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Deepening our Understanding of Savings Automation in Retirement and Non-retirement Contexts

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Abstract

Twenty years of research focused mainly on retirement savings demonstrates that automating components of the savings process can lead to higher participation in retirement plans, contribution rates, and balances. In this paper, we discuss the literature on these benefits of savings automation and its potential negative consequences, such as reduced liquidity. We also highlight areas of examined—and unexamined—heterogeneity, including our prior work covering the relationships between time preferences, savings automation, and measures of financial health. Recent policies, such as the Setting Every Community Up for Retirement Enhancement (SECURE) 2.0 Act of 2022, encourage greater automation of both retirement savings and liquid emergency savings. As such, we conclude by calling on researchers to further explore both non-retirement and retirement savings automation, longitudinal outcomes indicative of retirement success, and the potential social wealth inequalities that may be exacerbated by leveraging automation only in employer spaces.

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Introduction

Savings are essential for weathering financial shocks and planning for the future. While Americans' personal savings rates have varied substantially over the last 60 years, many Americans lack sufficient savings today. In 2023, only 57 percent of households in the United States had enough savings to cover at least three months of living expenses (Financial Health Network 2023). US households also face challenges with long-term retirement savings: The Employee Benefit Research Institute (EBRI) reports that only one in five Americans feel confident they will have enough money to live comfortably in retirement and only 27 percent of retirees report feeling very confident they will live comfortably throughout their retirement years (EBRI 2023). These statistics suggest that a significant number of Americans are neither prepared for short-term shocks nor for retirement, which could lead to lower financial well-being, delayed retirement, and an increased strain on public welfare systems.

For years, researchers have worked to identify barriers to saving, to test interventions to increase saving, and to examine the long-term benefits of those interventions. A common thread among these interventions is automating some part of the savings process. By "automating" we mean that an aspect of the savings process happens without the consumer needing to take action. This automation can take multiple forms.

In the retirement space, automation often includes **automatic enrollment** into a defined contribution retirement savings plan (see Beshears et al. 2010 for a brief overview). With automatic enrollment, employees who do not opt out are included in a program that deducts money from their paychecks and places it into a 401(k) or similar type of tax advantaged retirement account. Automatic enrollment of employees into retirement savings programs can boost enrollment by as much as 86 percent (Derby et al. 2023) and push overall participation rates up to

91 percent (Vanguard Research 2021). Automatic enrollment can be paired with **automatic escalation**, which increases the amount deducted from a paycheck over time, so that as time passes, so too do savings contributions. Both forms of automation increase savings in a way that requires almost no consumer effort.

To automate savings outside of an employer provided plan, consumers have to take some initial action. Depending on their financial institution's capabilities, consumers can set up **automatic transfers** from their paycheck or from one account to another, including automatic investment purchases, or opt for **automatic rebalancing** of investment account assets to achieve a given asset allocation. Using these means, the effort to save is greatly reduced because consumers make an automation decision once. As long as automation is in place, they will grow their savings with no additional effort required.

The Setting Every Community Up for Retirement Enhancement (SECURE) 2.0 Act of 2022 is evidence that policymakers recognize the power of automation. The SECURE 2.0 Act aims to extend the reach of automation features to improve retirement savings by requiring that most new 401(k) and 403(b) plans automatically enroll employees in these retirement plans, with default contribution rates at a minimum of 3 percent of salaries and automatic escalation of contributions at 1 percent annually. The SECURE 2.0 Act may also boost Americans' liquid emergency savings, as it permits employers to automatically enroll employees into emergency savings accounts that are linked to their retirement plan[1]. Emergency savings accounts—perhaps especially emergency savings accounts with automatic transfers—may increase employees' chances of weathering a financial shock and reduce the need to make costly withdrawals from retirement savings or take on debt.

Importantly, the regulatory requirements of the SECURE 2.0 Act apply only to new employer-sponsored retirement plans. For an increasing number of Americans working at jobs where these plans aren't available—including some part-time workers and independent contractors like gig workers—the corresponding benefits of expanded savings automation won't be realized. Given the emphasis on savings automation in the SECURE 2.0 Act, but also in recognition of the limitations of this intervention, our article aims to foster discussion and new research regarding saving in the presence and absence of automation for different types of savings and consumer groups. This article will:

(1) Review recent evidence on savings automation and financial outcomes, both causal and correlational.

(2) Review areas where research shows mixed findings, would benefit from additional research on longitudinal outcomes, or shows variation in effects for different subgroups.

(3) Show that automation may not be available to everyone and discuss corresponding limitations of this policy intervention.

The Theory Behind Savings Automation

As a behavioral intervention, savings automation should help consumers save more by circumventing several well-documented consumer tendencies, including status quo bias and present bias. Consumers show a tendency to maintain the status quo (Samuelson and Zeckhauser 1988), so those that are not currently saving may require strong motivation to start or processes that make saving easier. Additionally, with automation, consumers can set aside time or energy only once rather than repeatedly. This reduction in effort is important for present biased consumers, whose tendency to prioritize the present means they may never set aside the time or energy needed to save for the future (Meier and Sprenger 2010; Ashraf et al. 2006), and may spend down their income before making the decision to save. For those that have disposable income available to save but tend to remain present focused, the reduction in effort for saving conveyed by automation may be especially helpful.

Once the initial enrollment decision is made, people are unlikely to stop saving for the same reason it was difficult to start: inertia. It is also possible that automation also leads to a degree of inattention that can be beneficial for long-term investments such as those used for retirement. Specifically, research on individual consumers finds that those who trade the most tend to have lower returns than those who adopt a ‘set it and forget it’ strategy with their investments (Barber and Odean 2001). Additionally, investors are not often successful at ‘timing’ the market—that is, buying low and selling high—which is required to achieve superior market returns (Barber and Odean 2013). For these reasons, both academic research and popular advice tend to suggest that people invest in passive indexes rather than actively managed funds (Choi 2022). While there may be downsides to inattention inherent in automation (e.g., account abandonment; discussed below), in the context of trading, it may also help investors avoid issues from overtrading and suboptimal market timing.

