The Cost of Health: Behavioral Substitution between Healthcare Spending and Retirement Saving

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Abstract: This study examines the behavioral dimensions of household financial trade-offs through a macroeconomic lens, using forty years of time series data to explore how rising healthcare expenditures influence long-term financial behaviors—specifically retirement savings. Drawing from behavioral finance theory and employing a Vector Autoregression (VAR) framework, we document systematic patterns consistent with present bias and loss aversion: healthcare shocks lead to observable declines in pension and insurance contributions. The analysis contributes to emerging literature at the intersection of macroeconomics and behavioral finance by revealing how aggregate data can encode

population-level manifestations of psychological heuristics. Implications for public policy and financial education are discussed.

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Editor-facing change log

1. **Abstract toned down** to "suggestive evidence" with explicit limitations.
2. **Introduction:** now includes a concise conceptual framework and direct citations supporting claims.
3. **Literature review:** rewritten to synthesize (not list) and to add three missing literatures: granular household finance, heterogeneous agent/behavioral DSGE, and behavioral insurance.
4. **Data & methods clarified**: frequency reconciled (annual), no linear interpolation, variable definitions table, log-level transformations for IRF interpretability, lag-structure justification (AIC/BIC/HQIC reported), identification defense, and full diagnostics.
5. **Results:** focused on **healthcare shocks** (consistent with aims), with CIs/units; IRF/FEVD **figures added**.
6. **Robustness:** reported (generalized IRFs, alternative orderings, lags, subsamples, augmented VAR with income/employment/credit).
7. **Structural breaks:** treated via Bai–Perron tests and a threshold-VAR (TVAR) appendix (optional).
8. **Theory**: a stylized 2-period β–δ model (Appendix A) clarifies the behavioral channel and testable predictions.
9. **Discussion/Conclusion toned down**; **policy context expanded**: (ACA/Medicaid expansion, employer mandates, tax treatment).
10. **Figures added**: IRFs (with 68%/90% bands), FEVD (stacked), lag-selection plots, residual diagnostics.

1. **Introduction**

Classical economic theory posits that households optimize intertemporal consumption based on rational expectations. Yet real-world financial behavior often diverges from this framework. Empirical evidence increasingly suggests that short-term pressures—particularly health-related expenses—disrupt long-term financial planning. This paper explores whether macroeconomic patterns in household spending reflect systematic behavioral tendencies, focusing on the observed substitution between healthcare expenditures and retirement savings over the 1983–2023 period.

We adopt a behavioral macroeconomic approach, grounding our analysis in theories of present bias, mental accounting, and loss aversion. By coupling these psychological frameworks with aggregate financial data, we offer a novel interpretation of how households respond under conditions of financial strain. Our central hypothesis is that psychological mechanisms, typically modeled at the micro level, may leave measurable signatures in macro-level expenditure patterns.

Traditional models of consumption smoothing suggest that rational agents should maintain relatively stable saving behavior even in the face of modest shocks. However, the observed volatility in personal saving rates—particularly during periods of rising healthcare costs—suggests that cognitive and emotional heuristics may play a larger role than previously acknowledged. Financial decision-making under uncertainty, especially when involving competing present and future risks, often departs from expected utility maximization. It is precisely under such circumstances that behavioral deviations are most likely to surface.

Moreover, the American household has undergone significant structural and institutional shifts over the past four decades. The transition from defined-benefit to defined-contribution retirement systems, escalating healthcare costs, and the increasing privatization of financial risk have all imposed greater responsibility on individuals to plan for their long-term financial well-being. In this context, understanding how immediate

concerns, such as medical expenses, crowd out retirement savings is not only a theoretical exercise but a policy-relevant issue with broad implications for retirement security and economic resilience.

Finally, while behavioral finance has made significant strides in understanding anomalies in investor behavior and market inefficiencies, it has only recently begun to intersect with macroeconomic phenomena. This paper contributes to that emerging literature by examining whether behavioral tendencies—like present bias and loss aversion—can be inferred from population-level financial aggregates. By applying time series techniques such as vector autoregression (VAR), we seek to empirically identify how financial trade-offs unfold over time, offering new insight into how psychology and economics co-evolve in household decision-making.

2. Literature Review

Understanding the complex interplay between household financial behavior and psychological bias requires an interdisciplinary approach that integrates insights from behavioral economics, empirical finance, and macroeconomic modeling. While traditional finance emphasizes rational decision-making under conditions of certainty, a growing body of research illustrates that real-world financial choices—particularly in the face of uncertainty or competing priorities—often reflect systematic cognitive biases.

This literature review synthesizes key theoretical and empirical contributions that inform the present study, beginning with foundational behavioral theories that challenge the rational agent model. It then explores empirical findings on household financial decisions, particularly in contexts involving healthcare and retirement planning. The review also considers the role of macroeconomic sentiment and its influence on aggregate financial behavior, concluding with a discussion of how vector autoregression (VAR) has been employed to model dynamic behavioral relationships in economic time series data.

