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Crowding-out in savings decisions, portfolio default adoption and home ownership: evidence from the Chilean retirement system

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Abstract
This paper studies crowd-out effects across choices regarding different sources of investment and savings in the Chilean pension system (e.g., voluntary savings within and outside the retirement system, housing status, and default portfolio adoption). Because preferences over choice sets are unobserved and it is expected that individual unobserved characteristics may be correlated across decisions, I jointly estimate a dynamic reduced-form life cycle model of wealth accumulation. Simulation results indicate no short- or long-run crowd-out effects across voluntary savings accounts within and outside the retirement system. There is evidence that in the short run, there is crowding-out between mandatory savings and other forms of investments, such as home ownership or savings in the financial-banking sector. Results also show that in the long run, individuals treat home ownership and participation in voluntary retirement programs as substitute goods. Finally, the long-run effects of participating in voluntary savings programs are important in increasing active participation in portfolio decisions.

Keywords Retirement income policy · Default behavior · Crowd-out effect

JEL Classification J26 · J46 · C33 · C14

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1 Introduction

This paper studies crowding-out across savings, home ownership, and retirement investment portfolio choices in the Chilean defined contribution (DC) retirement system.[1,2] The literature has extensively demonstrated the benefits of default rules, showing that tehy increase participation in retirement savings plans (e.g., Madrian and Shea (2001), Thaler and Benartzi (2004), Gelber (2011), Chetty et al. (2014) and Thaler (2016)).

However, it is not clear whether policies for increasing retirement savings increase total savings or just savings within retirement systems (Chetty et al. 2014).[3] It is expected that individuals behave differently regarding different savings choices. For example, retirement wealth is not liquid, and the rate of returns over retirement savings are different than that over other savings (Attanasio and Brugiavini 2003). The same can occur with other investments. Individuals may be willing to quit on retirement savings to focus on down or mortgage payments. Previous evidence shows that each dollar of pension wealth is associated with a 37 to 50 cent decline in nonpension wealth, although most of the effect is concentrated in the upper tail of the distribution (Blau 2016; Engelhardt and Kumar 2011). Evidence shows that crowd-out results are very sensitive to the empirical specifications (Blau 2016).

One of the difficulties in studying crowding-out is that preferences are unobserved (Beshears and Choi 2012). Workers may have different unobserved preferences for savings, which might be correlated with other choices (Gelber 2011).[4] For example, an individual could select into the labor market and commit to contributing to her retirement account while holding voluntary savings because of high unobserved tastes for savings. Many papers in the literature use reduced-form approaches that do not consider the non-linearity of the individual's maximization problem or made oversimplified assumptions (Blau 2016; Card and Ransom 2011; Engelhardt and Kumar 2007).

There are other limitations that have affected the generalization of results. Many studies rely on policy reforms for identification where counterfactuals for alternative reforms are not observed (Blau 2016). Others, consider non-representative experiments (e.g., Madrian and Shea (2001), Choi et al. (2004), Thaler and Benartzi (2004) and Carroll et al. (2009)). Many articles consider only the immediate impact of the reforms. Finally, papers that use survey data typically have selection bias and measurement error (Engelhardt and Kumar 2007). Some exceptions are Chetty et al. (2014), who use a 41 million observation administrative dataset from the Danish retirement system, and Engelhardt and Kumar (2007), who use survey data merged with administrative records while controlling for selection using non-standard econometric approaches.

[1] Crowd-out effects are shifts in savings decisions across accounts. For instance, increases in participation in voluntary savings accounts might result in a reduction in savings outside the retirement system.

[2] In DC systems, individuals contribute a defined share of their pretax earnings. The pension an individual earns depends on her accumulated savings.

[3] Total savings include mandatory and voluntary savings within the retirement system and savings outside the retirement system.

[4] Through the paper, I refer to this effect as correlated unobserved heterogeneity.

To consider these issues, I jointly estimate a multiple equation, reduced-form dynamic model. The equations capture simultaneous decisions such as labor market participation, formality and contribution status, default adoption in investment portfolios, participation in voluntary savings within and outside the retirement system, and housing asset choices. All equations are correlated through a permanent and a time-varying individual-level unobserved heterogeneity component. Unobserved heterogeneity captures differences in preferences, risk tolerance, tastes, etc. The distribution of unobserved characteristics is jointly estimated with the coefficients of the model using semi-parametric full information likelihood methods.[5] The approach allows to address several sources of estimation bias: selection, endogeneity, and measurement error.[6]

Unbiased estimates arise from many corrections. First, because non-random selection into behaviors is jointly modeled. This correction is achieved by considering several choices, all forming the estimated set of equations. Second, because unobserved heterogeneity that is correlated across decisions and with endogenous determinants of choices is flexibly modeled. Thus, estimated reduced-form parameters are not a function of biases coming from the omission of relevant variables. Third, the estimated parameters are cleaned of classical measurement error bias. This source of bias is accounted by modeling the error term of variables that might be reported with error (e.g., portfolio adoption, savings decisions). Measurement error bias is also reduced by using administrative records on accumulated wealth.[7] The estimation also allows me to incorporate the non-linearities that come from the individual's decision-making process without making any assumptions about preferences and expectation processes.

Since I model the decision-making process over time, I analyze crowding-out of simulated policies rather than depending on observed policy reforms. I use the estimates of the model to simulate contemporaneous (short-run) and life-cycle (long-run) effects of increasing participation in voluntary retirement accounts, increasing housing assets, and extending compulsory participation on retirement programs to self-employed workers.

The paper is built upon Parada-Contzen (2019). Specific differences are: (1) I disaggregate savings based on their liquidity. (2) I study housing choices to incorporate other sources of wealth. (3) An important focus is put on the employment, formality, and contribution status so that policy experiments concerning them can be simulated. (4) I consider active investment decisions, meaning that I classify individuals according to their decision to be on the default or to opt-out. (5) I do not consider changes in financial risks faced by individuals, thus, I am able to estimate a simpler model.

[5] A complete description of the estimation method is presented in Section 4.

[6] Selection bias results from participation behaviors that may be correlated with other modeled behaviors (e.g., optional savings and earnings). Endogeneity bias results from behaviors that are jointly chosen at period t and that depend on previous behaviors (e.g., savings decisions depend on accumulated wealth, which depends on previous decisions). Measurement error is present in self-reported survey measures (e.g., self-reported voluntary savings decisions).

[7] Details on bias correction using semi-parametric full-information methods in Gilleskie et al. (2017).

I use the first four waves (2002–2009) of the Chilean Survey of Social Protection (EPS) merged with administrative records of the Chilean Bureau of Pensions. The EPS is a validated survey used for retirement policies (Behrman et al. 2011; Joubert 2015). Using this dataset has several advantages: (1) the Chilean model has served as a prototype for the implementation of DC systems in several countries.[8] (2) In the Chilean model, there are two levels of default. On the one hand, there are no participation conditions once the individual has selected into the labor market. On the other hand, once enrolled, workers can choose their own investment portfolio or follow a default scheme provided by the system (opt-out default). (3) It includes rich individual data and administrative records on retirement wealth. Kristjanpoller and Olson (2015) use a cross-section of the EPS to study default adoption. Differently, I consider a dynamic setting and focus on a larger number of choices.

The remainder of the paper is as follows. The empirical model and estimation strategy are presented in Section 2. Details about the data are presented in Section 3. Results are presented in Section 5, and finally, Section 6 concludes.

2 Empirical model

2.1 Institutional background

In the Chilean system, formal workers are required to contribute 10% of their pre-tax earnings. Any individual eligible to contribute to the system at least once, is enrolled. Contributions are automatically deducted from the worker's paycheck and transferred to her mandatory retirement account. I refer to retirement wealth (A_{it}) to denote accumulated assets in the mandatory contribution account. Informal employees, self-employed workers and the non-employed may voluntary contribute or not contribute at all. Contribution choices are denoted by c_{it}. Any individual may hold voluntary savings within the retirement system regardless of her employment and contribution status. Participation choices in retirement voluntary programs are denoted by s^r_{it}.

Enrollees may select one or two voluntary retirement accounts out of five available accounts to invest retirement savings. These accounts are offered by the system, and vary in their level of financial risk. The riskiest fund is Account A, which invests 40–80% in equities, whereas the range for Account B is 25–60%, that of Account C is 15–40%, that of Account D is 5–20%, and that of Account E is less than 5%.

