Mental Barriers to Investing: Psychological Costs and Stock Market Participation *

Fiona Hoellmann†

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Abstract

This study examines how affective states, referring to individuals mood, psychological condition, and ability to process uncertainty, influence household stock market participation. Using mental health data from the German Socio-Economic Panel (SOEP) as a proxy for affective states, we show that better mental health significantly increases the likelihood of stock ownership, while symptoms of depression and chronic worry reduce participation. Our estimates suggest that a one-standard-deviation improvement in overall mental health translates to approximately 120,000 stock market entering households annually in Germany. To address endogeneity, we exploit the COVID-19 pandemic as a natural experiment using a Difference-in-Differences Instrumental Variables (DiD-IV) approach. We find that individuals with weaker pre-crisis social networks experienced larger declines in mental health during the pandemic and are significantly less likely to become stockholders than those with stronger social ties.

JEL Classification: D1, G50, G41

Key words: Behavioral Household Finance, Affect, Mental Health, Risk Preferences, Stock Market Participation

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†Fiona.Hoellmann@wiwi.uni-muenster.de, Finance Center Münster, University of Münster

1 Introduction

Why do many individuals avoid investing in the stock market despite historically high returns? This question remains a central puzzle in household finance (Campbell, 2006; Gomes, Haliassos, & Ramadorai, 2021; Guiso & Sodini, 2013). In the absence of constraints, and accounting for risk preferences, standard portfolio choice models predict stock market participation rates far higher than those observed empirically (Fagereng, Gottlieb, & Guiso, 2017; Merton, 1969). Yet, persistent non-participation is observed even among higher income, well-educated households (e.g., Haliassos & Bertaut, 1995; Mankiw & Zeldes, 1991).

Over the past three decades, a substantial body of research has attempted to explain this participation puzzle by identifying cognitive and informational barriers. For example, some studies link demographic characteristics to investment decisions (e.g., Kaustia, Conlin, & Luotonen, 2023), while others examine the role of financial literacy (e.g., Van Rooij, Lusardi, & Alessie, 2011), social interaction (e.g., Hong, Kubik, & Stein, 2004), and personality traits (e.g., Jiang, Peng, & Yan, 2024). Although these explanations have significantly advanced our understanding, they fail to fully account for the low participation rates and heterogeneity in household investment behavior (Gomes et al., 2021).

A common implicit assumption in much of this literature is that once individuals possess the cognitive ability and intention to invest, they follow through. This overlooks a key psychological channel: the affective (or emotional) processes that shape whether intentions are translated into action.

This paper addresses this gap by introducing affective states, proxied by mental health, as an important determinant of stock market participation. Drawing on insights from neuroeconomics, we argue that financial decision-making is not purely cognitive but also affective - shaped by emotional experiences and constraints (Camerer, Loewenstein, & Prelec, 2005). Affective states such as anxiety, depression, or excitement can influence how individuals perceive risk, form expectations, and evaluate their own competence (Kuhnen & Knutson, 2011). Therefore, it is reasonable to expect that these affective factors may act as gatekeepers between intention and action, either enabling or blocking stock market participation by influencing risk attitudes, beliefs, self-confidence, and avoidance behavior.

We propose mental health as a meaningful proxy for individuals' affective states.[1] More specifically, we hypothesize that mental health conditions such as depression and anxiety are significantly related to affect-driven components of decision-making that influence households' willingness and ability to invest. These psychological mechanisms complement established economic concepts such as risk aversion and time preference, while offering new perspectives on the drivers of investors' behavior in stock markets.

Recent theoretical advances reinforce the importance of this perspective. Abramson, Boerma, and Tsyvinski (2024) develop a model showing how features of mental illness such as negative thinking, rumination, and self-reinforcing inaction can systematically alter economic outcomes. While prior research has linked mental health to well-being and labor market outcomes, its role in shaping financial decisions remains largely unexplored.

This paper asks whether and how affective states impact households' decisions to invest in the stock market. Rather than focusing solely on a correlation between mental health and participation, we take a novel approach by disaggregating mental health into three distinct components: depression, anxiety, and worry. This allows us to identify specific psychological barriers to financial market entry.