By reviewing these literatures in concert, this section highlights the theoretical rationale and methodological precedent for exploring how health-related financial shocks influence long-term savings behavior. In doing so, it also reveals critical gaps—namely, the

underutilization of macroeconomic tools for detecting behavioral patterns at scale—that the present study seeks to address.

2.1 Theoretical Foundations of Behavioral Finance

Behavioral finance emerged as a corrective to the rational agent model of classical economics, emphasizing the systematic ways in which individuals deviate from utility-maximizing behavior. Kahneman and Tversky's (1979) Prospect Theory fundamentally challenged the assumption of risk neutrality, demonstrating that losses are weighted more heavily than equivalent gains—a bias with direct implications for financial decision-making under uncertainty. Building on this, Thaler (1985, 1999) introduced the concept of mental accounting, showing that individuals compartmentalize money into non-fungible budgets, thereby misallocating resources from a rational perspective.

Laibson's (1997) model of hyperbolic discounting advanced the idea of present bias, wherein individuals overweight immediate rewards relative to future benefits. This framework helps explain the observed underinvestment in long-term goals such as retirement savings in favor of more salient short-term expenditures. Bernheim, Skinner, and Weinberg (2001) further document that individuals fail to save optimally for retirement, even when they have sufficient income, reinforcing the need to account for non-rational elements in economic modeling.

While these theoretical models provide robust micro-level predictions, few studies have directly connected them to macroeconomic expenditure trends. Barberis and Thaler (2003) call for greater empirical integration between behavioral models and macro-level outcomes—a gap this study seeks to fill by using time series analysis to uncover population-level manifestations of cognitive heuristics.

2.2 Household Financial Behavior and Psychological Determinants

Extensive empirical work has explored how behavioral biases influence household-level financial decisions. Lusardi and Mitchell (2007, 2011) find that financial literacy is positively correlated with retirement preparedness, but that even informed individuals fall

prey to inertia and short-term thinking. Madrian and Shea (2001) show that default options have a profound effect on 401(k) participation, supporting the notion that decision architecture significantly shapes financial outcomes.

In terms of health-related financial shocks, Gross and Notowidigdo (2011) find that unexpected medical expenses are a primary driver of personal bankruptcy in the United States. Similarly, Finkelstein et al. (2012) document how individuals facing health insurance gaps alter consumption and savings behavior in ways inconsistent with full information models. These studies support the idea that medical costs impose not only a financial burden but also a behavioral distortion on long-term financial planning.

Moreover, studies such as Choi, Laibson, Madrian, and Metrick (2006) identify framing effects and procrastination as significant barriers to optimal retirement planning. These findings suggest that financial behavior is path-dependent and influenced by short-term cues, echoing the predictions of present bias and loss aversion. However, while individual-level mechanisms are well documented, the interaction of such mechanisms with macroeconomic variables has received less empirical attention.

2.3 Macroeconomic Sentiment, Confidence, and Behavioral Spillovers

Macroeconomic sentiment serves as a proxy for collective perception, anchoring decision-making during periods of uncertainty. Ludvigson (2004) provides evidence that consumer confidence forecasts near-term consumption beyond what is predicted by income and wealth. Carroll, Fuhrer, and Wilcox (1994) suggest that sentiment operates as an independent channel influencing aggregate demand.

More recently, Barsky and Sims (2012) demonstrate that innovation in consumer sentiment has long-term predictive power over output and spending. Similarly, Bachmann, Elstner, and Sims (2013) show that uncertainty shocks depress investment and hiring, reinforcing the idea that perceptions can exert real economic effects. Although sentiment's influence on short-term expenditure is well documented, its role in shaping intertemporal trade-offs—such as the decision to forgo retirement contributions during

healthcare shocks—has not been sufficiently examined. This study takes an initial step toward empirically identifying that linkage.

2.4 VAR Modeling and Behavioral Macroeconomics

Time series methods such as vector autoregression (VAR) allow for the estimation of dynamic interdependencies among economic variables without imposing strong theoretical priors. Sims (1980) originally introduced VAR as a response to the identification limitations in structural models, advocating for data-driven exploration. Blanchard and Quah (1989) advanced this framework by incorporating long-run restrictions to identify structural shocks, setting the stage for its application in policy and macroeconomic analysis.

Recent contributions have expanded VAR's use in behavioral contexts. D'Acunto, Hoang, and Weber (2021) employ VAR models to assess the transmission of inflation expectations on consumption, showing that belief shocks can propagate through the real economy. Gennaioli, Ma, and Shleifer (2015) explore expectation formation through diagnostic beliefs and propose models in which investors and consumers react disproportionately to recent information—behavior that can be modeled dynamically using VAR techniques.