If an individual does not explicitly choose an account, she is defaulted into a predetermined investing scheme according to age and gender. In the default, individuals under the age of 35 are assigned to Account B; women between the ages of 35 and 50 years old are assigned to Account C, and those aged 50+ years old are assigned to Account D. Men between the ages of 35 and 55 are assigned to Account C,

8 With the support of the World Bank, the Chilean experience became an archetype for the implementation of DC systems in Latin America, Europe, and Asia (Orszag and Stiglitz 2001).

whereas those aged 55+ years are assigned to Account D.[9] In the model, portfolio default status is denoted by d_{it}. Note that an individual can choose her default accounts, which means she is not defaulted into that account but she still is observed to be in the default.[10]

2.2 Timing and notation

Individual i begins period t with an information set Ω_t. The individual observes a wage offer w_{it}^* (unobserved for the econometrician) drawn from the wage distribution and jointly decides her employment status (e_{it}), contribution status (c_{it}) and portfolio status (d_{it}). Additionally, the individual decides her optional savings status within (s_{it}^r) and outside the retirement system (s_{it}^o), and housing category (h_{it}): an owner with no loan or an owner but paying, renting, or leasing from a relative. These decisions are the endogenous choice variables that are jointly estimated.

Informality is defined through pension coverage (Joubert 2015). A worker can be formal (covered by the pension system) or informal (uncovered by the pension system). Formal workers are dependent employees who sign a contract, while informal workers might be informal employees (salaried workers with no contract) or self-employed (at the survey was run, self-employed workers were not required to contribute).

Because these decisions are jointly made, they are all a function of the same observable characteristics (Ω_{it}). The information set contain stock variables up to period $t-1$ and lagged decisions. Lagged decisions include previous contribution status ($c_{i,t-1}$), default path adoption ($d_{i,t-1}$), housing status ($h_{i,t-1}$), and saving choices ($s_{i,t-1}^r$ and $s_{i,t-1}^o$). Stock variables include accumulated assets ($A_{i,t-1}$), accumulated work experience ($E_{i,t-1}$), marriage history ($M_{i,t-1}$) and history of children ($N_{i,t-1}$). These variables are endogenous control variables, also referred to as predetermined. Endogenous choice variables are different from the endogenous control variables. Endogenous choices are behaviors chosen at period t, while endogenous control variables are lagged decisions and stock variables that are not decisions itself but are affected by lagged choices (e.g, work experience is affected by previous employment choices).

The information set also includes a vector of exogenous individual characteristics (X_{it}, such as age, gender, and education) and a vector of exogenous market-level characteristics (Z_{it}), such as unemployment rates, interests rates, and prices from related markets, among others. $\widetilde{\Omega}_{it}$ is the set of endogenous control variables in the information set that also behave as explanatory variables, and Ω_{it} refers to $\{\widetilde{\Omega}_{it}, X_{it}, Z_{it}\}$.

After the decisions are made, the econometrician observes the wage draw w_{it} if the individual is working. The individual observes the realization of two endogenous characteristics: her marital status (m_{it}) and number of children (n_{it}), which are a function of choices in period t, $\widetilde{\Omega}_{it}$, X_{it}, and supply-side market-level characteristics (Z_t^M for the marriage market and Z_t^N for the children market).

9 A detailed description of the system can be found in Berstein et al. (2010).

10 This case is treated as a separate category.

The individual observes the realization of financial returns and updates her information set. The individual moves to the next period with information set $\Omega_{i,t+1}$. The timing of the model is presented in Fig. 1 in Appendix A.

Endogenous variables in t are predetermined in $t+1$, serving as instruments. There are other sources of identification (see Section 4.4). Market-level characteristics capture relevant factors that might affect decisions. For example, deposits per capita at a regional level. An area with fewer deposits might pay higher interest rates. A complete model should include both, individual and market characteristics to describe the problem appropriately. Market-level characteristics serve as the typical exclusion restrictions.

2.3 Estimable model

2.3.1 Wages

The wage equation follows the specification proposed by Mincer (1974) and includes demographic characteristics (X_{it}), endogenous predetermined variables, such as work experience (E_{it}), and job characteristics. Productivity may also vary among individuals with the same human capital characteristics.[11] Since productivity is unobserved, I assume that work productivity also depends on family characteristics, such as the number of children and marriage duration. I also include demand-side factors (Z^E_{it}) at a regional level. Finally, I include permanent (μ^1_i) and time-varying unobserved wage determinants (ν^1_{it}).

$$ln\ w_{it} = w(e_{it}, \tilde{\Omega}_{it}, X_{it}, Z^E_{it}, \mu^1_i, \nu^1_{it}) \tag{1}$$

2.3.2 Endogenous choice variables

Recall that upon observing a wage offer w^*_{it}, individuals make choices. These wage offers are unobserved to the econometrician: she observes wages if the individual decides to be employed, w_{it}. Thus, if there are individual unobserved characteristics that simultaneously affect selection into employment, contribution status and wages, there is a risk of potential selection bias. To account for this source of bias, I jointly estimate employment choices with contribution status and wages in period t by allowing for correlation in the error terms that affect each equation.

If unobserved characteristics are correlated across savings choices, default status, and home ownership, even after correcting for selection into employment, potential biases arise. It is expected that saving choices, portfolio choices, and home ownership are endogenous to earnings. Higher earnings may generate higher availability of resources allocated to savings and investments. Similarly, higher earning levels generate higher levels of retirement wealth, which might affect portfolio default adoption.

[11] See Gilleskie et al. (2017) for further details.

Consequently, all decisions that impact wealth accumulation are jointly modeled and estimated with wages. I refer to these variables by endogenous choice variables (a subset of the dependent variables of the model). Because behaviors are jointly chosen, they are all specified as a function of the variables in the information set Ω_{it}. Behaviors are also specified as a function of equation-specific permanent and time-varying unobserved characteristics. The distributions of unobserved characteristics are jointly estimated with the parameters of the model. Demand equations representing choices are presented from eqs (2) to (7).

$$ln\left[\frac{P(e_{it}=j)}{P(e_{it}=0)}\right] = e^j(\tilde{\Omega}_{it}, X_{it}, Z_{it}, \mu_i^2, \nu_{it}^2); \quad j=\{1,2\} \tag{2}$$

$$ln\left[\frac{P(c_{it}=j)}{P(c_{it}=0)}\right] = c^j(\tilde{\Omega}_{it}, X_{it}, Z_{it}, \mu_i^3, \nu_{it}^3); \quad j=\{1,2\} \tag{3}$$

$$ln\left[\frac{P(d_{it}=j)}{P(d_{it}=0)}\right] = d^j(\tilde{\Omega}_{it}, X_{it}, Z_{it}, \mu_i^4, \nu_{it}^4); \quad j=\{1,2\} \tag{4}$$

$$ln\left[\frac{P(s_{it}^r=1)}{P(s_{it}^r=0)}\right] = s^r(\tilde{\Omega}_{it}, X_{it}, Z_{it}, \mu_i^5, \nu_{it}^5) \tag{5}$$

$$ln\left[\frac{P(s_{it}^o=1)}{P(s_{it}^o=0)}\right] = s^o(\tilde{\Omega}_{it}, X_{it}, Z_{it}, \mu_i^6, \nu_{it}^6) \tag{6}$$

$$ln\left[\frac{P(h_{it}=j)}{P(h_{it}=0)}\right] = h^j(\tilde{\Omega}_{it}, X_{it}, Z_{it}, \mu_i^7, \nu_{it}^7); \quad j=\{1,2,3\} \tag{7}$$

where $\tilde{\Omega}_t = \{c_{i,t-1}, d_{i,t-1}, s_{i,t-1}^r, s_{i,t-1}^o, h_{i,t-1}, E_{i,t-1}, A_{i,t-1}, M_{i,t-1}, N_{i,t-1}\}$. Vector X_{it} includes individual characteristics. Vector Z_t includes exogenous market-level characteristics at a regional level from the labor market (such as the unemployment rate, total employment, local minimum wage), the credit market (share over national deposits and credits, deposits and credits per capita, and banks per capita), the marriage market (gender ratio, marriages per capita) and the family market (college tuition). The equation-specific components μ_i and ν_{it} represent non-linear unobserved heterogeneity that is correlated across equations (from now on, correlated unobserved heterogeneity).

To model this correlation, total unobserved heterogeneity is decomposed into three parts. First, there is an idiosyncratic shock that is independent and identically distributed and is assumed to be a type I Extreme Value distributed error (ϵ_{it}), giving the functional form to each choice equation. Second, there is a permanent component representing permanent unobserved heterogeneity (μ_i). Third, there is a time-varying component representing time-varying unobserved heterogeneity (ν_{it}).

Per-period alternatives are constructed based on the survey questions and are the following: $e_{it} = \{0, 1, 2\}$, indicating formal workers, self-employed or informal workers, and non-employed workers, respectively; $c_{it} = \{0, 1, 2\}$, indicating non-contributors, mandatory contributors, and voluntary contributors, respectively; $d_{it} = \{0, 1, 2\}$, indicating defaulted into the system's default scheme, opting into the default scheme, and opting out of the default, respectively; $s_{it}^r = \{0, 1\}$, indicating no or some optional savings within the retirement system; $s_{it}^{o} = \{0, 1\}$, indicating no or some other savings outside the retirement system; $h_{it} = \{0, 1, 2, 3\}$, indicating a home owner with no loans and a home owner but paying, renting, or leasing from a relative, respectively.