We use longitudinal data from the German Socio-Economic Panel (SOEP), covering the period from 2002 to 2020, to provide empirical evidence on how these affective states impact stock market investment decisions. Our main empirical framework consists of linear probability models that control for a rich set of socioeconomic and demographic characteristics, including income, wealth, education, and risk preferences. To the best of our knowledge, this is the first study to examine how different dimensions of mental health influence stock market participation in a general population sample over such a long horizon.[2]

A major empirical challenge in this analysis is that mental health and financial decision-making often evolve simultaneously, raising concerns about reverse causality and unobserved confounding factors. To address endogeneity concerns, we exploit the COVID-19

[1]The World Health Organization (2024) defines mental health as "a state of mental well-being that enables people to cope with the stresses of life, realize their abilities [...] and underpins [one's] individual and collective abilities to make decisions".

[2]Previous research of Bogan and Fertig (2013) has studied the impact of diagnosed mental health conditions on portfolio choice but is limited to older adults (aged 53+).

pandemic as an exogenous shock to mental health and employ a Difference-in-Differences-Instrumental-Variables (DiD-IV) approach. While financial behavior may influence affective well-being, and both may be shaped by unobserved individual traits (e.g., personality or cognitive ability), the pandemic introduced a plausibly exogenous shift in mental health across the population. Recent psychological research shows that social isolation worsens mental health (Kirkbride et al., 2024). Building on this, we propose that individuals with weak pre-pandemic social networks were more vulnerable to the mental health impact of lockdowns. We use this heterogeneity in exposure to construct a source of exogenous variation in mental health. Our identification strategy is implemented in two steps. First, we estimate a DiD to isolate the impact of the COVID shock on mental health across individuals with varying levels of pre-pandemic social ties, while controlling for individual fixed effects. Second, we use the predicted mental health from this estimation as an instrument in a two-stage regression framework to estimate the causal effect of mental health on the likelihood of stock market participation.

Our findings provide compelling evidence that mental health significantly impacts financial decision-making. Individuals with better mental health are more likely to participate in the stock market, while those experiencing depression and chronic worry are notably less likely to invest. Interestingly, we find that moderate levels of anxiety are positively associated with participation. While this may seem counterintuitive, it is consistent with psychological research suggesting that moderate anxiety can serve as a motivator, prompting individuals to act in order to reduce uncertainty (Sweeny & Dooley, 2017).

These results are robust across alternative model specifications, including controls for macroeconomic shocks and individual characteristics. Importantly, the effects of mental health are robust even after controlling for individual risk preferences, suggesting an independent role for belief-based mechanisms. Our DiD-IV estimates confirm the robustness of these results: individuals with stronger social ties, and thus lower exposure to the mental health shock, exhibit significantly higher stock market participation following the onset of COVID-19. This supports the interpretation of mental health as a causal force behind investment decisions. To address potential confounding from differential economic impacts of the pandemic, we examine labor income dynamics in the treatment and control groups and find no meaningful divergence over time, suggesting that the increase in stock ownership that can be explained by our instrumented mental health is not subject to changes in economic conditions between treated and untreated individuals.

To explain why individuals with poor mental health are systematically less likely to participate in the stock market, we propose a conceptual framework that distinguishes between three affective channels through which affective states may influence financial decision-making. First, mental health conditions may distort external beliefs by fostering overly pessimistic expectations about future returns, thereby reducing the perceived benefits of participation (Puri & Robinson, 2007). Second, they may alter internal beliefs, lowering individuals' perceptions of their own investing capabilities and increasing subjective complexity or cognitive cost of investing. For example, individuals suffering from depression or anxiety may overestimate the effort required to participate or feel overwhelmed by decision-making tasks due to rumination or reduced cognitive capacity. Third, affective states may influence core preferences by increasing aversion to risk and uncertainty, reducing willingness to hold volatile assets, even when expected returns are favorable (Edwards, 2010).

Understanding the role of mental health in shaping financial decisions is increasingly important given recent global trends. Across many countries, especially among younger generations, rates of depression, anxiety, and psychological distress have risen sharply in recent years (Blanchflower & Bryson, 2024; Blanchflower, Bryson, Lepinteur, & Piper, 2024; Twenge & Blanchflower, 2025; Udupa, Twenge, McAllister, & Joiner, 2023). These trends have been extensively studied in relation to well-being and social outcomes, but much less attention has been paid to their potential economic consequences. If worsening mental health systematically reduces stock market participation, younger generations may face growing disadvantages in wealth accumulation, retirement security, and intergenerational financial mobility.