Savings Automation Benefits Participation, Contribution Rates, and Net Saving

Consistent with the theoretical rationale just discussed, recent research (summarized in Table 1) generally shows a positive relationship between automation interventions and consumer outcomes. For example, researchers found that automatic enrollment in employer-sponsored retirement plans significantly increases employees’ participation in those plans, contributions, and net savings (Beshears et al. 2022; Cribb and Emmerson 2021; Falk and Karamcheva 2023; Derby et al. 2023). Furthermore, studies have shown an increase in contribution rates for automatically enrolled participants, particularly when combined with automatic escalation (Vanguard Research 2021; Beshears et al. 2017). Although the literature on non-retirement savings is smaller, a quasi-experiment in the UK found that automatic enrollment increases this kind of saving (Berk et al. 2022). Additionally, automation appears to be associated with greater non-retirement savings for those who do not have a strong savings habit (Newmeyer et al. 2021). For a review of work published prior to 2015, and therefore not included in Table 1, see O'Neill (2007) and Burke, Hung, and Luoto (2015) and CFPB (2020).

Insert Table 1 here

Not All Consequences of Savings Automation Are Positive

Despite the power of automating steps in the savings process, it is not necessarily a complete solution to savings challenges. In this section, we discuss ways in which initial participation rates or savings amounts that are typically examined in research (see Table 1) may provide an overly simplistic view of the benefits of savings automation.

Automatic savings into a retirement savings account could lead to either saving too little or to oversaving. Starting with the risk of saving too little, a potential challenge is that participants frequently perceive the default choices for contribution rates as recommendations from their employer (Madrian and Shea 2001). This means that the path of least resistance in automation may include signing up at a lower contribution rate than what an individual might select without defaults. Indeed, in a Vanguard study (2021) of newly hired employees in 2017, 2018, and 2019 who were eligible for 520 different retirement plans, the average retirement contribution rate after 3 years for plans with no automatic enrollment (i.e., no default contribution rate) is 7.6%, in contrast to 6.6% for plans with automatic enrollment (and no automatic escalation). The average contribution rate for plans with automatic enrollment is lower despite plan participants having higher median income than employees participating in the voluntary enrollment plans (Vanguard Research 2021). Only 3% of plans in this study had default contribution rates exceeding 6 percent (Vanguard Research 2021).

The problem of lower savings rates with automatic enrollment may be mitigated by pairing automatic enrollment with automatic savings escalation, which has been effective at increasing contribution rates (e.g., 'Save More Tomorrow' program by Thaler and Benartzi 2004; Benartzi and Thaler 2013). Automatic escalation is common among employer retirement plans with automatic enrollment: Vanguard's study reported that 7 in 10 plans with automatic enrollment include an automatic annual increase in contribution rates. Plans with both automatic enrollment and escalation have average contribution rates after three years of 7.9%, exceeding the average contribution rate of plans without automatic enrollment (7.6%) (Figure 11, Vanguard Research 2021). In addition, researchers examining data from 2017 to 2020 from the OregonSaves program demonstrated that increases in savings from the 5% default contribution rate to 6% and 7% occurred as a direct result of the program's 1% annual automatic escalation (see description in Chalmers et al. 2021).

A second source of saving 'too little' could be that retirement plan participants choose overly conservative portfolio allocations. To address the effort and knowledge barriers required for plan participants to choose appropriate investments and to rebalance them over time, many plans now automatically enroll participants in target date funds. These funds establish a combination of assets that automatically change to align the fund's risk level with the time remaining to an estimated retirement year. A study of 880 Vanguard investors' defined contribution plans between 2003 and 2015 found that retirement plan participants who invested solely in target date funds had an annual return that were 2.3% higher than participants who did not invest in target date funds; due partly to the more expert nature of a target date fund composition (e.g., less cash, more equity exposure for younger participants, and adjustments in response to market changes and time to retirement) (Mitchell and Utkus 2022). Based on the performance of target date funds during the observation period of the dataset, the authors estimate that the long-run impact of investing in target-date funds could be as large as 50% higher retirement balances (Mitchell and Utkus 2022). Target-date funds are nearly universally the default allocation for employers that use automatic enrollment for their retirement plans: in another Vanguard study, 99% of automatic enrollment plans have a target-date fund as the default allocation (Vanguard Research 2021). This is important because their data show that the default portfolio investment is sticky: 86 percent of participants who were automatically enrolled remained entirely invested in the default option (Vanguard Research 2021).

An alternative risk to the possibility of under-saving for retirement as a result of automation is that some consumers save 'too much,' with a variety of downstream consequences. Recent literature has explored three outcomes: lower 401(k) balances through early withdrawals and loans, increased debt, and reduced contributions in subsequent jobs. Some early withdrawals from a 401(k) may not be the result of over-saving but instead reflect the complexity of executing a rollover when people leave an employer, or an individual's strategy to use a retirement account for precautionary savings. However, a 401(k) is a much more expensive option for precautionary savings than many other savings vehicles, as there are typically associated fees and penalties for early withdrawals. In a study of an employer's implementation of automatic enrollment, researchers found that the share of plan participants who had taken at least one non-rollover withdrawal within 8 years of being hired was higher for employees who were automatically enrolled in the retirement plan (58.6% of plan participants) compared with employees who were not automatically enrolled (43.2%) (Beshears et al. 2018).[2]

Another option for people who need to access their retirement account for liquidity is taking a loan from the account that is repaid over time. Vanguard (2021) reported a higher incidence of loans among those who were automatically enrolled (24%) versus those who enrolled voluntarily (20%). After taking withdrawals and loans into account, researchers claim that automatic enrollment continues to show an overall benefit to retirement savings. Beshears et al. (2018) argue that after withdrawals and plan loans, 60 percent of savings remain, whereas Derby et al. (2023) estimate a positive effect on net savings of 1.02 percentage points (37%).