Once choices are made, wealth accumulates according to exogenous market returns R_{it}, which is portfolio-specific, and to new contributions. Thus, wealth at the end of t is updated following $A_{it} = A_{i,t-1} \times R_{it}(d_{it}) + 0.1w_{it}$.

2.3.3 Endogenous individual characteristics

While I do not explicitly model changes in marital status and the number of children as choices, I endogenize them into the problem by allowing realizations in period t to depend on current choices (see Fig. 1 for the timing in Appendix A).[12] Therefore, the transitioning of family outcomes are not exogenous processes. Because it is expected that unobserved characteristic affect both choices and family outcomes (e.g., an individual may jointly decide her employment status and whether to have children in that period), I allow for correlation between family outcomes and the rest of the equations in the model through an equation-specific permanent and time-varying unobserved component.

The probability of being married ($m_{it} = 1$) relative to not being married ($m_{it} = 0$) is given in eq. (8) and depends on period t choices, such as employment status (e_{it}), predetermined state variables ($\tilde{\Omega}_{it}$), and exogenous individual characteristics (X_{it}). Although not modeled explicitly, I assume that there is a marriage market such that supply-side factors (Z_{it}^{M}) also impact marriage probability. As before, there is a permanent (μ_i) and time-varying (ν_{it}) correlated error term and an idiosyncratic shock (ε_{it}) assumed to be type-I extreme value distributed.

$$ln\left[\frac{P(m_{it} = 1)}{P(m_{it} = 0)}\right] = m(e_{it}, \tilde{\Omega}_{it}, X_{it}, Z_{it}^{M}, \mu_i^{8}, \nu_{it}^{8}) \tag{8}$$

Children in the household may increase or decrease over time (due to pregnancies, age of the child, changes in marital status, mortality, etc). These transitions depend on that period's employment decisions (e_{it}), predetermined endogenous choices ($\tilde{\Omega}_{it}$), individual exogenous characteristics (X_{it}), supply-side factors specific to the child market (Z_{it}^{N}), such as education prices, permanent (μ_i) and time-varying (ν_{it}) correlated unobserved heterogeneity, and a random, type-I extreme value distributed shock (ε_{it}^{N}). The probability of increasing the number of children ($n_{it} = 1$) and of decreasing the number of children ($n_{it} = -1$) in period t relative to no change ($n_{it} = 0$) is given by:

$$ln\left[\frac{P(n_{it} = j)}{P(n_{it} = 0)}\right] = n^{j}(e_{it}, \tilde{\Omega}_{it}, X_{it}, Z_{it}^{N}, \mu_i^{9}, \nu_{it}^{9}); \quad j = \{-1, 1\} \tag{9}$$

[12] To endogenize an individual characteristics means to model these characteristics as a dependent variable of the system of equation so that the evolution of the variable depends on individual choices and histories.

3 Data and research sample

I use four waves (2002, 2004, 2006, 2009) of the EPS merged with administrative records of the Chilean Bureau of Pensions. The EPS is administered by the Ministry of Labor and Social Security in Chile jointly with the University of Chile and the University of Michigan. Its design was based on the Health and Retirement Study. Its implementation was sponsored by the University of Pennsylvania.[13]

3.1 Research sample

The estimation sample contains 7179 individuals observed 4 times. Because the objective is to model life-cycle wealth accumulation, individuals aged from 25 to 59 years old in 2002 are included.[14] Due to the dynamic nature of the model, only individuals observed in all four waves are considered. Individuals included have no missing information in work experience, optional savings, marital status, and region of residence.

No statistical differences between average age and gender shares for the whole sample and the reference sample (aged between 25 and 59 years in 2002) are detected. The only difference is in the education as the reference sample has considerably less missing information since most of those individuals attrited or contain missing information in other variables. The share of individuals with less than high school education is higher for the research sample than for the reference sample (53% and 41%, respectively).

Summary statistics are presented in Appendix B. Most individuals in the sample are formal workers. Informality represents around 20% of the sample. Voluntary contributors and participation in voluntary retirement savings accounts represent 4.5% and 5.6%, respectively. Individuals who participate in other voluntary savings programs represents around 14% of the sample. Most individuals are home owners, married, and with no changes in the number of children in the household.

4 Estimation

4.1 Error structure

Unobserved characteristics may be correlated across the $k = \{1, 2, \ldots, 9\}$ equations of the model. The total error (ε_{it}) in each equation is decomposed in three parts:

$$\varepsilon_{it}^{k} = \mu_{i}^{k} + \nu_{it}^{k} + \epsilon_{it}^{k} \tag{10}$$

μ_i and ν_{it} represent permanent and time-variant unobserved individual characteristics. ϵ_{it} is an idiosyncratic independent and identically (iid) distributed shock that is

[13] All data is publicly available and can be downloaded from the website of the Subsecretary of Social Prevision of Chile in the next url: https://www.previsionsocial.gob.cl/sps/biblioteca/encuesta-de-proteccion-social/bases-de-datos-eps.

[14] The lower limit is defined to simplify the model and to avoid modeling schooling choices.

assumed to be a type-1 extreme value for discrete variables and normal for continuous variables.

The decomposition allows for nonlinear unobserved individual-level heterogeneity. To estimate the parameters of the unobserved heterogeneity distribution, I use a semi-parametric discrete factor random effect (DFRE) estimation method. This methodology is a generalization of Heckman and Singer (1984), by Mroz and Guilkey (1992) and Mroz (1999), which allows the econometrician to not impose any functional or distributional form for the correlated unobserved heterogeneity. Instead, its cumulative distribution is approximated by a step function where mass points weights are jointly estimated with the other parameters of the model (Guilkey and Lance 2014). The assumption on the iid component for the total error, allows one to semi-parametrically estimate the distribution on unobserved heterogeneity.

Evidence from simulations shows that the DFRE performs better than other estimation approaches (Guilkey and Lance 2014). This evidence is important when the error distribution is not jointly normal and when there is a high correlation across equations; which is expected to happen in microeconomics applications.[15,16,17]

One could follow a single equation approach and estimate each behavioral equation using fixed or random effects. Nevertheless, single equation estimation methods generate biased results. There are endogenous variables (e.g., selection into employment and simultaneity with savings decisions), omitted information (e.g., savings amounts, risk preferences, tastes for alternatives), and measurement error (e.g., self-reported survey measure) in the set of equations. Recall that reduced-form parameters are a function of the primitives of the structural model. Therefore, each estimated parameter is a function of unobserved characteristics. To correct for these biases, it is necessary to model all of these processes (i.e., the correlated error terms).

The DFRE differs from standard random effects estimation as it jointly estimates the distribution of unobserved characteristics together with the reduced-form parameters. Regarding fixed effects, the DFRE method does not present a substantial loss of degrees of freedom and uses both variation over individuals and over time to account for unobserved heterogeneity (Fout and Gilleskie 2015; Gilleskie et al. 2017).

[15] A nice evaluation of the benefits of the method concerning other estimation methods can be found in Guilkey and Lance (2014). The DFRE method has been used in several other papers. For some examples see Gilleskie et al. (2017), Morales et al. (2016), Fout and Gilleskie (2015), Gilleskie and Hoffman (2014), Gardner and Gilleskie (2012) and Yang et al. (2009).

[16] For the estimation, a Fortran pre-coded program is used. The code used has been modified from a copyrighted version by Dr Jeff Rous (Associate Professor, Department of Economics, University of North Texas), modified by Dr David Guilkey (Distinguished Professor, Department of Economics, University of North Carolina at Chapell Hill) and Dr Thomas Mroz (Professor, Department of Economics, Georgia State University).

[17] What one sacrifices when using the DFRE is the simplicity of the estimation. The DFRE estimation routine is not yet available in standard statistical packages (e.g., STATA). However, because of the method's potential, some of the econometricians that have developed the method are working on a making the estimation routine available in STATA (Guilkey and Lance 2014).

4.2 Initial condition equations

In the first wave of the EPS, some of the endogenous variables are non-zero. Because I do not observe the history of decisions before this wave, the dynamic specification cannot be used to explain this variation. Thus, I specify static reduced-form equations that depends on exogenous individual characteristics. These initial condition equations are correlated with the other equation through a permanent unobserved component.

Initial conditions consider all endogenous variables entering the first period. These include: employment status (polychotomus: full- and part-time, self-employed and informal, not employed), work experience (continuous variable), contribution status (polychotomus: mandatory, voluntary, not contributing), savings inside and outside the retirement system (both dichotomous variables), housing status (polychotomus: owner, owner with loan, renting, lending), marital status (dichotomous) and number of children (continuous). Each initial equation is denoted by k where $k = \{10, \ldots, 17\}$.