The literature on stock market participation is vast and has identified an extensive number of contributing factors. Research highlights the importance of even small nonmonetary barriers such as information acquisition costs or perceived complexity in deterring participation (Duraj, Grunow, Chaliasos, Laudenbach, & Siegel, 2024; Haliassos & Bertaut, 1995; Luttmer, 1999; Vissing-Jorgensen, 2004). Other studies point to institutional and trust-based explanations, including investor protection, trust in financial advisors and corporate structures (e.g. Georgarakos & Pasini, 2011; Giannetti & Koskinen, 2010; Giannetti & Wang, 2016). Demographic variables such as age, gender, wealth, stature, IQ, geographic location (Addoum, Korniotis, & Kumar, 2017; Barber & Odean, 2001; Briggs, Cesarini, Lindqvist, & Östling, 2021; Christelis, Georgarakos, & Haliassos, 2013; Grinblatt, Keloharju, & Linnainmaa, 2011; Heaton & Lucas, 2000) also play a role, as do personal experiences and social influences, including political beliefs (Kaustia & Torstila, 2011; Meeuwis, Parker, Schoar, & Simester, 2022), own or friend's past experiences (Choi & Robertson, 2020; Knüpfer, Rantapuska, & Sarvimäki, 2017; Laudenbach, Malmendier, & Niessen-Ruenzi, 2020; Malmendier & Nagel, 2011), sociability (Brown, Ivković, Smith, & Weisbenner, 2008; Changwony, Campbell, & Tabner, 2015; Hong et al., 2004), religion (Kumar, Page, & Spalt, 2011), personality traits (Jiang et al., 2024), financial literacy (Van Rooij et al., 2011), and health status (Fan & Zhao, 2009; Love & Smith, 2010; Rosen & Wu, 2004). Digital inclusion, through internet banking and broadband access has also recently been shown to matter (Hvide, Meling, Mogstad, & Vestad, 2024; Michelangeli & Viviano, 2024).[3]

While this literature has significantly expanded our understanding of household investment decisions, the overwhelming focus remains on cognitive, informational and structural determinants. In contrast, affective states have received far less attention as potential barriers to participation. Our study addresses this gap by identifying affective states, proxied by mental health conditions, as an additional and distinct set of psychological constraints on investment decisions.

Our study makes three key contributions to the literature on household finance and investor behavior. First, we provide novel and robust evidence that mental health conditions are significant and economically meaningful predictors of stock market participation. Using rich panel data, we show that mental health shapes financial decision-making beyond what can be explained by standard socio-economic variables, by influencing inputs such as risk preferences, beliefs about future returns, and self-perceived investment capabilities. Second, we contribute to the theoretical understanding of household investment behavior by formally incorporating affecting states into a conceptual portfolio choice framework. We argue that omitting mental health from models of household finance may lead to biased estimates and a misattribution of behavioral heterogeneity to purely cognitive

[3]For comprehensive reviews, see Beshears, Choi, Laibson, and Madrian (2018) and Kaustia et al. (2023).

or informational factors. Third, our results carry important policy implications. They suggest that interventions narrowly focused on improving financial literacy or reducing participation costs may be insufficient to close participation gaps for individuals affected by mental health conditions. Addressing emotional and psychological barriers could be a necessary complement to traditional approaches aimed at broadening financial inclusion.

Taken together, our results call for a broader approach to financial inclusion, one that integrates psychological support with financial education. As mental health challenges continue to rise globally, understanding their role in financial decision-making is essential not only for improving individual outcomes but also for promoting economic inclusion and reducing long-term wealth inequality.

The remainder of this paper is structured as follows. We introduce the conceptual framework in Section 2. Section 3 describes the data. Section 4 outlines the empirical strategy and presents the main findings. Finally, Section 5 concludes.

2 Conceptual Framework

To provide a theoretical foundation for our empirical analysis, we introduce a conceptual framework based on a simple model of financial decisions, integrating insights from behavioral finance and psychology. Following Markowitz (1952); Merton (1969) and recent advances by Jiang et al. (2024), we argue that an investor i's portfolio choice is not solely determined by standard financial considerations such as expected returns and risk, but also significantly influenced by non-pecuniary factors, e.g., psychological and emotional factors.[4] Specifically, our framework incorporates three central components shaping investment decisions: investors' external beliefs about future market returns and risks, their

[4]Previous studies have acknowledged the role of non-pecuniary factors in financial decision-making. For example, Hong et al. (2004) highlight that social interactions significantly influence stock market participation, as investors derive utility from discussing investments with peers. Gao and Lin (2015) find that some investors perceive stock trading similarly to gambling, driven by the excitement rather than purely financial motives. Jiang et al. (2024) show that personality traits, specifically Neuroticism and Openness, have significant explanatory power for equity investments. Our framework incorporates affective states into the analysis, emphasizing the role of psychological factors alongside traditional financial considerations.

internal beliefs regarding their personal ability to effectively engage in investment activities, and their risk preferences that determine their attitudes towards uncertainty and volatility.