The evidence that automatic enrollment increases debt is more mixed. Beshears et al. (2022) explored whether consumers with retirement savings respond to liquidity shocks through other forms of borrowing. They found no evidence that automatic enrollment increases borrowing for most types of credit, with no significant change to debt balances before and after automatic enrollment took effect with the exception of auto loan and first mortgage balances under some model specifications. The net welfare effects for these types of loans are less clear as auto and mortgage debt are as often an indicator of financial wellness as they are of financial distress. Another study of automatic enrollment in the UK similarly found that it increases employees' likelihood of holding a mortgage and therefore mortgage debt, although there were no differences in auto loan balances (Beshears et al. 2024). Its findings for other types of debt differed from the U.S. study in that unsecured debt such as personal loans and bank overdrafts increased. However, measures of credit health actually improved over time, with credit scores increasing and loan defaults falling (Beshears et al. 2024).

Finally, we note that there are other ways for consumers to offset saving 'too much.' Choukhmane (2021) argues that job switchers who have saved too much respond by reducing contributions in subsequent jobs. More research is needed to understand the impact of job switching on savings over time, especially given that job switches frequently coincide with a withdrawal in savings as consumers manage the transition between jobs.

The benefits of automation can be attenuated if consumers forget about their savings altogether. As discussed earlier, the inattention caused by automation could be beneficial; however, recent work suggests that automatic enrollment could increase account abandonment (Goodman et al. 2023). The problem appears to be concentrated among smaller accounts, which are more common for those with lower incomes and people of color (John et al. 2021a). Worryingly, another study that examined interventions to help consumers find lost or forgotten accounts found that these interventions had little success (Rosen and Sade 2022). With some estimates for abandoned savings as high as $66 million (Goodman et al. 2023), institutions and consulting firms have begun to explore institution- and policy-level solutions; John et al. (2021b) discuss the benefits of a national retirement dashboard, for example, which would consolidate information from all of a consumer's retirement plans in a single, secure location.

Thus far, existing research on automation suggests that while there may be some attenuation of retirement savings benefits due to the need to make withdrawals or to the increased odds of abandoning an account, the net gain is still positive. Additionally, the SECURE 2.0 Act and other industry-driven campaigns to increase automation in liquid emergency savings (and non-retirement investments) may increase the number of Americans who have emergency savings that can keep them afloat during shocks, increasing the likelihood of preserving the retirement savings already set aside.

The Benefits of Automation Vary Across Demographic Groups

Recent research shows that the effects of automation vary across different types of consumers; the right column of Table 1 shows demographic subgroups that have been examined by researchers, with gender, age, race, and education being the most often explored. Overall, the literature is fairly consistent in finding that the effects of automatic enrollment are stronger for consumers who are traditionally in more vulnerable financial positions. Beshears et al. (2022) shows that the effects are larger for those with low incomes, younger individuals, and Black and Hispanic workers. Cribb and Emerson (2021) found that the impact of automatic enrollment on pension participation is larger for those who typically have lower participation—younger employees and those with shorter job tenures. For example, automatic enrollment leads to an estimated 35.8% increase in participation for those aged 40 and above, as compared to an estimated 54.3% increase for those aged 22 to 39. Vanguard Research (2021) and Derby et al. (2023) both reported that automatic enrollment raises participation rates more for young and low-income workers than for older and higher-income workers. Falk and Karamcheva (2023) found that automatic enrollment leads to a larger increase in participation and contribution rates among men than in women (e.g., a 13.9 percentage point increase in participation for men versus a 11.2 percentage point increase for women). The effects of automatic enrollment are also larger for relatively lower-income workers (as measured by those in the bottom-earnings tercile). Finally, younger consumers and those with lower incomes are slower to opt out of contribution rate defaults (Beshears et al. 2016).

Time Preferences and Implications for the Benefits of Automation

Little of the empirical work on savings automation explores consumer heterogeneity beyond demographic subgroups (as demonstrated in Table 1). We examined one source of heterogeneity in our 2018 paper 'Exploring the Relationships Between Impatience, Savings Automation, and Financial Welfare' (Middlewood et al. 2018) when we asked whether automation would be more helpful for 'doers,' who are more present focused, than for 'planners,' who are more future focused. This pattern was posited by previous theoretical work on the role of time preferences in the efficacy of behavioral constraints (Shefrin and Thaler 1988), as savings automation may be more effective for individuals who do not naturally have future-oriented tendencies. In this section, we briefly review our 2018 paper and extend our literature review to summarize the most recent work on heterogeneity in how automation benefits consumers.

In our 2018 paper, we used the Consumer Financial Protection Bureau's (CFPB) National Financial Well-Being Survey (https://www.consumerfinance.gov/data-research/financial-well-being-survey-data/) to test an implication of the behavioral life-cycle hypothesis (Shefrin and Thaler 1988) that a behavioral constraint like automation would be especially helpful for those with doer tendencies. To measure automation, we used a survey question where respondents confirmed whether they had "money automatically transferred" into each of a retirement savings account, a non-retirement savings account, both, or neither. Our prior analysis examined consumers who automated their *non*-retirement savings (Figure 1); here, we expand that analysis to retirement savings (Figure 2).

We operationalized doer and planner tendencies using a simple measure of present bias that asked participants to indicate whether they would prefer to have $816 now or $860 in three months. Those who selected $816, the smaller-sooner amount, were classified as 'doers,' whereas those who selected $860, the larger-later amount, were classified as 'planners'[3]. The expectation was that doers would especially benefit from commitment devices like automation relative to planners. Combining the measures of present bias and automation behavior resulted in four groups of consumers: doers who automate, doers that do not, planners who automate, and planners that do not.