The error structure for initial conditions is as follows:

$$\varepsilon_{it}^{k} = \mu_{i}^{k} + \epsilon_{it}^{k}, \text{ where } k = \{10, \ldots, 17\} \tag{11}$$

The initial condition equations are identified with exogenous market-level characteristics and individual exogenous characteristics that do not enter subsequent equations (e.g., father's and mother's schooling).

4.3 Estimated likelihood function

The likelihood function conditional on correlated unobserved heterogeneity is:

$$\mathcal{L}_{ct}(\Theta, \mu, \nu_t) = \prod_{i=1}^{N}\left\{ f_w(\mu, \nu_t) \prod_{j=1}^{J} \left[Pr(I(a_t^j = a^j)|\mu, \nu_t) \cdot f_j(\epsilon_t^j|\mu, \nu_t) \right]^{I(a_t^j = a^j)} \right\} \tag{12}$$

where Θ represents the vector of all parameters to be estimated, a_t^j is a choice $j = \{E, C, D, S^r, S^o, H, M, N\}$, $f(\cdot)$ represents the density function of the error term of each equation, $Pr(\cdot)$ is the cumulative distribution function for each choice, and $I(a_t^j = a^j)$ is an indicator of a particular choice.[18]

The unconditional likelihood function for the joint estimation of the system is:

$$\mathcal{L}_t(\Theta) = \sum_{q=1}^{Q} W_{\mu q} \sum_{r=1}^{R} W_{\nu r} \prod_{t=1}^{T} \mathcal{L}_{ct}(\Theta, \mu, \nu_t) \tag{13}$$

where $W_{\mu q}$ is the probability of observing q mass points for the permanent component μ and $W_{\nu r}$ is the probability of observing r mass points for the time-varying component ν_t. These approximate the true distributions of μ and ν_t.[19]

[18] The subscript i is dropped for simplicity.

[19] While the optimization routine can be programmed in any language, Fortran provides important gains in convergence time. Note that the routine should optimize over the likelihood function defined in equation (13) jointly with respect to the reduced-form parameters of the models and location of the mass points along the unit interval and their associated probabilities (Surette 1997).

4.4 Identification

The reduced-form life-cycle model consists of 17 jointly estimated equations. The total number of estimated coefficients correspond to the number of coefficients on observed characteristics (886) plus the coefficients that capture the distribution of unobserved heterogeneity, whose mass points are empirically determined.[20]

The empirical specification is presented in Table C.1 in Appendix C. Explanatory variables can be classified as predetermined (or endogenous control variables), exogenous (individual and market-level characteristics), or unobserved heterogeneity. Predetermined variables capture the dynamic nature of the decision-making process. While predetermined variables represented endogenous choices in the previous period, they are predetermined to individual choices in t.[21] The number of explanatory variables in each equation is presented in Table C.2 in Appendix C. Observed explanatory variables may enter linearly as higher-order moments and interacted (e.g., a variable and its squared).

The system is completely identified and therefore, causal effects can be distinguished. Identification comes from several sources. First, identification comes from the dynamic nature of the model and timing assumptions on the decision-making process, following the standard requirements for dynamic-panel estimation, even with general patterns of correlation across equations (Arellano and Bond 1991; Bhargava 1991). As instruments there are two types of variables: (1) predetermined (lagged) choices and (2) market-level characteristics.[22] Because endogenous variables in t are predetermined in $t + 1$, I am able to achieve identification by incorporating lagged endogenous behaviors as instruments. For example, employment decisions in t depend on predetermined variables such as work experience, which is known for the individual at the beginning of t and depends on past choices (i.e., employment decisions in the previous period). Thus, work employment is a predetermined variable each period that can be used as an explanatory variable. There is sufficient variation considering the four waves of data. This set of instruments is valid if there is no auto-correlation steaming from the idiosyncratic component which is an assumption commonly used with the DFRE (Yang et al. 2009). Observed values of endogenous variables are included in the specification instead of predicted values.

Some of the predetermined variables are excluded from some equations. Most lagged choices are excluded from the wage equation and family equations (only employment status shows up). All lagged choices are excluded from initial condition equations. Some of these market-level characteristics that explain choices in t are excluded from the outcome equations in the same period and therefore serve as exclusion restrictions. Table C.1 in Appendix C also shows sources of identification based on the theoretical exclusion restrictions.

[20] Thus, in addition to the parameters on observed characteristics, there are $q - 1$ estimated coefficients for the permanent individual unobserved heterogeneity distribution and $r - 1$ estimated coefficients for the time-variant individual unobserved heterogeneity distribution, where q and r represents the permanent and time-variant mass points of the distributions.

[21] Predetermined with respect to the timing of the decision-making process.

[22] All market-level characteristics enter in all behavioral equations as the vector Z_{it} enters the information set.

Regarding exclusion restrictions, all equations depend on some market-level characteristics denoted by Z. Exclusion restrictions summarize characteristics of the market where the individuals are participating. The individual's choices do not affect the market-level information. Thus, these variables are exogenous to the individual decision-making problem. All the exclusion restrictions are theoretically justified.

For example, wages in period t depend on current characteristics of the labor market (Z_{it}^{E}) but not on characteristics of other markets, conditional on choices made at period t. Similarly, conditional on choices at period t, only characteristics of the marriage market (Z_{it}^{M}) and of the family market (Z_{it}^{N}) affect marital status and children variation, respectively. Moreover, the dynamic specification of the model includes lagged endogenous variables (pre-determined at period t) that are a function of market-level characteristics (i.e., $Z_{i,t-1}$ explains choices in period $t-1$). This argument follows the standard argument to identify dynamic models (Arellano and Bond 1991).

Second, the functional form assumption for the distribution of the idiosyncratic error term in each equation (ϵ_{it}) serves to identify the system as it gives the functional form to equations. It is impossible to identify the distribution of the correlated unobserved heterogeneity if there is no inclusion of an idiosyncratic component into total unobserved heterogeneity and if no assumptions regarding its distribution are made. Thus, the method is a semi-parametric estimation method that non-parametrically estimates the distribution of permanent and time-variant unobserved characteristics.

Third, identification comes from the number of factors allowed for the step approximation for the correlated unobserved heterogeneity. Ideally, one would like to identify a distribution of permanent and time-varying unobserved heterogeneity affecting each behavioral equation and each outcome of the model. Nevertheless, this cannot be identified. Instead, I estimate two distributions (one permanent and one time-variant) affecting all choices. Lastly, identification comes from the nonlinear nature of the system of equations (Guilkey and Lance 2014; Morales et al. 2016).

5 Results

5.1 Specification and model fit

There are 1082 estimated parameters. The model that best captures the distribution of unobserved characteristics and has the best model fit has five mass points for the permanent unobserved heterogeneity and four mass points for the time-varying unobserved heterogeneity. Before presenting the simulations, I compare the observed data with the simulated outcomes from the data generating process. Evaluating the model fit is important since the model is used to simulate counterfactual policies. Simulated values are obtained using observed explanatory variables without updating and with 100 replications for the types' probabilities. The comparison shows the model fits the data well (see Table C.3 in Appendix C).

5.2 Estimation results

5.2.1 Preferred model

I now refer to the results for equations that capture individual choices. All results tables are presented in Appendix C in Tables C.4–C.10.[23] Because I model behaviors simultaneously, estimates effects are causal.

Earnings There is a statistically significant wage gap of 18.9%. This gap goes in line with other findings in the literature. Using the first three waves of the EPS (2002–2006), Perticará and Bueno (2009) find a wage gap between 12.7 and 18.7%. Using administrative records on unemployment insurance between the years 2004 and 2009, Cruz and Rau (2019) find a wage gap of 24.5%. It is found that informal workers earn 32.3% less than their formal counterparts. No significant effect of children on wages is found. The results show a significant but small effect of marital status.

Employment status (relative to formal workers) Individuals are significantly less likely to be informal workers or not work if they were mandatory contributors in the previous period. Individuals with more wealth and work experience are more likely to be formal workers. As an individual ages, she is more likely to be informally employed or not employed. There is a significant decrease in the probability of being informally employed or not employed as education increases. I find no gender effects, except for the marriage-female interaction, meaning that married women are more likely to be informally employed or not employed. I find no significant effect of previous default status or savings holdings.

Contribution status (relative to not contributing) There is significant inertia in contribution status: individuals are significantly more likely to be mandatory (voluntary) contributors if they were mandatory (voluntary) contributors in the previous period. Being a voluntary contributor in $t-1$ increases the probability of being a mandatory contributor in t, while the opposite is not true (no significant effect of previous mandatory contribution status on voluntary savings).

Individuals with previous voluntary savings within the system are more likely to contribute, while individuals with previous savings outside the system are significantly more likely to be voluntary contributors. This suggests that individuals who are not forced to contribute use other available savings tools. The likelihood of being a mandatory contributor increases with wealth and work experience (both with significantly diminishing rates). The wealth effect is barely significant for voluntary contributors, and no work experience effect is found. In both cases, no gender effects are found, except when interacting female with family characteristics. For females, marriage and more children increase the probability of not contributing. The probability of not contributing decreases as education increases.