Formally, we consider a simplified market with two assets: a risk-free asset with an interest rate of zero and a risky asset (stock) characterized by a stochastic return r. An investor i decides on the portfolio share w_i to allocate to the risky asset, considering both pecuniary and non-pecuniary factors. This decision-making process is modeled by an objective function that integrates standard mean-variance optimization with non-pecuniary factors:

$$\underbrace{\max_{w_i}(1-\alpha)\left(w_iE_i[r]-\frac{1}{2}\cdot\gamma_i\cdot w_i^2Var_i[r]\right)}_{\text{standard mean-variance maximization}}-\underbrace{\alpha(\frac{1}{2}w_i-w_i^*)^2}_{\text{non-pecuniary factors}} \tag{1}$$

The first component reflects the standard mean-variance optimization: γ_i represents individual risk aversion, while $E_i[r]$ and $Var_i[r]$ capture the investor's subjective expectations and associated risk of stock returns. The second component introduces a penalty for deviations from a subjective target portfolio w_i^*, capturing psychological and emotional considerations, such as self-perception and emotional stability and time loss due to rumination. Here, the parameter $\alpha \in [0,1]$ measures the weight the investor assigns to non-pecuniary factors. When $\alpha = 0$, investment decisions are purely rational, driven exclusively by expected risk-return trade-offs. In contrast, when $\alpha = 1$, portfolio choices are shaped entirely by psychological factors outside standard utility maximization.

Solving for w_i, the optimal investment share in risky assets, yields:

$$\Leftrightarrow w_i = \frac{(1-\alpha)\mathbb{E}_i[r]+\alpha w_i^*}{(1-\alpha)\gamma_i\mathrm{Var}_i(r)+\alpha} \tag{2}$$

This expression shows that investment decisions jointly depend on three factors: (i) external beliefs about returns and risks ($E_i[r]$ and $Var_i[r]$), (ii) preferences towards risk (γ_i), and (iii) internal beliefs or emotional factors summarized in the target portfolio (w_i^*).

We argue that affective states, proxied in our study by mental health conditions, can significantly impact each of these three components. Poorer mental health may lead investors to adopt overly pessimistic external beliefs, expecting lower returns and higher risks. Similarly, it may distort internal beliefs, undermining individual's confidence and perceived capability to participate effectively in stock markets, or by consuming cognitive resources through rumination, leaving little mental space for financial decision-making. Finally, it may increase investors' aversion to risk, amplifying their discomfort with investment uncertainty.

This framework provides a useful lens for interpreting how affective states can influence stock market participation, offering clear testable hypotheses about the psychological mechanisms driving households' investment decisions.

3 Data

3.1 Data Source and Sample

This study utilizes data from the German Socio-Economic Panel (SOEP), a nationally representative, longitudinal household survey administrated annually by the German Institute for Economic Research (DIW Berlin). Initiated in 1984, the SOEP covers more than $35,000$ individuals in over $20,000$ households and collects rich information on demographics, socioeconomic background, social networks, and financial behavior.

We employ data from the 2002, 2007, 2012, 2015, 2019, 2020 and 2022 survey waves which provide consistent and repeated measures for both financial and psychological variables. The analysis is conducted at the individual level and restricted to household heads, as stock ownership is recorded at the household level. This ensures consistency in the unit of analysis while capturing the financial decision-maker within each household, which is important when linking individual mental health to investment behavior.

The dependent variable is stock market participation (SMP), measured as a binary indicator that takes the value one if the respondent reports stock ownership in the corresponding survey year, and zero otherwise.

The SOEPs rich panel structure allows us to observe the same individuals over time, enabling the use of identification strategies that exploit within-individual variation. A key advantage of the SOEP dataset is its ability to track individual-level mental health changes over time, allowing for a more dynamic analysis of stock market participation.

3.2 Mental Health Measurement

We proxy affective states through mental health, using two complementary measures derived from the SF-12v2 health module in the SOEP, both widely used in health psychology. The first is the **Mental Component Summary (MCS)**, a broad measure of mental well-being constructed using exploratory factor analysis (PCA with varimax rotation). It follows a norm-based scoring approach, standardized to the 2004 SOEP population (mean = 50, SD = 10), and captures emotional stability, vitality and social functioning.

The second measure is **Mental Health Score (MH)**, designed to capture more acute symptoms of psychological distress. It is constructed using z-standardization, and reflects self-reported symptoms of anxiety, depression and emotional well-being. While the MCS provides a general assessment of mental health trends over time, the Mental Health Score is more sensitive to short-term variations in distressed affective states (Andersen, Mühlbacher, Nübling, Schupp, & Wagner, 2007). Appendix A.1 provides the wording of all questions used to construct the MH score.