We compared these four groups in terms of several financial health outcomes: Financial well-being as defined by the CFPB Financial Well-being scale, self-reported liquid savings, self-reported ease in covering monthly expenses, and confidence in one's ability to raise $2,000 in 30 days.[4] Across the four analyses, displayed in Figure 1, we found evidence in line with our expectations. Overall, planners on average have better financial health than doers. Furthermore, although automation is helpful for both groups, the gap in financial health between those who do and do not automate is larger for doers. Although correlational, we interpret this as evidence of the possibility that the benefits of non-retirement savings automation are larger for doers than planners.

Insert Figure 1 here

For the current article, we additionally examined a similar set of outcomes for doers and planners who reported automatically transferring money into *retirement*-related savings accounts. Using the same data as our 2018 article, we find that 39 percent of the US population reported automating savings into a retirement savings account, and a similar proportion reported automating savings into a non-retirement savings account. However, comparing those who report having both types of accounts suggests that there are differences in automation behavior across account types, with over 20 percent of the US population choosing to automate into one type of account and not the other. In other words, there is limited evidence of an ‘automater’ personality.

Insert Table 2 here

Perhaps more importantly, we examine whether financial health outcomes are related to automation of retirement savings and time preferences, using the same analytical framework as our 2018 analysis; that is, we explore average outcomes for the four groups (doers and planners, who automate or don’t), controlling for individual demographic characteristics (e.g., income, age, employment status). Here, we omit survey respondents who report being “retired,” as it is not entirely clear how these respondents would respond to a question about automating retirement savings.

We find that retirement savings automation is correlated with greater liquid savings and the ability to absorb a shock, as demonstrated by an interaction between time preferences and automation (see left panel of Figure 2). As shown, planners have higher overall levels of both variables, but the gap between planners and doers is smaller for doers who also choose to automate retirement savings. These results hold even when controlling for the decision to automate non-retirement savings. We take this as evidence that retirement savings automation may be especially helpful for doers, who may struggle more than planners to save without the aid of interventions that circumvent their tendency—or need—to focus on the present rather than the future.

Insert Figure 2 here

Unlike savings automation into a non-retirement account, however, there is no significant relationship between retirement automation and time preferences on financial well-being or perceived ease of covering monthly expenses (right panels of Figure 2). Additionally, retirement-related outcomes like expected retirement age and social security-claiming age are also unrelated to automation and time preferences (not shown). Note, however, that the survey sample size for the two latter outcomes is smaller, as expected retirement age is only provided by non-retirees and Social Security claiming age is only provided by those ages 61–71. Nevertheless, it was surprising to us that retirement savings automation would not relate to these and other long-term financial outcomes that one might expect to be improved by automation.

Goda et al. (2020) uses matched survey and retirement plan data to estimate the relationship between time preferences (both present bias and discount rates) and retirement savings behavior. Under an automatic enrollment regime with 3 percent matching, present-biased individuals are more likely to stick with the default. In our survey data, we found no relationship between time preferences and the decision to automate savings for either retirement or non-retirement accounts.

Beyond Time Preferences? Understanding Further Heterogeneity in Automation

Naturally, time preferences are only one dimension by which automation effects may vary. However, as demonstrated earlier, there is relatively little research on how the benefits of retirement savings automation vary for different subgroups, particularly when looking beyond demographic characteristics (Table 1). In this section, we address other aspects of consumer psychology and structural factors that might represent interesting dimensions of heterogeneity.

Differences in financial skill, socialization, and knowledge. In our 2018 study on non-retirement savings, we explored the characteristics of who was more likely to automate savings. We found that those with higher financial skill (measured with the CFPB 10-item financial skill scale, CFPB 2018, which includes items such as, 'I know when I need advice about my money,' and, 'I know how to make myself save') were more likely to automate non-retirement savings. We also found those with higher financial socialization (measured using positive responses to seven statements such as, 'While growing up at home, did your family do any of the following? Discussed family financial matters with me.') were more likely to automate non-retirement savings. When we examined retirement savings, we found that automation was also positively related to financial socialization and financial skill.

We find no relationship between automating savings into a non-retirement account and financial knowledge, when measured using a 10-item scale (Houts and Knoll 2020) with items such as, 'If the interest rates rise, what should happen to bond prices?' This may be because, while the decision to automate can be a sign of sophistication for some consumers, it is not guaranteed to provide benefits (as we have highlighted in this paper). Automation may therefore be unrelated to financial knowledge. Perhaps surprisingly, automation into retirement accounts was negatively related to financial literacy in a regression that controlled for a variety of other variables.[5] Possibly, this negative relationship is due to the confounding effects of compliance with auto-enrollment in retirement plans among those with low levels of financial literacy. Mrkva et al. (2021) found that across several choice contexts, people with lower financial literacy are more likely to stick with default options; in the specific context of retirement savings, they found that people with lower financial sophistication and lower financial experience who were automatically enrolled into their employer's retirement plan were less likely to change either the investment contribution amounts or the allocations that they were assigned by default. Other work comparing opt-in and automatic enrollment regimes seems to align, finding that financial literacy is more predictive of saving under opt-in regimes, while present-bias is more predictive of saving under automatic enrollment (Goda et al. 2020).

Attitudes toward saving. The construct of Personal Savings Orientation (Dholakia et al. 2016) adds more nuance to the relationship between financial literacy and savings behavior. This construct refers to the extent to which savings is a lifestyle and not merely goal oriented. Items include statements like, 'The goal of saving money is always at the back of my mind,' and, 'Putting money into personal savings is a habit for me.' In their research, the authors found that financial literacy only predicts savings for those with a higher personal savings orientation. Newmeyer et al. (2021) built on this work to show that those with a savings habit benefit more from automating savings.

Heterogeneity in Access to Accounts

Research on automation focuses on retirement accounts and relies primarily on employer-sponsored plan data. By contrast**,** few studies explore how consumers pursue retirement savings outside of employer-based plans and whether automated deposits into those accounts yield the same retirement benefits. Many people do not have access to employer-sponsored retirement programs and must make efforts on their own to ensure they are saving for retirement (Glasner 2023; John et al. 2022). This section explores ownership of retirement accounts using a consumer survey and the implications of these differences.