Default adoption (relative to defaulting with no action) Previous contribution status (relative to not contributing in the previous period) increases the probability of choosing or opting out of the portfolio default, relative to following the default.

[23] Results for the initial condition equations are available from the author.

There is also a significant inertia in default status, meaning that an individual is more likely to choose (opt out) the default if chosen (to opt out) previously. Individuals with voluntary savings within the retirement system are significantly more likely to choose the default and to opt out.

Interestingly, individuals with voluntary savings outside the retirement system are more likely to opt out, but no significant effect is found for choosing the default. This suggests that individuals who use savings tools outside the retirement system are more sophisticated in their investment strategies. As retirement wealth increases, individuals are less likely to be assigned to the default. No significant experience effects are found. Similarly to other research, younger individuals are more likely to be defaulted and as wealth increases, the probability of opting out increases (Kristjanpoller and Olson 2015). Women are less likely to choose the default than men, while no significant differences are found with respect to opting-out from the default. These results complement others in the literature (Kristjanpoller and Olson 2015).

Voluntary savings There is significant inertia in savings status. As retirement wealth increases, the likelihood of holding voluntary savings within the retirement system increases, but the same cannot be accepted for savings outside the system. No significant effect of previous contribution status is found, and little effect with respect to previous default adoptions is evidenced. Contrary to our expectations, individuals paying for a home and renting are more likely to hold savings within the system.

5.2.2 Single equation models and alternative DFRE specifications

I now compare the estimation results with fixed-effects and alternative DFRE specifications. Results are presented in Appendix D in Tables D.1–D.6. The comparison is done in log odd terms. Generally, the estimates obtained from single equation fixed-effects are statistically different from the ones obtained after correcting for endogeneity biases.

Let's take for example the multinomial logit on employment status (Table D.1 in Appendix D). Most predetermined behaviors (e.g., lagged choices such as contribution status, housing status) and stock variables (e.g., retirement wealth, work experience) are statistically different from DFRE estimates. The difference is the bias that one is not able to pull out when applying methods that do not correct for correlated errors. As a second example, let's take the multinomial logit on contribution status (Table D.2 in Appendix D). The fixed-effects estimation show that coefficients on predetermined variables, both lagged choices and stock variables, are statistically different than the DFRE results, evidencing the estimation bias that arises when assuming that errors are uncorrelated and only capture permanent unobserved characteristics. In both cases, exogenous individual characteristics (e.g., age and education) also present statistical differences.[24]

[24] Single-equation estimates can be easily replicated using any standard econometric software as it is just a fixed-effect estimation for each equation.

Additionally, I compare the results with: DFRE with one equation (multinomial logit), DFRE with two correlated equations, full DFRE without exclusion restrictions, and fixed-effects with no market-level exclusion restrictions (see Table D.6 in Appendix D).

The one-equation DFRE (column (2)) evidences the bias when one does not control for correlated heterogeneity. Results indicate that differences with respect to the full model (column (1)) are substantial and statistically significant. Results from the two-equations DFRE model allows controlling for correlation across two equations (column (3)). In particular, employment decisions are jointly modeled with wages. Note that the results are very similar to the ones obtained from a one-equation model, suggesting that modeling only two outcomes is not enough to control for estimation biases.

The omission of supply-side relevant factors result in biased estimates toward zero (column (4)). Fixed-effect models (with and without exclusion restrictions, columns (5) and (6), respectively) do not show substantial differences for key variables. Thus, log odd terms on predetermined endogenous variables are not sensitive to the inclusion of market-level characteristics for the single equation panel estimation. However, note that when controlling only for uncorrelated permanent unobserved heterogeneity the bias does not disappear and the estimates change in the opposite direction.

5.3 Contemporaneous marginal effects

To calculate marginal effects I use the standard procedure in DFRE papers.[25] Marginal effects are computed without updates in response to previous choices (i.e., short-run effects). Standard errors are calculated using predictions based on 100 draws of the estimated coefficients from the estimated variance-covariance matrix. I focus on effects of stock variables (work experience, age and wealth) and the following behaviors: lagged optional savings choices and lagged default behavior. All results are expressed in percentage change with respect to the baseline scenario.

Work experience partially captures experience in the system; while age captures the aging evolution of choices. Retirement wealth captures the effect of accumulating assets (Table 1). A marginal increase in wealth significantly increases the probability of being a formal worker by 0.12% (column 3 in Table 1). I argue that the 0.12% is the causal effect only of retirement wealth. The probability of not contributing and of being assigned to the default significantly decreases by 0.25% and 0.30%, respectively. An increase in retirement wealth also generates a small but significant (at 10% level) increase in savings outside the system and in home ownership with a loan (at 5% level). This finding suggests that as retirement wealth needs are covered, individuals switch to other forms of investment. The evolution of investments through the life cycle is not attributable to aging, as the short-run effect of age does not significantly explain portfolio default adoption, savings choices and home ownership (column 2).

[25] See for example, Section 6.2.3. in Gilleskie et al. (2017), Section V.C in Gilleskie and Hoffman (2014). Simulation codes for Stata are available in Appendix B (Supplementary material) in Gilleskie et al. (2017) available online https://www.sciencedirect.com/science/article/pii/S1094202517300418.

Table 1 Contemporaneous marginal effects of stock variables (%)

Behavior	Work experience (1)	Age (2)	Wealth (3)
Employment			
Formal worker	0.90 (0.31)***	−0.78 (0.31)**	0.12 (0.04)***
Informal worker	1.05 (0.36)***	−0.36 (0.45)	−0.21 (0.08)***
Not working	−1.95 (0.56)***	1.13 (0.53)**	0.09 (0.06)
Contribution			
Non-contributor	−12.53 (13.22)	0.62 (0.18)***	−0.25 (0.03)***
Mandatory contributor	14.78 (15.78)	−0.59 (0.17)***	0.23 (0.02)***
Voluntary contributor	−2.25 (5.75)	−0.03 (0.04)	0.02 (0.01)
Default			
Defaulted	0.08 (0.15)	0.16 (0.13)	−0.30 (0.13)**
Chose default	0.03 (0.13)	−0.13 (0.17)	0.10 (0.15)
Opted out of default	−0.11 (0.11)	−0.03 (0.06)	0.20 (0.16)
Optional savings			
Within system	0.00 (0.11)	0.00 (0.01)	0.04 (0.05)
Outside system	0.12 (0.12)	−0.13 (0.09)	0.03 (0.02)*
Housing status			
Owns house (no loan)	0.11 (0.11)	0.11 (0.07)	0.00 (0.07)
Owns house (paying loan)	−0.14 (0.07)**	0.01 (0.08)	0.12 (0.06)**
Rents house	0.00 (0.11)	−0.06 (0.05)	0.00 (0.02)
Uses house	0.03 (0.10)	−0.06 (0.09)	−0.12 (0.08)

*Significant at the 10% level; **5% level; ***1% level

These results are consistent with other findings in the literature, such as Attanasio and Brugiavini (2003) for Italy and Attanasio and Rohwedder (2003) for the U.K.[26] Unlike Attanasio and Brugiavini (2003), I attribute the switching to retirement wealth rather than to aging. The insignificance of age effects is also consistent with other studies, where for the U.S., using a sample of older individuals, Gustman and Steinmeier (1999) find little and insignificant effects of retirement wealth on other savings. Because individuals are transitioning to other forms of savings, this finding might explain why participation in voluntary savings retirement programs are low.

An additional year of work experience (column 1) mostly explains employment status (e.g., an additional year of work experience significantly increases the probability of being a formal worker by 0.90% and decreases the probability of not working by 1.95%. No effects are found for savings or investment behavior.

Contemporaneous marginal effects of lagged saving choices and default behavior are presented in Table 2. Optional savings within the system (column 1) significantly decreases the probability of not contributing by 2.30% and increases the probability of mandatory or voluntary contribution by 1.13% and 1.17%, respectively. Optional

[26] In the latter, the authors investigate the crowding-out between public retirement wealth and other sources of savings. This line of study has received big attention. See, for example, Hurd et al. (2012), Arnberg and Barslund (2014) and Blau (2016).