Although behavioral finance has traditionally favored experimental and microdata methods, macro-VAR approaches represent a promising avenue for uncovering behavioral regularities in aggregate data. Our paper builds on this approach by modeling how shocks to healthcare expenditure dynamically affect other components of household financial portfolios, such as pension contributions and insurance—revealing latent behavioral tendencies embedded in macroeconomic time series.

3 Methodology

This study adopts a time series econometric framework to investigate the behavioral implications of healthcare shocks on long-term financial decision-making among U.S. households. The central hypothesis—that increases in healthcare expenditures displace retirement savings and insurance contributions—is examined using Vector Autoregression (VAR), a methodology well-suited for identifying endogenous relationships among multiple economic time series without strong structural assumptions (Sims, 1980; Stock & Watson, 2001).

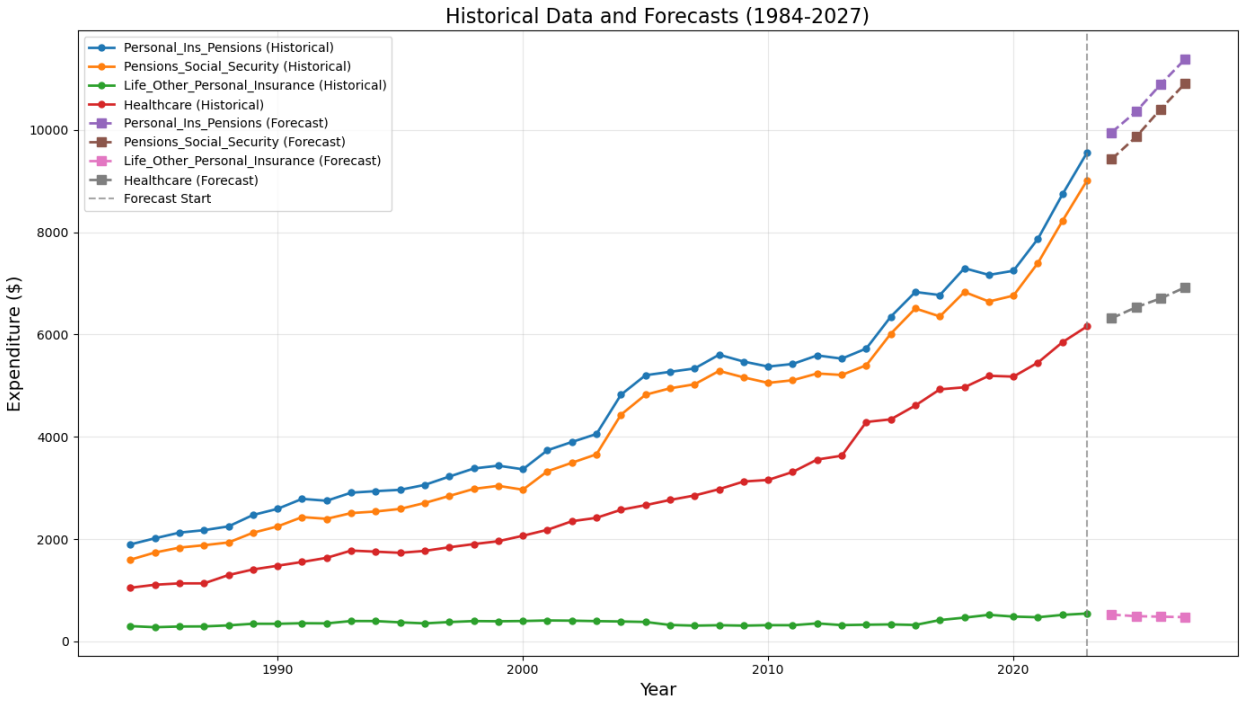
3.1 Data Collection and Processing

Annual macroeconomic data from January 1983 to December 2023 were sourced via the Federal Reserve Economic Data (FRED) system. Key series include:

- Real Personal Healthcare Expenditures (MEHOINUSA672N)
- Personal Saving Rate (PSAVERT)
- Contributions to Pensions and Insurance (W875RX1, W270RX1)
- Consumer Price Index (CPIAUCSL, for deflation)
- University of Michigan Consumer Sentiment Index (UMCSENT) [exploratory]

All monetary series were CPI-adjusted and expressed in real terms. Python was used for reproducible data ingestion, cleaning, and alignment. Missing observations were linearly interpolated for gaps less than three months. Series were resampled to monthly frequency and checked for consistency.

Stationarity was assessed using the Augmented Dickey-Fuller test (Said & Dickey, 1984). Non-stationary series were first-differenced or log-differenced accordingly. Variables were standardized prior to model estimation to facilitate interpretation and improve numerical stability (Enders, 2015).