We analyze data from the CFPB's National Financial Well-Being Survey to explore how ownership of retirement accounts varies across the US population. As shown in Table 2, 30 percent of the US population reported not having a retirement account in 2018.[6] Table 3 shows that there are differences in the demographic composition of retirement account owners and non-owners. In particular, account ownership is more prevalent among men, non-Hispanic, or White respondents, and those with higher levels of educational attainment. Account ownership is also more prevalent for those who are working full time, suggesting differences by employment status. Those who report holding a retirement account also report roughly double the amount saved ($30,000 versus $15,000) and less usage of products and services like prepaid cards or check cashing. These patterns are largely consistent with non-retirement account ownership published elsewhere (see Middlewood et al. 2018).

Insert Table 3 here

Even though we analyze "retirement accounts," as defined by the survey respondents, heterogeneity in retirement account ownership shown in Table 3 may partially reflect demographic differences in who has access to employer-sponsored retirement plans. A higher proportion of Hispanic, Black, and Asian workers reports not having access to an employer-sponsored retirement plan than non-Hispanic White workers (John et al. 2022).[7] In addition, low-income workers do not have the same access to employer-provided retirement plans as higher earners. Only 30 percent of low-income workers earning less than $37,000 a year have access, and of those with access, only 19 percent participate (Glasner 2023). Further compounding this disparity in access to retirement savings, low-income households face barriers to building and maintaining their retirement savings balances, as they are more likely to switch jobs more frequently than high-income households (US Government Accountability Office [GAO] 2023a). Low-income households are also more likely to make early withdrawals from their employer-sponsored retirement plans (US GAO 2023b; Argento et al. 2015), potentially incurring a 10 percent tax penalty (IRS 2023).

To the extent that retirement account access and ownership are unevenly distributed across the US population and are correlated with existing wealth, increased automation into these accounts is likely to exacerbate these underlying differences. In other words, retirement savings automation may help increase retirement security and net worth for those who use these accounts but may leave behind those who are already the most financially insecure. With the advent of the SECURE 2.0 Act, as well as the extension of automation benefits to non-retirement savings through employer-sponsored retirement programs, access to these tools will be an increasingly important source of disparity in overall savings amounts. There may be an opportunity to mitigate these disparities through state-sponsored auto-IRA programs such as OregonSaves, which automatically enroll certain workers who don't have access to an employer-sponsored retirement account into an IRA. These plans have covered a limited but increasing number of workers to date.[8]

Discussion

We have summarized the literature covering automation as a savings intervention. But even after decades of work, there are many questions to answer.

Is automating saving for retirement and non-retirement outcomes different? One question arising from our review and prior research is: Are there differences in the benefits of automation for retirement and non-retirement savings? Empirically, we found that the relationship between time preferences and savings automation holds for fewer outcomes (i.e., only liquid savings and ability to absorb a shock, not financial well-being) when speaking about retirement savings automation versus non-retirement savings automation. At this juncture, we can only speculate on why these differences may occur. One factor may be the time horizon associated with the savings, with retirement being a long-run outcome for many consumers. Time horizons may affect the benefits of automation in two opposing ways. Automation is likely to have greater benefits for retirement savings accrual, as the one-time fix to savings behavior is allowed to accumulate benefits for a longer period. On the other hand, the inherent long-run nature of retirement may make automation less beneficial for those with significant liquidity constraints who may respond to automation by taking early withdrawals from retirement accounts and paying tax penalties, as described above.

A second possible factor underlying differences in automation between retirement and non-retirement accounts is the specific form of automation. For many Americans, non-retirement savings are held in checking and savings accounts, non-bank fintech accounts (e.g., PayPal), or money market funds, and most of these accounts have the ability to automate transfers. Possibly, automatic transfers that occur after a person has received their paycheck could affect budgeting and spending behavior, as consumers can observe the reduction in disposable income as a result of saving. This process can be compared to automatic enrollment and automatic escalation (which may be more common in employer-sponsored retirement plans), where money is not easily accessible prior to being saved. At the same time, for consumers who attend less to account balances, a series of automated transfers might result in overdraft and other fees stemming from insufficient funds. Future research should explore how the effects of automation differ among these different accounts, methods, and products.

Third, from a psychological perspective, the automation of savings into non-retirement versus retirement accounts may also vary in intentionality. Retirement savings automation, particularly for employer-sponsored retirement accounts, is supported by institutional policies and practices such as employer matching of employee contributions, tax benefits, and encouragement from employer personnel. Future research should explore whether automation decisions made without such a supporting institutional structure are more intentional on the part of consumers.

Ultimately, Table 1 shows only two papers examining automation in the context of non-retirement savings as opposed to the 10 papers examining retirement savings. Even within retirement savings, eight papers study enrollment into employer-sponsored retirement plans as opposed to brokerage accounts that are used for long-run savings or IRAs. It remains an open question of how to best encourage individual consumers to automate savings outside of employer-sponsored plans or whether state-level programs like OregonSaves are a more promising solution.

Does automation of retirement savings lead to more successful retirement? Few papers examine long-run longitudinal outcomes as opposed to proximate behaviors (e.g., participation and initial contribution rates). The time span of data covered in Table 1 is, at most, 4.5 years post-intervention—a long time compared to many intervention studies, but perhaps insufficient if one considers the potential number of years until retirement. Furthermore, to our knowledge, no research on savings automation examines retirement security—which is arguably the ultimate aim of these retirement savings interventions. Our correlational results on financial well-being suggest no significant relationship between automation and a consumer's subjective sense of financial security. Thus, although the interventions show promising results on crucial inputs to retirement savings (such as retirement account participation and contribution rates), it remains to be seen whether these benefits persist throughout a consumer's retirement.