Table 2 Contemporaneous marginal effects of previous investment behaviors (%)

Behavior	Lagged optional savings		Lagged default	
	Within system (1)	Outside system (2)	Chose (3)	Opt out (4)
Employment				
Formal worker	0.20 (0.62)	0.31 (0.44)	0.77 (1.01)	0.42 (0.99)
Informal worker	0.92 (0.67)	0.37 (0.75)	0.61 (0.99)	2.03 (1.30)
Not working	−1.12 (0.76)	−0.68 (0.80)	−1.38 (1.32)	−2.45 (1.44)*
Contribution				
Non-contributor	−2.30 (0.60)***	−0.59 (0.36)*	−2.11 (0.49)***	−2.40 (0.50)***
Mandatory contributor	1.13 (0.33)***	−0.14 (0.22)	1.49 (0.30)***	1.66 (0.27)***
Voluntary contributor	1.17 (0.49)**	0.73 (0.31)**	0.61 (0.40)	0.74 (0.44)*
Default				
Defaulted	−4.26 (1.65)***	−0.95 (0.70)	−14.64 (4.49)***	−14.77 (5.40)***
Chose default	1.20 (1.75)	0.24 (0.63)	8.32 (7.13)	0.10 (2.62)
Opted out of default	3.06 (2.25)	0.71 (0.71)	6.32 (4.72)	14.67 (7.01)**
Optional savings				
Within system	6.56 (5.82)	1.43 (1.75)	1.05 (1.56)	0.47 (0.93)
Outside system	1.07 (0.72)	11.49 (5.86)*	1.10 (1.01)	0.60 (0.89)
Housing status				
Owns house (no loan)	−1.51 (0.93)	0.65 (0.72)	1.05 (1.44)	−0.72 (1.58)
Owns house (paying loan)	0.96 (0.80)	−0.29 (0.50)	−0.36 (0.92)	−0.50 (1.13)
Rents house	0.21 (0.84)	0.14 (0.66)	−0.14 (1.30)	−0.58 (1.41)
Uses house	0.34 (1.09)	−0.50 (0.69)	−0.55 (1.45)	1.81 (1.54)

*Significant at the 10% level; **5% level; ***1% level

savings within the system also significantly decreases the probability of being defaulted into the system's designed portfolio by 4.26%. This latter result suggests learning with respect to portfolio choices, as it shows that individuals with higher exposure to the system pursue more sophisticated investment strategies. These results follow the same pattern of results documented by Chetty et al. (2014), who find that active savers are more financially sophisticated than passive savers, among other findings.

An investment action in the previous period (i.e., choosing or opting out of the default) significantly decreases the probability of being defaulted by ~15% (see columns 3 and 4). Once an individual opts out, the probability of maintaining that decision in the next period significantly increases by 14.67%. Generally, individuals are free to choose any investment account, but there are restrictions to older individuals. For example, men over 55 years old and women over 50 years old cannot choose account A. If they are in that investment plan before, they can be defaulted if they have not transfer at the time they achieve the limit age. Even if individuals made an active choice in the past, that does not necessarily mean that they will make another active choice in the future. This result might suggest that sophisticated individuals regarding their portfolios, tend to follow their own choices rather than following the system's designed investment path. Unlike other papers that evidence inertia in retirement investment decisions once individuals are defaulted into plan characteristics, I find a substantial inertia when individuals decide to opt out of the default (Carroll et al. 2009; Choi et al. 2004; Madrian and Shea 2001).

There is substantial inertia in savings outside the system (column 2). Holding savings outside the system in $t-1$ significantly increases the probability of holding savings in t by 11.49%. Previous choices regarding outside savings significantly decreases the probability of not contributing by 0.59%. Although this effect follows the same pattern as the effect generated by previous choices with respect to voluntary savings within the system, the effect is significantly smaller for savings outside the system. Both previous choices significantly increase the probability of voluntary contribution, but we cannot reject the null that the effects are significantly different from each other.

Some key issues regarding participation in the system arise. Even though there are no significant impacts on formal market participation, any action taken, significantly decreases the probability of not contributing by at least 2% and increases the probability of mandatory contribution by almost 2%. Opting out of the default increases the probability of voluntarily contributing by almost 1%. However, this is not the case for individuals who take action but follow the suggested investment path, where no significant effect is found. This finding is an important one, as it suggests that as individuals become more sophisticated in investment strategies, they are also more likely to go beyond compulsory savings (see Chetty et al. (2014)).

5.4 Counterfactual simulations

Simulations quantify long-run effects by incorporating the dynamic effects of behavior on future outcomes. Because the estimated dynamic decision model allows me to model the sequential decision-making process, I use the estimated model as the data-generating process.[27] Simulating counterfactual scenarios is ultimately the main goal of papers that applied the DFRE method. The simulations are perform in the standard way.[28]

I obtain the matrix conformed by the estimated coefficients for each equation, and use it as input to predict behaviors based on observed characteristics.[29] Simulated outcomes are used to update next period's endogenous explanatory variables. Each individual is replicated 100 times, from draws from the unobserved heterogeneity distribution. Individuals enter the first period with their initial characteristics, and the treatment is permanently applied starting in period $t = 2$. Standard errors are calculated using predictions based on 100 draws of the estimated coefficients from the estimated variance-covariance matrix. All results are expressed in percentage change with respect to the baseline scenario.

[27] Since seven years were considered for the estimation, to assure the reliability of results, the simulations can only be performed for the same period length.

[28] See for example, Section 6.2.4. in Gilleskie et al. (2017), Section V.B. in Gilleskie and Hoffman (2014), and Section V.B. in Yang et al. (2009).

[29] Once the estimation of the system of equation is ready, any software can be used for the simulations. The researcher just need to import the estimated coefficients and the matrix with observed characteristics into her preferred software. Simulation codes for Stata are available in Appendix B (Supplementary material) in Gilleskie et al. (2017) available online https://www.sciencedirect.com/science/article/pii/S1094202517300418.

Table 3 Crowd-out effects across voluntary savings accounts in the treated group (%)

	Effect of holding voluntary savings within retirement on savings outside retirement (1)	Effect of holding voluntary savings outside retirement on savings within retirement (2)
$t = 3$	0.15 (6.14)	2.16 (15.76)
$t = 4$	0.20 (6.93)	1.56 (18.15)
$t = 5$	0.18 (7.12)	1.35 (17.97)
$t = 6$	0.19 (7.01)	1.15 (18.47)
$t = 7$	0.19 (7.11)	1.17 (18.53)
$t = 8$	0.20 (6.96)	0.67 (19.12)

(a) Simulated percentage change in the outcome of interest when comparing the case where all individuals enrolled hold voluntary savings versus the case where no individual enrolled holds voluntary savings

(b) Individuals begin period $t = 1$ with their observed initial conditions. All individuals enrolled are treated starting in period $t = 2$. The dynamic nature of the model begins to affect outcomes in period $t = 3$

(c) Bootstrapped standard errors are given in parentheses, using 100 draws

5.4.1 Effect of participating in voluntary savings programs

I find no evidence of long-run crowding-out across savings. Table 3 shows the response per period. Note that no effect is statistically significant from zero, meaning that individuals do not treat these two type of accounts as substitute goods. Outside savings do not significantly affect behaviors within the system, such as the share of individuals with inside voluntary accounts, contribution status and default adoption.

Table 4 presents long-run effect of voluntary savings on default adoption. All enrolled individuals are treated. Savings outside the system have no effect on portfolio (column 2). There is evidence of an important long-run effect of voluntary retirement savings on portfolio adoption (column 1). For the first two years after the treatment, individuals who choose the default significantly increased by 20 and 26%. There is no effect on choosing more sophisticated portfolio actions (i.e., opt out). Individuals who chose the default or opt out increase by 31% and 41%, respectively at $t = 4$. In the last 4 years, individuals who follow the most sophisticated strategy increase from 41 to 48%. This suggests that long-run effects of participating in voluntary programs are important for increasing active participation in portfolio decisions.

I find no crowd-out effect between outside savings and home ownership (Table 5, column 2). Home owners with loans significantly decreases between 7 and 10% for the first four years after treatment. This suggests that home ownership and participation in voluntary retirement programs are substitute goods. Policy makers should be careful in the design of policies that seek to increase savings within the system, as there might be important welfare implications once the retirement age is reached.

