).

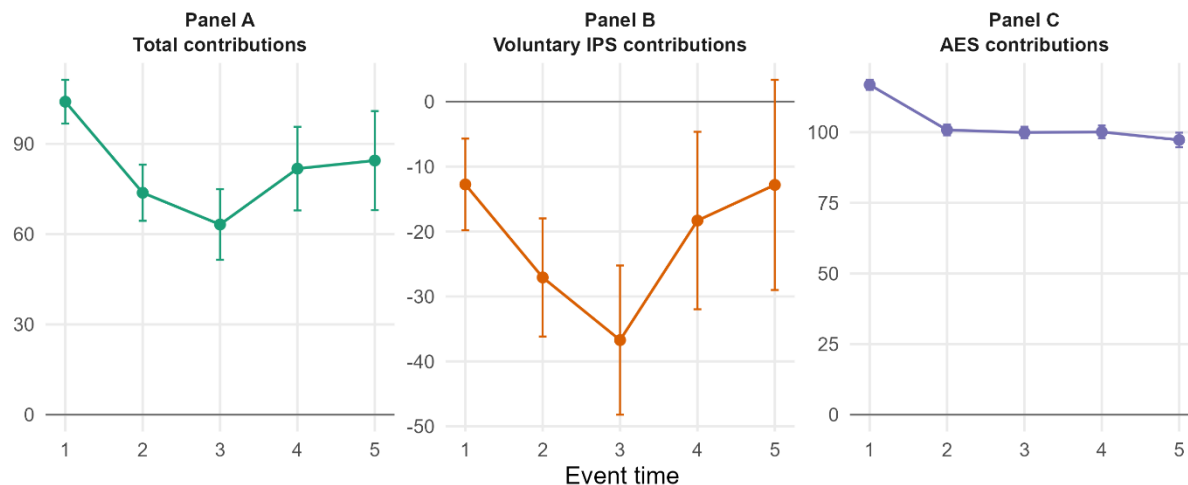
The within-retirement crowd-out rate is estimated to be approximately 35.1% for participants with net incomes below GMW, approximately 34.7% for participants with net incomes above GMW but less than three times GMW, and approximately 26.7% for those with net incomes more than three times GMW. Compared to new savers, the gains appear to be larger for high-income participants rather than for low-income participants. Furthermore, in parallel with education level results, there is evidence that higher income groups generate new retirement contributions rather than offsetting voluntary IPS contributions with AES contributions. In this context, our findings show that among participants who held a voluntary contract prior to the policy implementation, there is significant heterogeneity in terms of both education level and income group in their response to AES policy. Evidence from income heterogeneities support educational heterogeneities, and overall, as education and income increase, AES contributions are offset less; instead, they enter the retirement account balances as new retirement contributions.

Standard economic theory predicts that in an environment with low transaction costs, AES contributions are offset by a reduction in other savings accounts. In our sample, participants most likely to exhibit this type of behavior were those with low income and education. Friedberg et al. (2024) provides evidence that there may be full crowd-out in the low-income group but also confirms this for a minority of high-income participants. It is likely that participants in our sample exhibit high crowd-out given that they have exceeded their predetermined optimal retirement savings rate due to liquidity constraints. Jensen et al. (2025) show that mandatory retirement savings may not reduce voluntary savings, and therefore there is no offsetting. However, the presence of positive contribution balances in the voluntary IPS accounts allow them to reduce. High-education and high-income participants may exhibit a lower level of crowd-out due to two reasons. Firstly, the contributions in voluntary accounts are well below their optimal retirement saving rate, and AES contributions bring them closer to that rate. Secondly, their passive behavior (Chetty et al., 2014). Growing body of evidence suggest that high-income and highly educated participants are less likely to exhibit passive behavior, and crowd-out is concentrated primarily among low-income passive participants (Madrian & Shea, 2001; Choi et al., 2002, 2004; Benartzi & Thaler, 2007; Beshears et al., 2009). In contrast, a more recent study by Friedberg et al. (2024) argues that high education and income do not largely forestall passive behavior. Considering all this evidence, our findings from heterogeneity analysis, generally differing from those in previous studies, document that individuals with high education and income are less likely to respond to automatic enrollment by reducing their voluntary IPS contributions.