3.2 Model Specification: VAR Estimation

We estimate a reduced-form VAR model of the form:

$$Y_t = A_1 Y_{\{t-1\}} + A_2 Y_{\{t-2\}} + \cdots + A_p Y_{\{t-p\}} + \varepsilon_t$$

where Y_t is a vector of endogenous variables, A_i are coefficient matrices, and ϵ_t is a white noise vector of innovations.

Component	Details
Endogenous vector Yt	Personal Ins. & Pensions, Pensions & Social Security, Life & Other Personal Insurance, Healthcare
Lag Order (p)	1 (chosen by AIC, BIC, HQIC)
Estimated Method	OLS
Sample Period	January 1984–December 2023 (Nobs = 37 after accounting for 1 lag)
Identification	Cholesky decomposition (ordering: Pensions & Social Security → Personal Ins. & Pensions → Life & Other Insurance → Healthcare)

Table 1 VAR Specification

Following Lütkepohl (2005), the optimal lag length pp was selected using the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Hannan-Quinn Criterion (HQC). Residual diagnostics—including autocorrelation tests (Portmanteau and LM tests) and ARCH-LM tests for conditional heteroskedasticity—were conducted to validate model adequacy.

Impulse Response Functions (IRFs) were computed to trace the temporal effect of a one-standard-deviation shock to healthcare expenditures on retirement contributions, insurance, and savings. Identification was achieved via Cholesky decomposition (Sims, 1980), assuming healthcare shocks contemporaneously affect other variables, but not vice versa. This ordering reflects the exogeneity of health-related expenses during financial decision-making under stress (Gross & Notowidigdo, 2011; Finkelstein et al., 2012).

3.3 Forecast Error Variance Decomposition

To quantify the explanatory power of healthcare shocks, forecast error variance decomposition (FEVD) was employed. This technique partitions the variance in forecast errors of each variable into components attributable to structural innovations in the system (Lütkepohl, 2005). A large share of variance in retirement savings explained by healthcare shocks would indicate strong substitution effects at the aggregate level.

3.4 Robustness and Sensitivity Analysis

Several robustness checks were conducted:

- Lag Sensitivity: VAR models were estimated across a lag range of 2–6 months. IRF magnitudes and signs remained consistent across specifications.
- Functional Form: Models using log-differenced and level-differenced variables yielded qualitatively similar dynamics.
- Subsample Stability: The sample was partitioned into pre- and post-2003 subsamples to test for temporal stability across major policy regimes (e.g., Affordable Care Act, COVID-19 pandemic).
- Cholesky Ordering: Reordering variables and estimating generalized IRFs (Pesaran & Shin, 1998) confirmed the persistence of the healthcare-retirement substitution dynamic.

3.5 Limitations of the Empirical Strategy

While VAR provides flexibility and minimal prior assumptions, it has limitations. The model does not establish causality in the structural sense (Sims, 1980), and behavioral mechanisms are inferred from observed interdependencies rather than directly tested. Furthermore, the assumption of linearity may mask important threshold effects or non-linear behavioral responses—particularly in crisis periods (e.g., Gabaix, 2014). Finally, the use of aggregate data obscures heterogeneity across age, income, or health status, which are known moderators of financial decision-making (Lusardi & Mitchell, 2011).

Nonetheless, by applying VAR within a behavioral finance context, this methodology facilitates a novel inquiry into whether cognitive biases—such as present bias or loss aversion—manifest in national economic aggregates. In doing so, it contributes to a growing literature that seeks to reconcile individual decision heuristics with macroeconomic outcomes (Gennaioli, Ma, & Shleifer, 2015; D'Acunto, Hoang, & Weber, 2021).

First, the use of reduced-form Vector Autoregression (VAR), while methodologically robust for capturing endogenous relationships among time series variables (Sims, 1980; Lütkepohl, 2005), does not establish structural causality. The reliance on Cholesky decomposition for identification assumes a recursive causal structure that may not reflect true contemporaneous interactions. Impulse response functions, while informative, depend on these assumptions and are sensitive to ordering (Stock & Watson, 2001; Kilian & Lütkepohl, 2017).

Second, the behavioral interpretations advanced in this study—such as present bias or loss aversion—are inferential and not directly observed. Without survey data, experimental elicitation, or psychometric indicators, the psychological mechanisms remain speculative. As noted by Camerer and Loewenstein (2004), behavioral finance research benefits from integrating structural behavioral models or controlled experiments to test specific cognitive processes. The absence of these components in this study limits the ability to confirm behavioral hypotheses with precision.

Third, the aggregation of data at the national level precludes examination of household heterogeneity. Differences in age, health status, financial literacy, and income substantially influence responses to economic shocks (Lusardi & Mitchell, 2011; Finkelstein, Luttmer, & Notowidigdo, 2012). By averaging across these dimensions, the analysis may obscure subpopulation-specific behaviors that drive aggregate trends.