Table 4 Effect of holding voluntary savings on default adoption in the treated group (%)

	Voluntary savings within retirement (1)	Voluntary savings outside retirement (2)
Defaulted		
$t = 3$	−10.11 (6.69)	−0.06 (2.08)
$t = 4$	−13.78 (8.90)	−0.10 (2.82)
$t = 5$	−10.96 (9.36)	−0.07 (2.87)
$t = 6$	−9.10 (9.45)	−0.06 (2.79)
$t = 7$	−7.87 (9.30)	−0.05 (2.67)
$t = 8$	−7.50 (9.46)	−0.05 (2.74)
Chose default		
$t = 3$	19.86 (11.11)*	0.21 (4.02)
$t = 4$	25.83 (14.86)*	−0.12 (4.70)
$t = 5$	31.62 (17.71)*	2.53 (5.56)
$t = 6$	25.95 (16.89)	−0.35 (5.86)
$t = 7$	21.23 (17.36)	0.65 (6.22)
$t = 8$	31.14 (16.36)*	0.73 (5.93)
Opted out of default		
$t = 3$	20.47 (12.97)	0.12 (4.44)
$t = 4$	26.77 (17.11)	0.19 (5.76)
$t = 5$	41.15 (20.77)**	0.25 (6.83)
$t = 6$	45.66 (21.34)**	0.31 (7.08)
$t = 7$	48.01 (22.21)**	0.29 (7.23)
$t = 8$	48.64 (21.78)**	0.32 (7.15)

*Significant at the 10% level; **5% level

(a) Simulated percentage change in the outcome of interest when comparing the case where all individuals enrolled hold voluntary savings versus the case where no individual enrolled holds voluntary savings

(b) Individuals begin period $t = 1$ with their observed initial conditions. All individuals enrolled are treated beginning in period $t = 2$. The dynamic nature of the model begins affecting outcomes in period $t = 3$

[c]Bootstrapped standard errors are given in parentheses, using 100 draws

5.4.2 Home ownership effects

I now simulate all enrolled individuals to be homeowners (with no loan) and then evaluate how it impacts participation in contributions and in voluntary savings. No significant home ownership effect is found on savings outside the system (Table 6). Corroborating the substitution between retirement savings and home ownership, results indicate that once all enrolled individuals are homeowners (with no loan), their participation in voluntary retirement programs significantly decreases. Four years after the treatment, there is a decrease in such participation between ~16 and

Table 5 Effect of holding voluntary savings on default adoption in the treated group (%)

	Voluntary savings within retirement (1)	Voluntary savings outside retirement (2)
Owns home (no loan)		
$t = 3$	−6.55 (3.87)*	0.64 (2.52)
$t = 4$	−9.79 (5.11)*	0.67 (3.44)
$t = 5$	−10.21 (5.57)*	0.51 (3.60)
$t = 6$	−9.58 (5.69)*	0.39 (3.60)
$t = 7$	−8.31 (5.68)	0.31 (3.45)
$t = 8$	−8.45 (6.04)	0.28 (3.63)
Owns home (with loan)		
$t = 3$	3.74 (3.61)	−0.34 (2.80)
$t = 4$	5.17 (5.41)	−0.34 (3.04)
$t = 5$	7.26 (7.40)	−0.36 (4.21)
$t = 6$	9.53 (8.77)	−0.37 (4.61)
$t = 7$	11.90 (10.23)	−0.43 (5.64)
$t = 8$	11.68 (10.35)	−0.38 (5.03)
Rents home		
$t = 3$	−9.49 (8.23)	1.26 (4.23)
$t = 4$	−11.82 (11.57)	1.40 (5.03)
$t = 5$	−11.36 (13.01)	2.07 (5.88)
$t = 6$	−11.47 (13.40)	1.24 (5.69)
$t = 7$	−9.44 (13.22)	1.41 (5.59)
$t = 8$	−8.79 (13.45)	1.74 (6.36)
Uses home		
$t = 3$	−5.65 (6.05)	−0.61 (3.59)
$t = 4$	−9.87 (7.96)	−0.38 (4.56)
$t = 5$	−11.50 (8.48)	−0.30 (4.78)
$t = 7$	−10.09 (8.72)	−0.31 (4.91)
$t = 6$	−10.94 (8.66)	−0.27 (4.94)
$t = 8$	−9.76 (8.46)	−0.38 (4.84)

*Significant at the 10% level

(a) Simulated percentage change in the outcome of interest when comparing the case where all individuals enrolled hold voluntary savings versus the case where no individual enrolled holds voluntary savings

(b) Individuals begin period $t = 1$ with their observed initial conditions. All individuals enrolled are treated beginning in period $t = 2$. The dynamic nature of the model begins affecting outcomes in period $t = 3$

(c) Bootstrapped standard errors are given in parentheses, using 100 draws

21%. Homeowners are also less likely to contribute by between ~3 and 5% for three years after the treatment and permanently less likely to be mandatory contributors by between ~3 and 7%.

5.4.3 Effect of extending mandatory contributions to informal workers

I evaluate the effect of extending mandatory contributions to informal workers. A policy reform in Chile in 2008 implemented in 2019 anticipates that self-employed workers will be required to contribute. Because I cannot separately identify both categories of informal workers, the results are upper bounds of the effects of such a policy.

The treated are informal workers. I find no significant long-run effects on voluntary savings participation (columns 1 and 2 in Table 7). The likelihood of opting out increases by 18 and 28% between the first year after the treatment ($t = 3$) and the last

Table 6 Effect of home ownership on the treated group (%)

	Voluntary savings within retirement	Voluntary savings outside retirement	Contribution status		
			Non-contributor	Mandatory	Voluntary
	(1)	(2)	(3)	(4)	(5)
$t = 3$	−16.33 (9.24)*	0.07 (5.42)	2.75 (1.38)**	−3.14 (0.97)***	−0.02 (3.89)
$t = 4$	−20.86 (10.75)*	0.09 (6.73)	4.56 (2.45)*	−5.17 (1.56)***	−0.06 (6.32)
$t = 5$	−21.15 (11.04)*	0.08 (6.49)	5.37 (3.26)*	−6.43 (1.91)***	0.12 (7.49)
$t = 6$	−20.10 (11.43)*	0.06 (6.58)	5.29 (3.66)	−6.81 (2.11)***	0.05 (8.19)
$t = 7$	−18.19 (11.33)	0.05 (6.57)	4.65 (3.76)	−6.64 (2.25)***	−0.02 (8.77)
$t = 8$	−13.79 (11.10)	0.04 (6.45)	4.09 (3.98)	−5.79 (2.19)***	0.20 (7.04)

*Significant at the 10% level; **5% level; ***1% level

(a) Simulated percentage change in the outcome of interest when comparing the scenario in which all individuals own a home with the scenario in which no individual owns a home

(b) Individuals begin period $t = 1$ with their observed initial conditions. All individuals enrolled are treated beginning in period $t = 2$. The dynamic nature of the model begins affecting outcomes in period $t = 3$

(c) Bootstrapped standard errors in parentheses, using 100 draws

Table 7 Effect of extending mandatory contributions to informal workers (%)

	Voluntary savings within retirement	Voluntary savings outside retirement	Default adoption		
			Defaulted	Chose default	Opted out
	(1)	(2)	(3)	(4)	(5)
$t = 3$	−10.62 (10.40)	−0.04 (5.34)	−6.19 (6.71)	18.54 (13.41)	17.30 (10.29)*
$t = 4$	−11.35 (8.32)	−0.03 (7.27)	−8.45 (8.33)	20.30 (14.29)	21.98 (10.84)**
$t = 5$	−9.07 (8.10)	−0.07 (8.01)	−5.17 (7.81)	26.84 (15.59)*	27.03 (12.46)**
$t = 6$	−9.73 (8.18)	−0.06 (8.66)	−4.01 (7.49)	28.34 (15.47)*	28.11 (11.93)**
$t = 7$	−10.48 (8.96)	−0.06 (9.12)	−3.34 (6.63)	23.83 (15.59)	28.45 (11.81)**
$t = 8$	−5.34 (10.34)	−0.05 (9.23)	−3.14 (6.43)	21.02 (15.38)	28.76 (12.81)**

*Significant at the 10% level; **5% level

(a) Simulated percentage change in the outcome of interest when comparing the scenario in which all informal workers are forced to contribute and the scenario in which they are not

(b) Individuals begin period $t = 1$ with their observed initial conditions. All informal workers are treated beginning in period $t = 2$. The dynamic nature of the model begins affecting outcomes in period $t = 3$

(c) Bootstrapped standard errors in parentheses, using 100 draws year ($t = 8$). In periods 5 and 6, treated individuals significantly increase the probability choosing the default. These results indicate that forcing contribution does not result in a reduction in other savings. They also suggest that the treated group behave as sophisticated investors. Simulations indicate that home ownership and mandatory contributions work as substitute goods (see Table 8). When forcing individuals to contribute, home ownership significantly decreases, between 11 and 12%.

Table 8 Effect on housing status of extending mandatory contributions to informal workers (%)

	Effect on housing status (1)
Owns home (no loan)	
$t = 3$	−8.45 (6.10)
$t = 4$	−12.17 (6.93)*
$t = 5$	−11.91 (6.67)*
$t = 6$	−11.20 (6.75)*
$t = 7$	−9.62 (6.22)
$t = 8$	−10.64 (7.13)
Owns home (with loan)	
$t = 3$	4.43 (6.33)
$t = 4$	5.98 (8.14)
$t = 5$	8.00 (7.90)
$t = 6$	10.78 (12.08)
$t = 8$	14.12 (11.43)
$t = 7$	13.53 (17.26)
Rents home	
$t = 3$	−4.09 (10.10)
$t = 4$	−2.68 (10.72)
$t = 5$	0.25 (9.95)
$t = 6$	−5.76 (11.19)
$t = 7$	−0.20 (11.72)
$t = 8$	−4.17 (13.06)
Uses home	
$t = 3$	1.56 (7.78)
$t = 4$	−3.17 (9.03)
$t = 5$	−3.15 (8.47)
$t = 6$	−2.40 (8.94)
$t = 7$	−1.43 (9.82)
$t = 8$	−1.16 (8.60)

*Significant at the 10% level

(a) Simulated percentage change in the outcome of interest when comparing the scenario in which all informal workers are forced to contribute and the scenario in which they are not

(b) Individuals begin period $t = 1$ with their observed initial conditions. All informal workers are treated beginning in period $t = 2$. The dynamic nature of the model begins affecting outcomes in period $t = 3$

(c) Bootstrapped standard errors are given in parentheses, using 100 draws

6 Conclusions

This paper investigates crowding-out across savings choices and assets. Results indicate no short- or long-run crowd-out across savings. In the short run, once retirement wealth needs are covered, individuals switch to other forms of investments. These transitions are not attributable to aging or work experience. The transition in savings might prevent participation in voluntary retirement savings programs.