In addition to these aggregated measures, we include disaggregated data in our analysis to examine how specific mental health conditions affect stock market participation. These include three indicators of mental health symptoms: depression, anxiety, and excessive worry. Respondents were asked, *"Over the last two weeks, how often have you been bothered by any of the following problems?"* with items such as:

- *Little interest or pleasure in doing things*
- *Feeling down, depressed, or hopeless*
- *Feeling nervous, anxious, or on edge*
- *Unable to stop or control worrying*

Responses are recorded on a four-point scale ranging from 0 (*never*) to 3 (*always*), allowing for analysis of both symptom prevalence and intensity.

By including both general and specific measures of psychological well-being, our empirical analysis aims to identify not only whether mental health matters for stock market participation, but also which dimensions of affective states serve as the strongest barriers to market entry at individual level.

3.3 Sample Characteristics

To better understand the context of our empirical analysis, we now provide descriptive evidence on the individuals in our sample, with a focus on demographic characteristics, mental health status, and differences between stockholders and non-stockholders.

Table 1 summarizes key characteristics of our sample, which is restricted to household heads to ensure consistency between individual-level mental health assessments and household-level investment outcomes. Across 99,549 individual-year observations, 55% are male, and 29% report stock market participation.[5] The average respondent is 54.3 years old, with 12.5 years of education and average monthly labor income of 1,235. Mean total assets amount to 148,775, while liabilities average 22,418. The average mental health scores used as proxies for affective states are 50.65 (MH) and 50.55 (MCS), both standardized.

Table 2 compares these characteristics across stockholders and non-stockholders. Stockholders are more likely to be male (62% vs. 52%), have more years of education (13.8 vs. 11.9), and earn substantially higher labor income (1,774 vs. 1,020). Stockholders also report greater financial assets (279,057 vs. 96,771), and better mental health, with average MH and MCS scores of 51.97 and 51.63, respectively, compared to 50.13 and 50.12 among non-stockholders. These differences are statistically significant (t-stats) and highlight the potential role of mental health as a barrier to financial market participation.

Figures 1 and 2 illustrate how mental health levels varies across age and gender. Mental health scores are lowest among individuals aged 25-35, precisely the group for whom early financial market participation would be most beneficial, and consistently higher among men than women. Figure 3 further shows that stockholders report higher mental health than non-stockholders across the entire sample period. These descriptive

[5]The stock market participation rate in our sample is 29%, which is higher than the average in the general German population. This difference arises for two main reasons. First, our sample is restricted to household heads. Since younger individuals and other household members are excluded, the sample is skewed toward older, more financially established individuals, who are more likely to participate in the stock market. Second, due to the structure of the SOEP data, stock ownership is recorded at the household level rather than the individual level. This means that reported stockholding may reflect participation by any household member, not necessarily the household head alone (Meister, Menkhoff, & Schröder, 2024).

patterns suggest that mental health may play an important role explaining heterogeneity in household investment behavior.

Taken together, these descriptive insights motivate a deeper empirical investigation into the psychological underpinnings of stock market participation, which we turn to in the next section.

Table 1: Descriptive Statistics: Full Sample

This table reports summary statistics for the main variables used in the analysis. The sample is restricted to household heads. All monetary values are reported in euros. Mental health variables are standardized within each survey wave. Stock market participation (SMP) is a binary indicator equal to one if the household reports owning stocks.

Statistic	Mean	Median	St. Dev.	Min	Max	N
SMP	0.29	0	0.45	0	1	99,549
risk_aversion	4.66	5	2.31	0	10	99,549
education_years	12.47	11.50	3.11	0.00	18.00	99,549
labor_income	1,234.99	860	1,616.00	0	80,000	99,549
mental_health	50.65	50.26	9.83	19.73	86.90	99,549
mcs	50.55	52.33	10.14	3.59	80.60	99,549
tot assets	148,774.60	46,400.00	729,050.10	0.00	71,350,000.00	99,549
tot liabilities	22,417.97	0.00	85,537.04	0.00	5,250,000.00	99,549
age	54.33	53	15.82	19	104	99,549
male	0.55	1	0.50	0	1	99,549
single	0.41	0	0.49	0	1	99,549
HH size	2.42	2	1.29	1	14	99,549
sociability	4.12	3	3.53	0.00	200.00	99,549

Table 2: Descriptive Statistics by Stock Owner Groups

This table presents summary statistics for stockholders and non-stockholders. The sample is restricted to household heads. Stock market participation (SMP) is defined as a binary indicator equal to one if the household reports owning stocks. Mental health variables are standardized within each survey wave. All monetary values are reported in euros.