4.5. Dynamic persistence of automatic enrollment effects

A key question is whether the medium- and long-term effects of automatic enrollment persist. While it is known to increase retirement savings in the short term (Madrian & Shea, 2001; Choi et al. 2002, 2004; Beshears et al., 2009), evidence regarding its medium- and long-term effects is quite limited. A few significant studies document that contributions to automatic enrollment accounts converge to contributions to voluntary accounts in the medium term (Thaler & Benartzi, 2004; Choi et al., 2004). However, Choi et al. (2024) point out that a large percentage of employees withdraw their retirement savings upon leaving employment, and that many employees do not prefer automatic increases. Choukhmane (2025) confirms previous findings on the short-term effects of AE and predicts that the treatment effect will attenuate over a 3-year horizon. Although we cannot observe the long-term effects of AE, our study provides new evidence regarding its medium-term effects over a period of 4 years and 7 months. However, it should be noted that only those who enrolled in 2017 remained for 4 years and 7 months and represent a significant portion, approximately 72%, of the treatment group. Figure 4 shows the results of estimating the average monthly contributions of compliers of AE over the years following treatment.

Figure 4. Dynamic event time specific LATEs



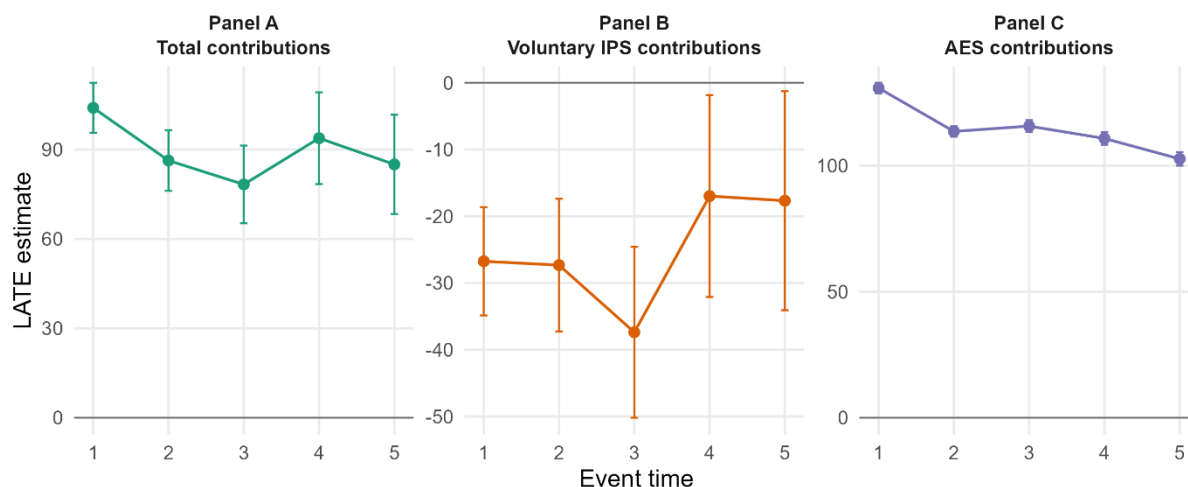
This figure illustrates the event-time (k) specific LATEs in the baseline model. $k = 5$ is not a full year, it represents the end of July 2021, and this value is only available for those who enrolled in 2017. $k = 4$ is available for both those who enrolled in 2017 and 2018. $k \leq 3$ is available for all participants, including those who enrolled in 2019. Source: Authors' calculations.

Panel A shows a clear U-shaped pattern in the effect of AES on total retirement contributions. The positive impact is strongest in the first year, declines over the next two years to a low point around year three, and then recovers in years four and five. Panel B displays the opposite pattern for voluntary IPS contributions. Crowd-out intensifies through the first three years, reaches its peak in the third year, and eases afterward and by the final horizon the estimate is no longer statistically different from zero. Panel C indicates that AES contributions fall modestly after the first year and then remain roughly stable. A mild downward drift in real contributions paid is consistent with the absence of auto-escalation in a high-inflation setting (Choi et al., 2024).

Taken as a whole, the panels point to a non-monotonic medium-term adjustment rather than continuous erosion of the initial gain. In the first three years the rising offset from voluntary IPS contributions gradually absorbs the early increase in total contributions, matching the gradual crowd-out that Choukhmane (2025) documents over a similar window. However, after year three the pattern appears to reverse: voluntary IPS crowd-out weakens while AES contributions stay broadly steady, allowing the net effect on total contributions to recover. Two features of the data, however, call for caution in reading this reversal. First, the fourth- and fifth-year estimates rest only on the 2018 and 2017 enrollment cohorts. The 2017 cohort consists of the largest firms and the public sector, so the later recovery may partly reflect a shift in sample composition toward higher-wage participants rather than a genuine within-person rebound in voluntary contributions. Second, the standard error at the final horizon is more than twice as large as at enrollment and the fifth-year null is therefore as consistent with a loss of statistical power as with true convergence. We address the first of these concerns directly below.