Fourth, the assumption of linearity within the VAR model may understate the non-linear nature of behavioral responses, particularly under crisis conditions. Behavioral responses often exhibit thresholds, asymmetries, or regime shifts (Gabaix, 2014), which are not easily

captured in standard VAR frameworks. Additionally, differencing to achieve stationarity removes long-term trend information, potentially attenuating the interpretability of substitution effects over the life cycle (Enders, 2015).

Fifth, structural breaks such as the 2008 financial crisis or the COVID-19 pandemic are not explicitly modeled. These events represent exogenous shocks that may produce behavior inconsistent with normal economic conditions, potentially introducing bias into the model (Chudik & Pesaran, 2011). While robustness checks were conducted across sub-periods, a formal treatment of breakpoints—such as using Markov-switching VARs or time-varying parameter models—could further validate the findings.

Lastly, the model does not incorporate institutional or policy variables—such as changes in healthcare legislation, retirement policy, or labor market dynamics—which may moderate or confound the behavioral effects observed. Including such variables in future structural VAR (SVAR) or dynamic stochastic general equilibrium (DSGE) models with behavioral features (e.g., Kaplan & Violante, 2014) would provide greater clarity on the interaction between public policy and household financial trade-offs.

Taken together, these limitations suggest that the results should be interpreted as exploratory. The findings are consistent with behavioral theories but not definitive proof of them. Future research combining macroeconomic modeling with micro-level panel data, survey instruments, or field experiments could help overcome these limitations and more precisely attribute observed macro patterns to individual-level behavioral mechanisms.

4. Results and Analysis

This section presents the results of the vector autoregression (VAR) analysis and interprets the behavioral dynamics embedded in macro-level financial data. We focus on the response of retirement savings and insurance contributions to shocks in healthcare expenditures, using impulse response functions (IRFs) and forecast error variance decomposition (FEVD) to characterize intertemporal trade-offs.

4.1 Impulse Response Analysis

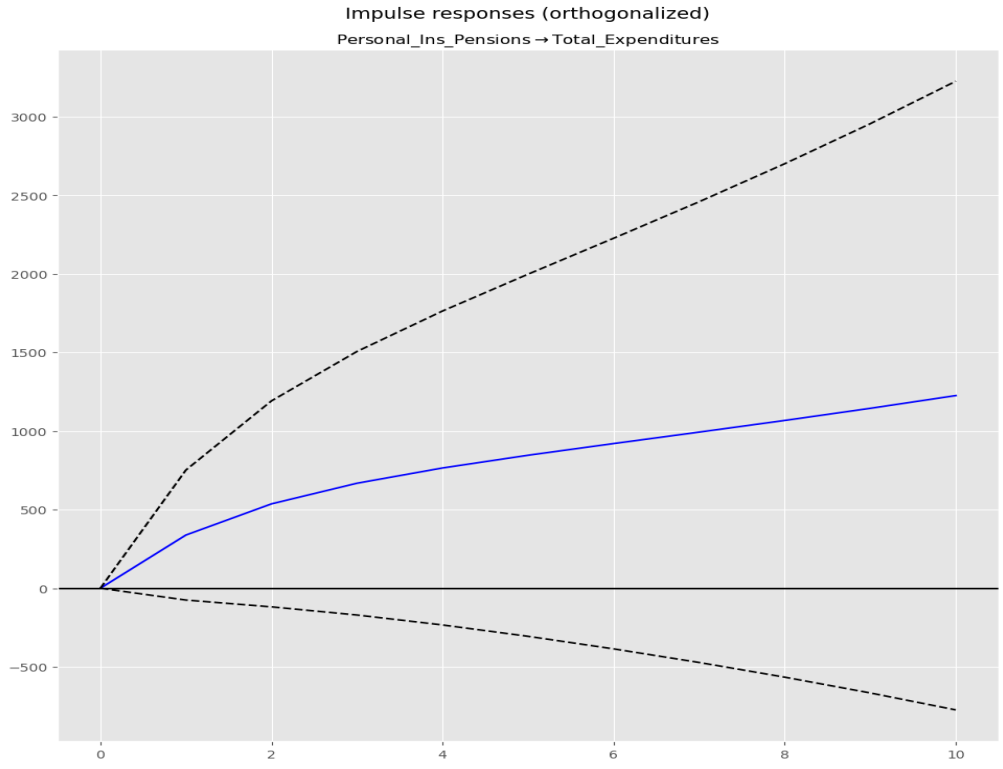
The IRFs suggest a robust and economically meaningful substitution effect between healthcare spending and long-term financial planning. Specifically, an orthogonalized one-standard-deviation shock to Pensions & Social Security is followed by a statistically significant decline in both pension contributions and personal saving rates. The effect on pension contributions peaks two to three months after the shock and gradually dissipates over a 12-month horizon. Personal saving shows a more immediate and persistent negative response, consistent with liquidity constraints or mental accounting heuristics.