	(1)	(2)	(3)	(4)
	Non-owners	Owners	Owners vs. Non	t-
Statistic	mean	mean	diff	stats
risk_aversion	4.556	4.921	-0.365	-23.77
education_years	11.942	13.804	-1.862	-85.79
labor income	1,019.936	1,773.754	-753.818	-56.726
mental health	50.13	51.966	-1.836	-27.912
mcs	50.118	51.633	-1.515	-22.317
tot assets	96,770.872	279,056.912	-182,286.04	-23.7
tot liabilities	18,164.694	33,073.486	-14,908.792	-20.722
age	54.59	53.683	0.906	8.592
male	0.524	0.62	-0.096	-27.97
single	0.448	0.317	0.13	39.086
HH size	2.366	2.544	-0.178	-20.284
sociability	3.973	4.502	-0.529	-21.828

Figure 1: Mental Health Across Age Groups

This figure illustrates average mental health across age groups over the period 20022022. Mental health is standardized within each survey wave. The figure is based on the full SOEP sample.

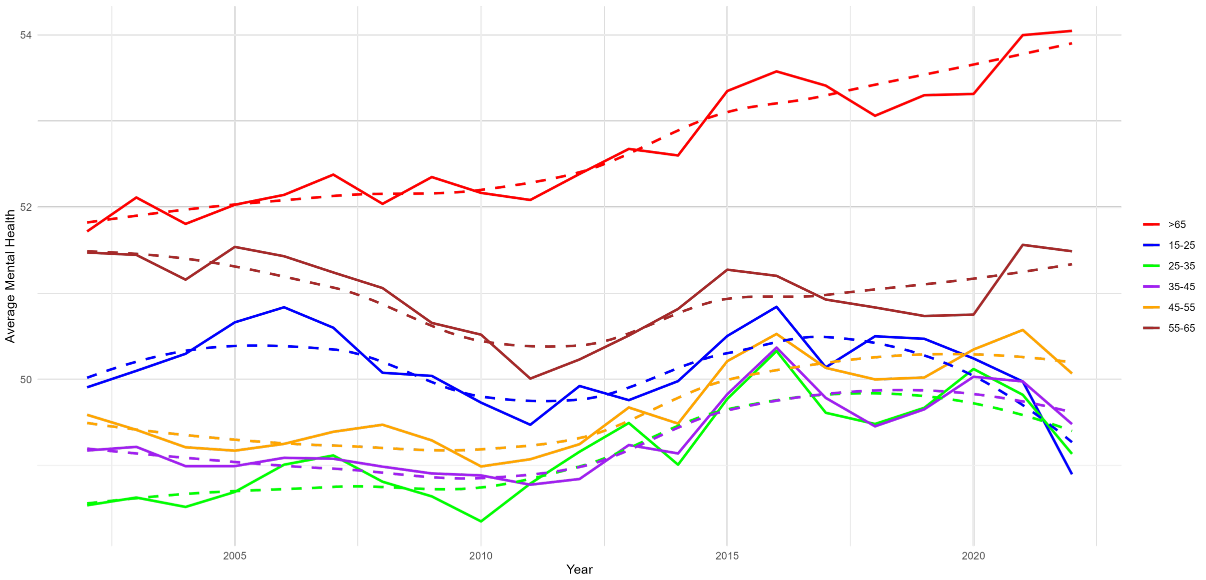


Figure 2: Mental Health Across Gender

This figure illustrates average mental health across gender over the period 20022022. Mental health is standardized within each survey wave. The figure is based on the full SOEP sample.