Long-run simulations suggest that home ownership and retirement voluntary savings are substitute goods. The same is observed with mandatory savings and home ownership. Individuals with greater exposure to the system are more sophisticated in investment strategies. Individuals that are more sophisticated in investment strategies are also more likely to participate in voluntary retirement savings programs.

The long-run effects of participating in voluntary savings programs are substantial for active portfolio decisions. This key finding could be important for the design of default rules. For example, we could consider policies that force individuals to make investment choices rather than assigning them to a default portfolio. This could have the increased benefit of increasing participation in voluntary savings programs.

Future research should analyze how crowding-out between voluntary savings and home ownership affect resources available after retirement. A hypothesis is that retirees might be better off by investing in home ownership. This hypothesis is conditional on the amounts of such investments, and characteristics of the housing market. Future research could explore the possibility of modeling amounts invested. It would also be of interest to consider intra-household decisions.

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Compliance with ethical standards

Conflict of interest The author declares that she has no conflict of interest.

References

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*, 277–297.

Arnberg, S., & Barslund, M. (2014). *The crowding-out effect of mandatory labour market pension schemes on private savings*. CEPS Working Document No. Vol. 389. Brussels, Belgium: Centre for European Policy Studies (CEPS).

Attanasio, O. P., & Brugiavini, A. (2003). Social security and households' saving. *The Quarterly Journal of Economics*, *118*, 1075–1119.

Attanasio, O. P., & Rohwedder, S. (2003). Pension wealth and household saving: evidence from pension reforms in the united kingdom. *American Economic Review*, *93*, 1499–1521.

Behrman, J., Calderon, M. C., Mitchell, O., Vasquez, J., & Bravo, D. (2011). *First-round impacts of the 2008 chilean pension system reform*. Working paper. Michigan, U.S.: Michigan Retirement Research Center Research.

Berstein, S., Castaneda, P., Fajnzylber, E., & Reyes, G. (2010). *The chilean pension system*. (Ed. Berstein, S.). Chile: Superintendence of Pensions.

Beshears, J., & Choi, J. J. (2012). *Default stickiness among low-income individuals*. Working paper. California, U.S.: RAND Corporation.

Bhargava, A. (1991). Identification and panel data models with endogenous regressors. *The Review of Economic Studies*, *58*, 129–140.

Blau, D. M. (2016). Pensions, household saving, and welfare: a dynamic analysis of crowd out. *Quantitative Economics*, *7*, 193–224.

Card, D., & Ransom, M. (2011). Pension plan characteristics and framing effects in employee savings behavior. *The Review of Economics and Statistics*, *93*, 228–243.

Carroll, G. D., Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2009). Optimal defaults and active decisions. *The Quarterly Journal of Economics*, *124*, 1639–1674.

Chetty, R., Friedman, J. N., Leth-Petersen, S., Nielsen, T. H., & Olsen, T. (2014). Active vs. passive decisions and crowd-out in retirement savings accounts: evidence from denmark. *The Quarterly Journal of Economics*, *129*, 1141–1219.

Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2004). For better or for worse: default effects and 401 (k) savings behavior. In *Perspectives on the economics of aging* (pp. 81–126). Chicago, U.S.: University of Chicago Press.

Cruz, G., & Rau, T. (2019). *The effects of firms' pay policies and equal pay laws on the gender wage gap in chile*. Working paper. Chile.

Engelhardt, G. V., & Kumar, A. (2007). Employer matching and 401 (k) saving: evidence from the health and retirement study. *Journal of Public Economics*, *91*, 1920–1943.

Engelhardt, G. V., & Kumar, A. (2011). Pensions and household wealth accumulation. *Journal of Human Resources*, *46*, 203–236.

Fout, B. T., & Gilleskie, D. B. (2015). Does health insurance encourage or crowd out beneficial non-medical care? a dynamic analysis of insurance, health inputs, and health production. *American Journal of Health Economics*, *1*, 125–164.

Gardner, L., & Gilleskie, D. B. (2012). The effects of state medicaid policies on the dynamic savings patterns and medicaid enrollment of the elderly. *Journal of Human Resources*, *47*, 1082–1127.

Gelber, A. M. (2011). How do 401 (k) s affect saving? evidence from changes in 401 (k) eligibility. *American Economic Journal: Economic Policy*, *3*, 103–22.

Gilleskie, D. B., Han, E., & Norton, E. C. (2017). Disentangling the contemporaneous and dynamic effects of human and health capital on wages over the life cycle. *Review of Economic Dynamics*, *25*, 350–383.

Gilleskie, D., & Hoffman, D. (2014). Health capital and human capital as explanations for health-related wage disparities. *Journal of Human Capital*, *8*, 235–279.

Guilkey, D. K., & Lance, P. M. (2014). Program impact estimation with binary outcome variables: Monte carlo results for alternative estimators and empirical examples. In *Festschrift in Honor of Peter Schmidt* (pp. 5–46). Springer.

Gustman, A. L., Steinmeier, T. L. (1999). Effects of pensions on savings: analysis with data from the health and retirement study. In *Carnegie-Rochester conference series on public policy* (pp. 271–324). Vol. 50. North-Holland: Elsevier.

Heckman, J., & Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica: Journal of the Econometric Society*, *52*, 271–320.

Hurd, M., Michaud, P.-C., & Rohwedder, S. (2012). The displacement effect of public pensions on the accumulation of financial assets. *Fiscal Studies*, *33*, 107–128.

Joubert, C. (2015). Pension design with a large informal labor market: evidence from chile. *International Economic Review*, *56*, 673–694.

Kristjanpoller, W. D., & Olson, J. E. (2015). Choice of retirement funds in chile: are chilean women more risk averse than men? *Sex Roles*, *72*, 50–67.

Kristjanpoller, W. D., & Olson, J. E. (2015). The effect of financial knowledge and demographic variables on passive and active investment in chileas pension plan. *Journal of Pension Economics & Finance*, *14*, 293–314.

Madrian, B. C., & Shea, D. F. (2001). The power of suggestion: inertia in 401 (k) participation and savings behavior. *The Quarterly Journal of Economics*, *116*, 1149–1187.

Mincer, J. (1974). Schooling and earnings. In *Schooling, experience, and earnings* (pp. 41–63). Cambridge, Massachuset: NBER.

Morales, L. F., Gordon-Larsen, P., & Guilkey, D. (2016). Obesity and health-related decisions: an empirical model of the determinants of weight status across the transition from adolescence to young adulthood. *Economics & Human Biology*, *23*, 46–62.

Mroz, T. A. (1999). Discrete factor approximations in simultaneous equation models: estimating the impact of a dummy endogenous variable on a continuous outcome. *Journal of Econometrics*, *92*, 233–274.

Mroz, T. A., & Guilkey, D. K. (1992). *Discrete factor approximation for use in simultaneous equation models with both continuous and discrete endogenous variables.* Working paper. Chapel Hill, N.C., U.S.: University of North Carolina Carolina Population Center.

Orszag, P. R., & Stiglitz, J. E. (2001). Rethinking pension reform: ten myths about social security systems. In *New ideas about old age security* (pp. 17–56). Washington D.C., U.S.: The World Bank.

Parada-Contzen, M. (2019). *Default behavior and risk aversion in defined contribution retirement systems: evidence from chile*. Working paper. Chile.

Perticará, M., & Bueno, I. (2009). A new approach to gender wage gaps in chile. *CEPAL Review*, *2009*, 131–147.

Surette, B. J. (1997). *The effects of two-year college on the labor market and schooling experiences of young men*. Board of Governors of the Federal Reserve System Finance and Econ. Disc. *Series* 97–44. Washington, D.C., U.S.

Thaler, R. H. (2016). Behavioral economics: past, present, and future. *American Economic Review*, *106*, 1577–1600.

Thaler, R. H., & Benartzi, S. (2004). Save more tomorrow: using behavioral economics to increase employee saving. *Journal of Political Economy*, *112*, S164–S187.

Yang, Z., Gilleskie, D. B., & Norton, E. C. (2009). Health insurance, medical care, and health outcomes a model of elderly health dynamics. *Journal of Human Resources*, *44*, 47–114.