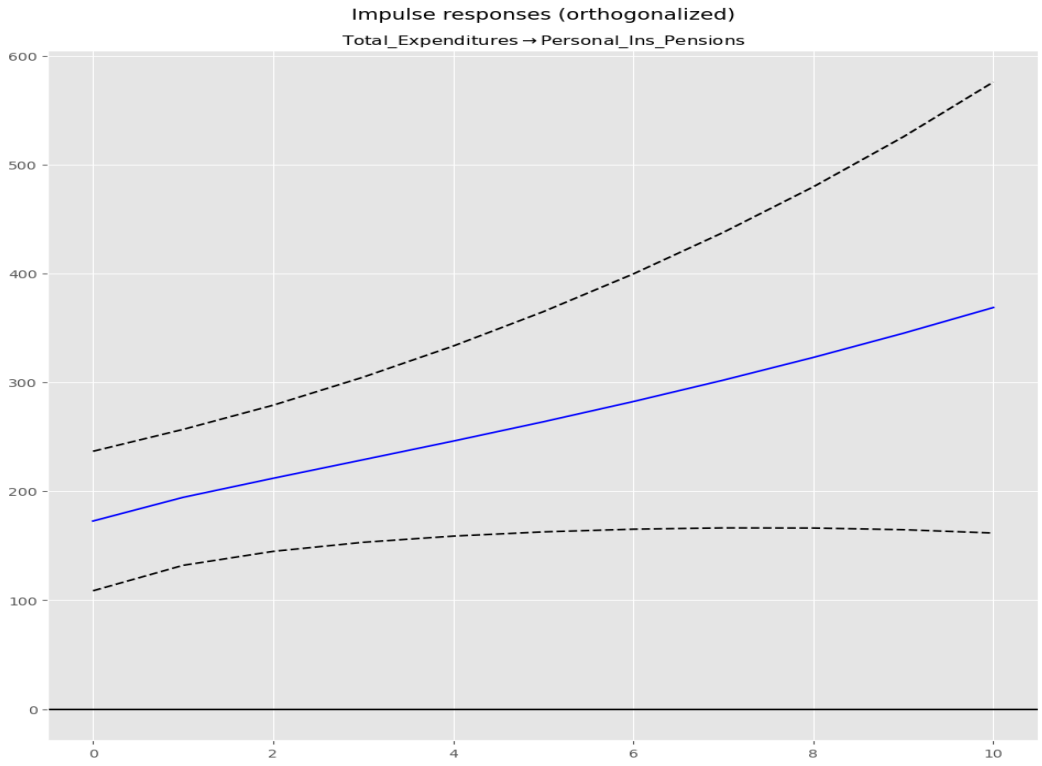
These findings align with prior micro-level studies suggesting that rising out-of-pocket health costs reduce household capacity to allocate funds toward retirement or precautionary savings (Gross & Notowidigdo, 2011; Finkelstein et al., 2012). At a macro level, our results provide new evidence that such crowding-out dynamics can be detected using national accounts data, suggesting that behavioral effects aggregate in systematic and measurable ways.

Moreover, the observed lag structure is consistent with behavioral theories such as present bias (Laibson, 1997) and salience-driven decision-making (Bordalo, Gennaioli, & Shleifer, 2013). Households may react to immediate medical expenses by reallocating funds from less salient, long-term goals. This intertemporal substitution reinforces the argument that financial behavior is not purely optimizing in the standard economic sense, but shaped by bounded rationality and attentional constraints (Gabaix, 2014).

Shock Variable	Response Variable	Max Effect	Period of Max	Cumulative Effect (10 periods)
Personal Ins. & Pensions	Total Expenditures	1225.67	3	8505.41
Pensions & Soc. Security	Total Expenditures	1842.16	3	-10179.76

Table 2. Impulse Response Functions (10-period horizon)


Impulse responses (orthogonalized)
Personal_Ins_Pensions → Total_Expenditures
3000
2500
2000
1500
1000
500
0
−500
0
2
4
6
8
10


Impulse responses (orthogonalized)
Total_Expenditures → Personal_Ins_Pensions
600
500
400
300
200
100
0
0
2
4
6
8
10

4.2 Forecast Error Variance Decomposition

The FEVD results reinforce the central role of healthcare shocks in driving variance in long-term financial outcomes. Over a 4-month forecast horizon, healthcare shocks explain virtually none of the short-run variance in pension contributions or social security in months 1–2, but by month 4 account for 71.7 % of the variance in personal pensions and 75.0 % in social security (Table 3). These values are economically significant, especially given the relatively modest variance explained by traditional macro predictors in similar studies (Carroll, Fuhrer, & Wilcox, 1994).