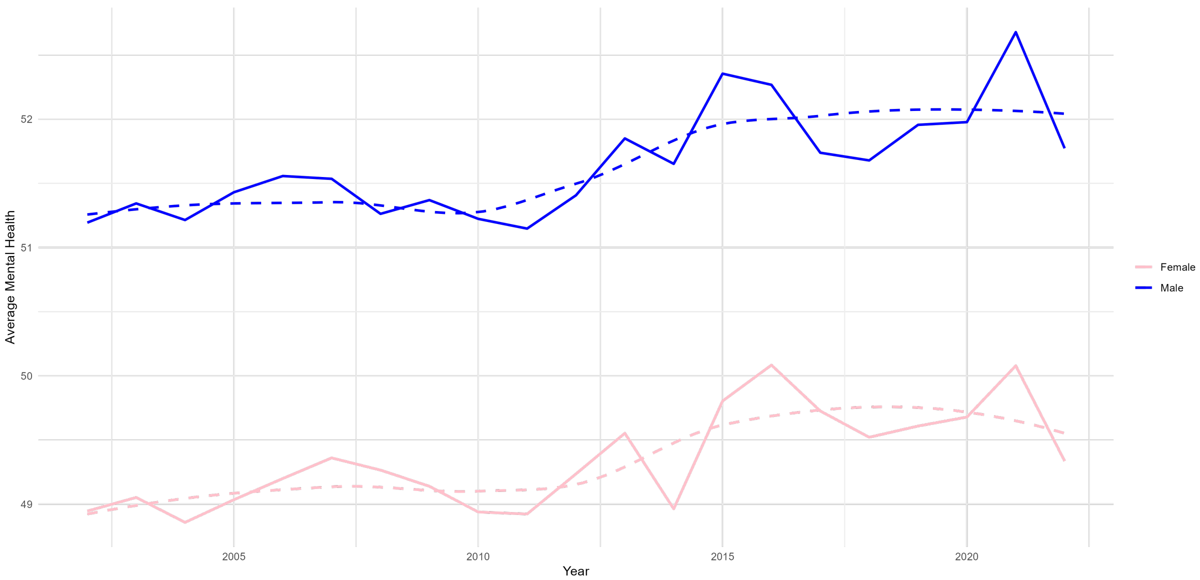
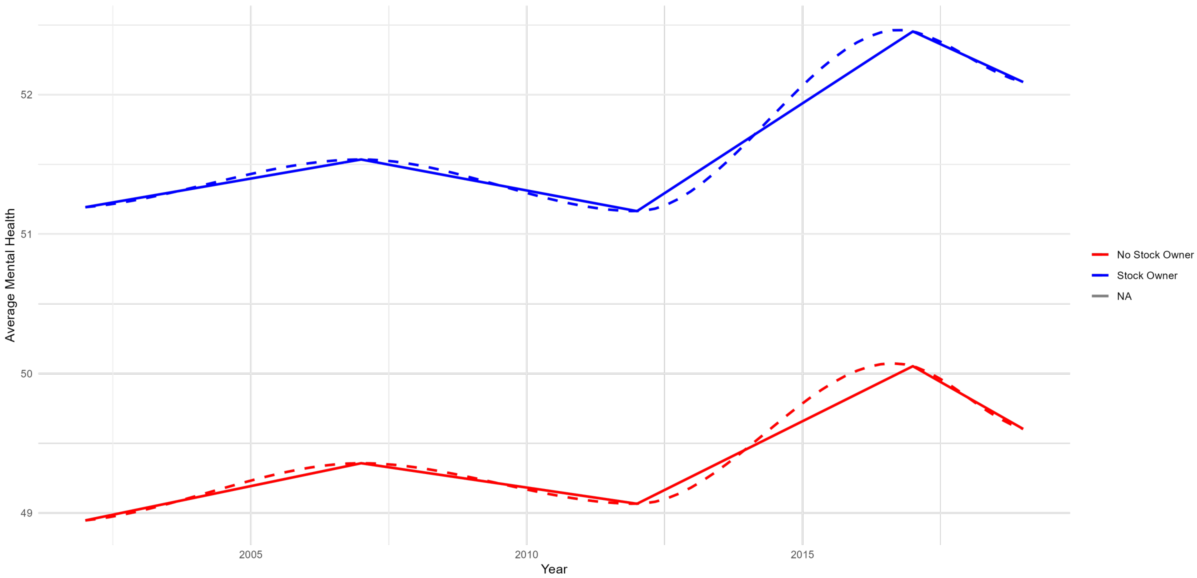


Figure 3: Mental Health Across Stock Owners and Non-Stock Owners

This figure illustrates average mental health for stock owners and non-stockowners over the period 20022022. Mental health is standardized within each survey wave. The figure is based on the full SOEP sample.



4 Methodology and Results

4.1 Do Affective States Influence Stock Market Participation?

We begin our empirical analysis by investigating whether mental health, as a proxy for affective states, influences households' stock market participation (SMP). We then explore which particular types of affective symptoms, such as depression, anxiety, or worry, drive the results.