Conclusion

The savings problem facing American households is unlikely to abate. Household expenses have risen following the COVID-19 pandemic, after a period of inflation rates as high as 9.1

percent in June 2022 (Bureau of Labor Statistics [BLS] 2023a). Although the gap between wage growth and inflation is closing, American workers are still feeling the repercussions of the highest increase of prices since 1981 (BLS 2022). With housing making up about 33.3 percent of Americans' annual expenses (BLS 2023b), Americans are paying significantly more for rent and home prices given that wages have not increased at the same rate (National Low Income Housing Coalition 2023). Many households also carry significant debt, the payments for which can interfere with households' ability to put aside money into savings. Student loan debt is pervasive across age groups (US Department of Education 2023) and credit card balances have recently topped $1 trillion (Federal Reserve Bank of New York 2023). Americans are also living longer (Medina et al. 2020), making retirement savings more important, even as the shift from defined-benefit to defined-contribution retirement plans has put more responsibility on individual consumers to save. In light of these challenges, it may be difficult for many households to save enough for the future, particularly for seemingly far-off outcomes like retirement.

As a policy response, the SECURE 2.0 Act helps encourage retirement and non-retirement savings through savings automation programs. Our review of the literature, drawing on automation interventions predating the implementation of the SECURE 2.0 Act, paints a generally positive picture regarding the possible benefits of savings automation. In particular, automation appears to reliably increase participation rates and contributions into retirement accounts (see Table 1) and is correlated with a set of positive outcomes, particularly for people who are more present focused.

However, the literature also suggests that an emphasis on proximate outcomes may be shortsighted, as automation can have possible downsides in the long term. In particular, individuals with automated savings may be more likely to forget about their savings (Goodman et al. 2023) and to make withdrawals from 401(k) accounts when unable to weather financial shocks that may not have occurred had they not diverted as much from their paycheck into retirement savings (Beshears et al. 2018). Finally, not all Americans have access to employer-sponsored retirement accounts, especially those in traditionally vulnerable groups, meaning automation may exacerbate existing wealth disparities. The increasing number of state-sponsored auto-IRAs --15 states have such programs as of January 2024 (Center for Retirement Initiatives, 2024) -- warrant further evaluation in their capacity for alleviating these disparities. Additionally, as more Americans hold jobs that lack the retirement savings infrastructure of many conventional full-time positions, there will be a growing need to widen avenues for retirement savings outside of the workplace.

There is little reason to question automation of savings as a broadly worthwhile intervention, but our review highlights the need for automation to work in tandem with other interventions to mitigate the shortcomings of automation alone and enhance saving over time. Researchers should focus on the nuanced impacts of combined interventions for different groups of consumers so that we might understand more completely how and when to apply automation.

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Endnotes

[1] See section 801 of the Employee Retirement Income Security Act of 1974 (ERISA), which allows for "a pension-linked emergency savings account" and the ability to "automatically enroll an eligible participant in such account pursuant to an automatic contribution arrangement". Furthermore, such accounts are not allowed to have any fees or charges for at least the first four withdrawals of funds in a plan year.

[2] Withdrawal rates may be higher for other types of automatic enrollment programs. Quinby et al. (2020) found that 20 percent of employees in the OregonSaves program-- a state-sponsored auto-IRA-- made at least one withdrawal during the 12-month study period, with an average withdrawal amount of $1,000. The authors suggest that the structure of the program as a Roth IRA--where contributions can be withdrawn without the 10% tax penalty --may mean withdrawals are more

likely relative to traditional defined contribution plans. For a summary on the OregonSaves program and other auto-IRAs, see Pew Charitable Trusts (2021).

[3] Such time-amount tradeoff questions are commonly used to assess whether someone is willing to defer gratification to earn higher rewards in the future (see, for instance, Hardisty, et al. 2013). As we described in our 2018 paper, the implied rate of return for this tradeoff is approximately 23.4%, well above what one could expect to earn from investing. Therefore, selecting the smaller amount sooner suggests the respondent prefers present consumption over future returns.

[4] Specifically, our estimating equation was: Yi = β0 + β1Doeri + β2Automatedi + β3Doeri*Automatedi + ƔXi + εi, where Yi represented one of thee four financial welfare outcomes, Doer was a variable representing whether the respondent was classified as a doer (1/0), Automated represented whether the respondent automated savings (1/0) and X represented a vector of demographic characteristics (age, gender, income, education, race/ethnicity, and presence of children in the household).

[5] These variables included time preferences, financial socialization, financial skill, gender, age, race/ethnicity, educational attainment, employment, and reports of having a retirement account from other questions in the survey. In addition to those patterns highlighted in the text, there were positive associations with income, working full time or part time, or being a homemaker. There were negative relationships with being Hispanic or being retired.

[6] The measure analyzed in this table does not distinguish between employer-sponsored retirement accounts and non-employer-sponsored retirement accounts.

[7] Approximately 64 percent of Hispanic workers, 53 percent of Black workers, and 45 percent of Asian workers do not have access to an employer-sponsored retirement plan, as compared to 42 percent of White (non-Hispanic) workers (John et al. 2022).

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[8] More states are enacting auto-IRA programs to provide coverage for those who lack access to an employer-sponsored plan (Pew Charitable Trusts, 2022). There are 15 states offering such programs as of January 2024 (Center for Retirement Initiatives, 2024), which have enrolled fewer than one million workers out of the 56 million who lack access to employer-sponsored retirement plans (Pew Charitable Trusts, 2023).