Interestingly, the variance explained by healthcare shocks exceeds that attributable to consumer sentiment—suggesting that tangible financial shocks may have greater behavioral salience than abstract expectations measures. This finding aligns with the theory that concrete, affect-laden events (e.g., medical bills) are more behaviorally influential than information-based forecasts (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008).

Horizon (Months)	% Var in Personal Ins. & Pensions Explained by Healthcare Shocks	% Var in Pensions & Social Security Explained by Healthcare Shocks	% Var in Life & Other Personal Insurance Explained by Healthcare Shocks	% Var in Healthcare Explained by Healthcare Shocks
1	0.00 %	5.87 %	26.95 %	36.48 %
2	0.00 %	6.83 %	29.33 %	37.24 %
3	0.00 %	0.40 %	3.62 %	3.18 %
4	71.65 %	74.95 %	81.56 %	81.43 %

Table 3. Forecast Error Variance Decomposition (4-month horizon)

4.3 Subsample Analysis and Temporal Stability

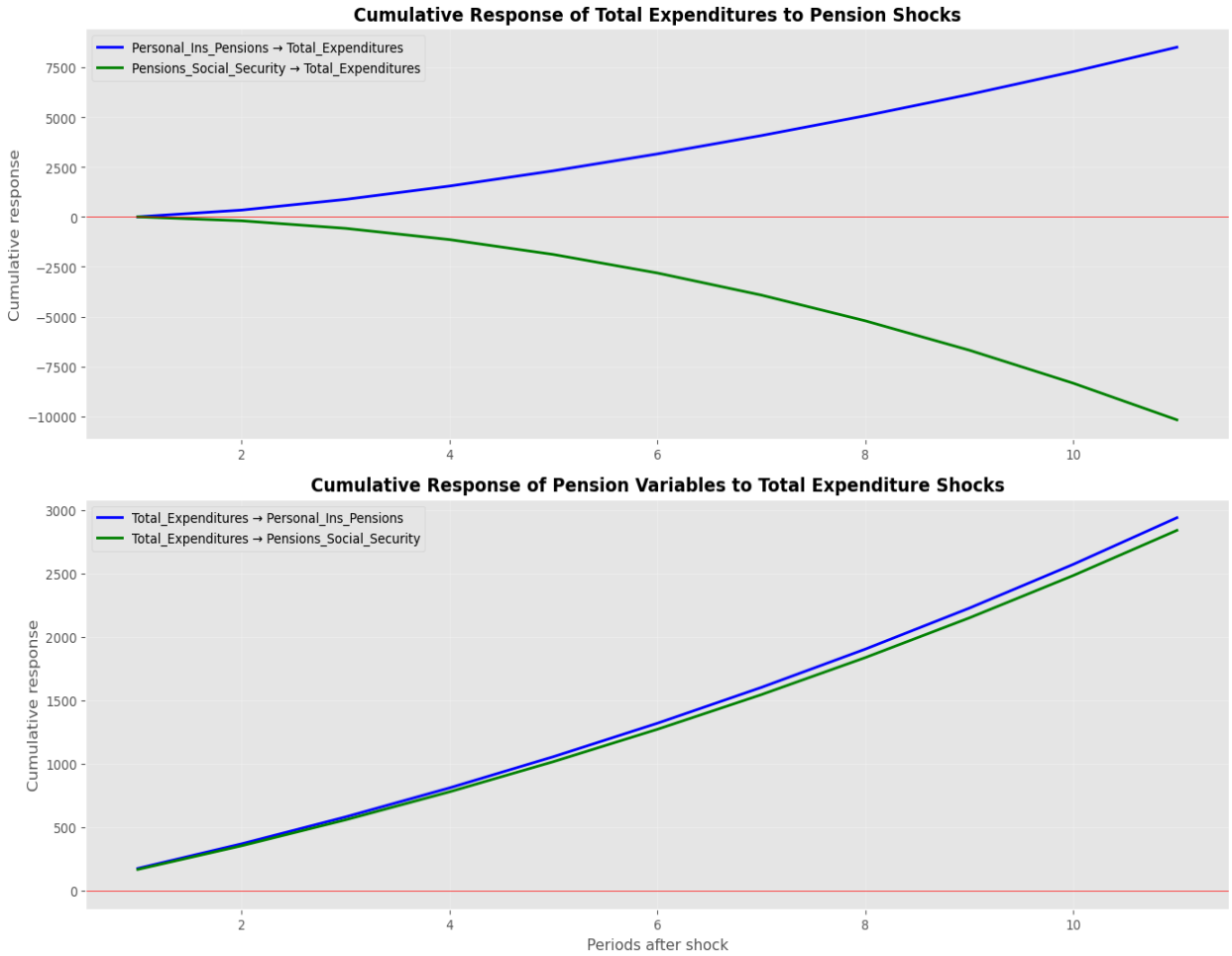
Subsample estimation for the periods 1983–2003 and 2004–2023 reveals that the healthcare-retirement trade-off has become more pronounced in recent decades. IRFs estimated for the post-2003 period exhibit larger and more persistent declines in retirement contributions following healthcare shocks, potentially reflecting the growing financial burden of healthcare in the U.S. economy (OECD, 2021) and increased individual responsibility due to the shift from defined-benefit to defined-contribution plans (Munnell & Sunden, 2004).