To assess whether the medium-term recovery stems directly from participants' own tendencies or from unobservable differences across enrollment cohorts, we re-estimate the dynamic analysis for 2017 entrants only. By restricting the sample to these participants and observing them for 4 years and 7 months, we eliminate effects from opt-in or opt-out of different enrollment cohorts. Figure 5 illustrates the results.

Figure 5. Dynamic event time specific LATEs (2017 Entrants)



Note: This figure illustrates the event-time (k) specific LATEs in the baseline model for 2017 entrants. Source: Authors' calculations.

The non-monotonic pattern persists. In Figure 5, panel B shows that voluntary IPS contributions reach 37€ in the third year and recover in the fourth and fifth years, thus following the U-shape shown in Figure 4. Therefore, the recovery in the fifth year is not a result of opt-in or opt-out of other cohorts; this trend is an adjustment within participants. Again, the U-shape is maintained in total contributions in Panel A, while in Panel C, AES contributions decrease by a fifth in real terms over time. This reflects the absence of auto-escalation in a high-inflation environment, rather than the observed change within participants.

When the sample is limited to just one enrollment cohort, the confidence intervals in the fourth and fifth years widen and include zero, and the recovery is more pronounced. Within retirement crowd-out rate in the 2017 entrants is greater than in other participants in the sample. This result can be explained by the fact that employees in large-scale firms and the public sector have higher voluntary balances and that these balances have more room for displacement. Overall, the single-enrollment cohort evidence is a result of how participants adjust their savings over time, rather than the cohort structure of the sample.

5. Conclusion

This study provides evidence for the impact of the Automatic Enrollment System, introduced in Türkiye in 2017, on voluntary individual pension contributions. The AES in which employees under the age of 45 automatically enrolled in a retirement plan as the default option with the option to opt-out, represented a second retirement plan for employees who held voluntary retirement plans prior to policy. Using the age of 45 eligibility cutoff, allowed opt-out options and variation in the timing AES enrollment we implement a event-time fuzzy DiD design with imperfect treatment compliance that compares cohorts just above and below the cutoff. The design allows us to separate the reform's effect on pre-existing voluntary retirement contributions from its effect on overall contributions into retirement accounts.

We document two robust patterns. First, AES induces a statistically and economically meaningful decline in voluntary IPS contributions: part of the retirement contribution that would have been channeled voluntarily into the system is re-routed through the automatic channel. Second, despite this crowding-out, total contributions to retirement accounts, combining voluntary retirement and AE flows, increase markedly after the reform. The automatic channel therefore does not simply re-label existing retirement contributions; it raises the level of retirement contributions on net. Automatic enrollment reshapes the saving profile of those already engaged with the system at least as much as it brings new participants into it.

Furthermore, we reveal the heterogeneities of participants' responses to AES in terms of education level and income groups. Education and income are two key demographic characteristics that have emerged since early studies as proxies for passive behavior in passive retirement savings decisions. While numerous studies have shown that low-educated and low-income participants exhibit passive behaviors, not adjusting the default contribution rate and sharply increasing retirement contributions, we present evidence that argues the opposite. We demonstrate that relatively high crowd-out emerges at both low education and low-income groups. Previous evidence suggests that participants adhere to the default contribution rate in the absence of other savings balances that could be reduced, but the available voluntary IPS savings plans of the participants in our sample incentivize them to offset AES contributions. The most plausible explanation is that a 3% bonus percentage would impose a liquidity constraint for low-educated and low-income participants, leading them to reduce their voluntary IPS contributions. Finally, although AE substitutes voluntary IPS contributions in the initial years, the crowding-out effect weakens and total retirement contributions recover in the medium term. Therefore, AE not only increases total retirement contributions in the short term, creating a jump effect, but also ensures that this increase is sustained in the medium term.

These results speak to a part of the retirement saving literature where hard evidence is still scarce. Only a small number of studies can jointly track retirement-account flows in order to measure net

retirement contribution and within-retirement crowd-out. Most work on automatic enrollment instead focuses on participation and balances in a single plan, in high-income settings where mandatory public or occupational schemes already cover most employees and where the scope for additional voluntary IPS contribution is relatively limited. By contrast, Türkiye entered the AES reform with a large, established voluntary defined-contribution pillar and with IPS already playing a meaningful role in household balance sheets, in a macro environment with elevated inflation and return volatility. In this setting, our findings demonstrate how contributions are reshuffled and total retirement contributions change when automatic enrollment policies are implemented in the presence of voluntary pension plans.

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