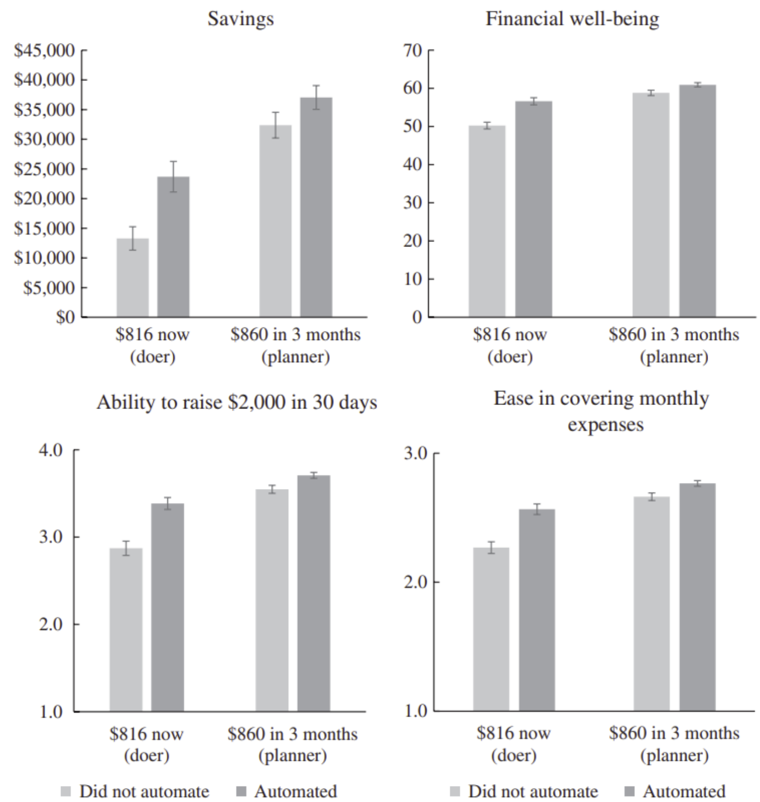

Figure 1. Financial welfare outcomes by doer and planner preferences and non-retirement savings automation

Note: Figures display the raw means. Error bars show 95 percent confidence intervals around the means.

Source: Middlewood et al. (2018).

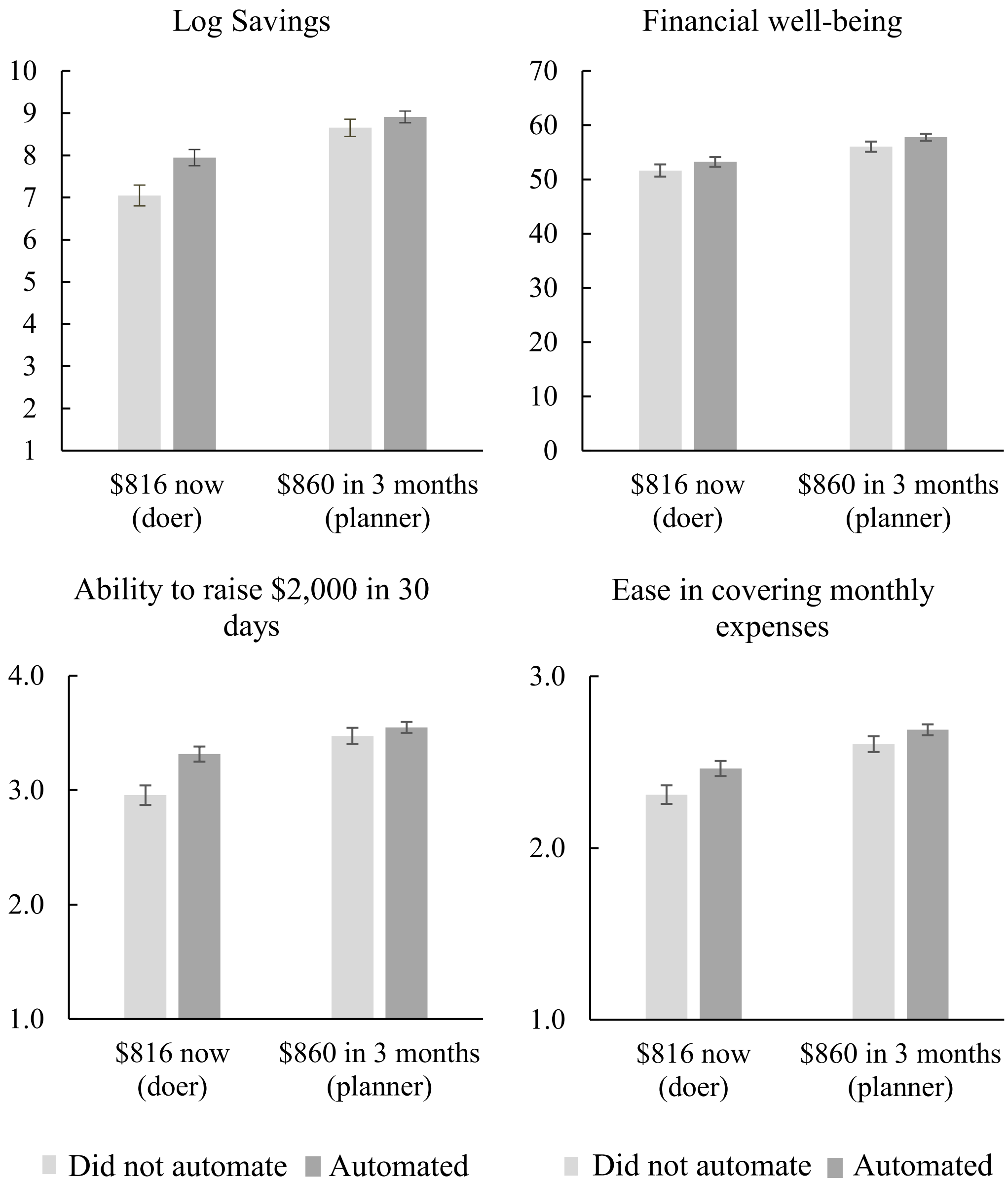

Figure 2. Financial welfare outcomes by doer and planner preferences and retirement savings automation

Note. Figure displays the means from unweighted regression analysis using a regression that also includes controls for non-retirement savings automation, time preferences, and demographic characteristics. Error bars show 95 percent confidence intervals around the means.

Source: Authors' calculations based on National Financial Well-Being Survey data.