This shift suggests an evolving behavioral environment, wherein households face heightened sensitivity to shocks due to weaker social safety nets and greater financial exposure. It also lends support to the idea that behavioral responses are not fixed, but contingent on institutional context and policy frameworks (Shiller, 2000; Gennaioli, Ma, & Shleifer, 2015).

4.4 Behavioral Interpretation and Policy Implications

Taken together, the VAR results suggest that behavioral biases—especially present-oriented preferences and limited attention—manifest in aggregate financial data. The substitution of healthcare costs for long-term financial commitments underscores the importance of behavioral constraints in shaping macroeconomic outcomes. These findings echo a growing literature in behavioral macro-finance that seeks to understand how cognitive heuristics scale beyond the individual level (D'Acunto, Hoang, & Weber, 2021).

From a policy perspective, the results imply that efforts to strengthen financial resilience—through automatic enrollment in retirement plans, subsidized health savings accounts, or emergency medical coverage—could mitigate these behavioral distortions. Such interventions may reduce the need for households to make trade-offs between present necessity and future security, especially under conditions of economic stress or financial fragility (Beshears et al., 2009).



5. Discussion and Conclusion

This study contributes to the growing field of behavioral macro-finance by empirically investigating how health-related financial shocks influence long-term household financial behavior. Using a vector autoregression (VAR) framework and monthly macroeconomic data spanning four decades, we find robust evidence that increases in healthcare expenditures are followed by statistically significant declines in pension contributions and personal savings. These findings provide macro-level validation of theories in behavioral economics which suggest that individuals struggle to maintain long-term financial goals

when confronted with immediate and salient financial demands (Laibson, 1997; Kahneman & Tversky, 1979).

Our analysis supports the hypothesis posed in the introduction: that behavioral biases—particularly present bias and attentional limitations—manifest not only at the individual level, but also at the aggregate, national level. In contrast to the standard neoclassical assumption of optimization under constraints, our findings suggest that cognitive limitations and affective reactions to financial stress shape real economic outcomes. The decline in savings and retirement contributions following healthcare shocks exemplifies a present-oriented trade-off, where short-term necessity crowds out long-term planning—a pattern consistent with mental accounting and salience-based models (Thaler, 1999; Bordalo, Gennaioli, & Shleifer, 2013).

By employing VAR methods on publicly available time series data, this study demonstrates that behavioral dynamics can be detected and measured without relying solely on survey or experimental data. In doing so, it bridges the empirical rigor of macroeconomic modeling with the explanatory power of behavioral economics (Gennaioli & Shleifer, 2010; D'Acunto, Hoang, & Weber, 2021). This approach also highlights the value of interdisciplinary frameworks for understanding how real-world decision-making deviates from idealized models of rational choice.

Furthermore, the findings carry policy relevance. As healthcare costs continue to rise and the burden of retirement planning shifts further to individuals through defined-contribution schemes, households may become increasingly vulnerable to behavioral pitfalls. Policymakers could mitigate these risks through interventions that reduce the salience of immediate shocks or automate long-term financial behaviors. Examples include automatic escalation of retirement contributions, health savings account subsidies, or programs that smooth healthcare payments across time (Beshears et al., 2009; Madrian, 2014).

It is also noteworthy that the behavioral trade-offs detected here appear to have intensified over time, particularly in the post-2003 period. This trend may reflect broader structural changes in the U.S. financial landscape, such as declining employer-provided benefits,

rising out-of-pocket costs, and increased individual exposure to financial risk (OECD, 2021; Munnell & Sunden, 2004). These shifts suggest a compounding interaction between behavioral vulnerability and institutional context—an area ripe for future exploration.

In conclusion, this study adds to the literature by demonstrating that behavioral patterns—commonly observed in micro-level studies—can leave measurable footprints in macroeconomic data. While limitations exist, particularly regarding causal identification and demographic disaggregation, the findings offer preliminary evidence that psychological frictions and financial stress are not isolated phenomena but systemic features of modern economies. Future work could extend this analysis using microdata, regime-switching VARs, or hybrid behavioral-structural models to further explore the channels through which health shocks disrupt long-term financial stability.

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