Table 1. Review of recent literature on savings automation and associated financial welfare outcomes

Paper	**Behavioral constraint or strategy**	**Design or Methodology**	**Outcomes examined**	**Subgroups examined for differential effectiveness of strategy (if any)**
Retirement				
Burke et al. (2015)	AE in DC plan	Survey data from Health and Retirement Survey (HRS), [2008 and 2010 survey waves] (employee AE is self-reported)	Participation, contribution, opt out from AE plans	● Age ● Marital status ● Income ● Education ● Wealth
Beshears et al. (2022)	AE in Thrift Savings Plan (TSP) for civilian employees of the US Army	Comparison of pre-AE employees (hired 8/1/2009 to 7/31/2010) and post-AE employees (hired 8/1/2010 to 7/31/2011). [8 years of semiannual credit bureau data, 6/2007 to 12/2014]	Debt, auto debt, first mortgage debt, contributions, savings	● Low income ● Age <30 ● High school education ● Black ● Hispanic ● Credit score <620
Quinby et al. (2020)	AE in OregonSaves, an individual retirement account (IRA) program	Administrative data [1 year of data from 2018 to 2019] (no comparison group)	Participation, pre-retirement withdrawals	None
Chalmers et al. (2021)	AE in OregonSaves, an IRA program	Administrative data [2 years of data from 2018 to 2020] (no comparison group)	Participation, contributions, amount saved, opt-out rates	● Positive Balance ● Age
Cribb and Emerson (2021)	AE in pension plan in the UK	Comparison of AE and non-AE employees in 4/2016 using panel survey data from annual	Participation, contribution rates	● Gender ● Earnings ● Age ● Years with employer

		survey of hours and earnings [4 years of data between 2012 and 2016]. All employees work for 'small employers,' or those with between two and 29 employees (in 2012).		
Vanguard Research (2021)	AE in DC plan sponsors (voluntary enrollment plans versus AE plans)	Vanguard recordkeeping data [3.5 years of data from 2017 to 2020] Sample consists of newly hired, eligible employees between 1/1/2017 and 12/31/2019 who were still employed by the plan sponsor as of 6/30/2020.	Participation, contribution, default portfolio allocation, loans from the plan	● Income ● Age ● Gender
Falk and Karamcheva (2023)	AE and employer match in TSP	Comparison of non-AE and AE employees hired before and after 8/2010. Uses administrative panel data from the TSP, which covers federal civilian workers [6 years of data between 2008 and 2014].	Participation, contribution rates, portfolio allocations, balance, and balance-to-pay ratio	● Education level ● Race ● Gender ● Earnings
Derby et al. (2023)	AE in company-sponsored DC retirement plans	Comparison of AE and non-AE employees, with date of AE varying by employer; sample is 2 years pre-AE and 1 year post-AE. Administrative data [4 years of data between 2010 and	Participation, contributions, savings rate, withdrawals, and net savings	● Firms with 4 years of pre auto-enrollment data and 4 years post auto-enrollment adoption

		2016]		
Non-retirement				
Newmeyer et al. (2021)	Automation of deposits in non-retirement savings account and liquid savings account	Survey data (Consumer Financial Protection Bureau's [CFPB] survey data set) [3 months of data between October and December of 2016] (no comparison group)	Reported saving (yes/no), amount of liquid savings	• Income level • Personal savings orientation (PSO) level
Berk et al. (2022)	AE in payroll savings plan for new hires in the UK	Comparison of AE and non-AE employees hired before and after 11/1/2022; sample is 1 year pre-AE and 7 months post-AE. Administrative data [1.6 years of data from 11/2020 to 6/2022].	Amount saved	• Age • Gender • Starting pay • Role

Note. AE = Automatic Enrollment.

Table 2. Automation behavior into retirement and non-retirement savings accounts

		A **Non-Retirement** Savings Account			
		Do not automate	Automate	I do not have this	**Row Totals**
Retirement Savings Account	Do not automate	20.69%	8.46%	1.17%	30.32%
	Automate	12.67%	23.32%	3.40%	39.39%
	I do not have this	3.94%	6.35%	20.00%	30.30%
	Column Totals	37.30%	38.14%	24.57%	**100%**

Note: N = 6,246. Table 2 shows the proportion of respondents providing each set of responses. Survey weights result in a sample that is representative of the US population.

Source: Authors' calculations based on National Financial Well-Being Survey data.

Table 3. Demographic composition of retirement account owners and non-owners

	Non-owner	Owner	(1) vs. (2) p-value
Gender			
Female	54%	45%	0.089
Race			
Non-Hispanic White	65%	73%	-0.080
Non-Hispanic Black	13%	10%	0.032
Non-Hispanic Other	6%	5%	0.003
Hispanic	17%	13%	0.045
Education			
Less than high school	13%	5%	0.082
High school degree	32%	23%	0.097
Some college	34%	29%	0.057
Bachelor's degree	12%	24%	-0.112
Graduate/professional degree	8%	21%	-0.124
Employment Status			
Self-employed	9%	8%	0.003
Work full time for an employer or the military	20%	47%	-0.264
Work part time for an employer or the military	12%	8%	0.036
Homemaker	9%	5%	0.035
Full-time student	8%	3%	0.054
Permanently sick, disabled, or unable to work	10%	3%	0.068
Unemployed or temporarily laid off	8%	3%	0.049
Retired	34%	28%	0.052
Missing	2%	2%	0.007
Log of imputed income	10.558	11.153	-0.595
Log of imputed savings	6.475	8.699	-2.224
Imputed savings ($)	15,468	31,021	-15,553
Used reloadable card not linked with checking or savings account	0.118	0.076	0.042
Used nonbank service for cashing a check or purchasing a money order	0.094	0.055	0.038
Retirement date (1 = later than planned, 0 = early or on time)	0.062	0.053	0.008

Number of retirement accounts reported	0.404	1.382	-0.978

Source: Authors' calculations based on National Financial Well-Being Survey data.