To estimate the relationship, we employ a linear probability model of the following form:

$$SMP_{i,t} = \alpha A_{i,t-1} + \beta X_{i,t-1} + \lambda_t + \varepsilon_{i,t}^{own}$$

where $SMP_{i,t}$ is a binary variable equal to one if individual i reports stock ownership in survey year t and zero otherwise. The key explanatory variable, $A_{i,t-1}$, includes either the MCS or the normalized MH score, measured in the previous wave to mitigate simultaneity concerns. The control vector $X_{i,t-1}$ includes demographics (e.g., age, gender, education, labor income, wealth etc.) and risk attitude. Year fixed effects are captured by λ_t.

Table 3 summarizes the results which indicate a strong and statistically significant relationship between mental health and stock market participation. In columns (1)-(2), we report estimates on the overall stock market participation. A one standard deviation increase in mental health is associated with a 1.2-3.6 percentage point higher likelihood of owning stocks. These estimates remain highly significant after controlling for demographics and risk preferences. Columns (3)-(6) shift the focus to stock market entry. Mental health continues to be a strong predictor of entry, with coefficients ranging from 0.3 to 0.9 percentage points, without and with controls, respectively. Importantly, in Columns (5)-(6), we restrict the sample to individuals who were not stockholders in the previous wave and estimate the probability of becoming a stockholder in period t. This captures a cleaner margin of entry and reflects a significant investment decision point. The estimated effect of mental health on this extensive margin remains highly statistically significant and economically meaningful.

To interpret the economic relevance and put things in perspective, consider the most conservative estimate: a one SD increase in mental health is associated with a 0.3 percentage point increase in SMP entry. Given approx. 40 million households in Germany, this translates to roughly 120,000 new stock-owning households per year, attributable to improvements in average mental health.

These findings support our central hypothesis that affective states help explain stock market participation, not only by correlating with existing ownership but by increasing the likelihood of new market entry.

Table 3: Regression Results

This table reports results from linear probability models estimating the relationship between mental health and stock market participation (SMP). Coefficients indicate the change in the probability of SMP, expressed in percentage points, associated with a one-standard deviation increase in the mental health measure. Columns (1) and (2) report unconditional effects on the overall likelihood of stock ownership. Columns (3)(6) restrict the analysis to individuals who were not stockholders in the previous wave. In Columns (3) and (4), past ownership is included as a control; in Columns (5) and (6), all previous stockholders are excluded from the sample. The sample is restricted to household heads. Standard errors are clustered at the household level. T-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions include demographic controls: gender, age, household income, total wealth, total liabilities, and education.

	SMP		**Becoming SMP**		**Becoming SMP**	
Dependent Variable	SMP	SMP	SMP	SMP	SMP	SMP
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Health	0.0360***	0.0124***	0.0073***	0.0034***	0.0089***	0.0036***
	(18.18)	(6.16)	(9.79)	(3.93)	(9.76)	(3.36)
Risk Attitude		0.0135***		0.0025***		0.0034***
		(6.19)		(2.73)		(3.04)
Demographics		Y		Y		Y
Year F.E.	Y	Y	Y	Y	Y	Y
Obs.	113,381	83,871	112,476	83,760	88,006	64866
Adj.R-squared	0.0113	0.1758	0.7317	0.7434	0.0039	0.0334
MSC	0.0315***	0.0098***	0.0078***	0.0043***	0.0092***	0.0047***
	(18.35)	(4.95)	(12.20)	(5.07)	(12.10)	(4.52)
Risk Attitude		0.0119***		-0.0001		0.0001
		(5.53)		(-0.07)		(0.08)
Demographics		Y		Y		Y
Year F.E.	Y	Y	Y	Y	Y	Y
Obs.	143,290	84,905	137,775	84,846	109,912	65,639
Adj.R-squared	0.0112	0.1742	0.7358	0.7466	0.0028	0.0310

4.1.1 Disaggregated Results: Which Affective States Matter?

To further understand which specific affective conditions drive this relationship, we disaggregate the composite mental health measures into symptom-specific dimensions: depression, anxiety, and worry.

Drawing on self-reported SF-12 items, we construct dummy variables indicating the presence of mild, moderate, and severe symptoms (1, 2, or 3 indicators) within each category. The omitted reference group includes individuals who report no symptoms for the respective condition. As in the previous analysis, we us a linear probability framework and examine both overall SMP and the probability of becoming a stockholder, restricting the sample to non-stockholders in the previous wave. The results are reported in Table 4.

Symptoms of **depression** are consistently and strongly associated with lower stock market participation. Even mild depressive symptoms (Row 1) reduce the probability of ownership by around 2 percentage points, when including controls. The relationship becomes more pronounced with increasing symptom intensity, reaching a drop of 4-8 percentage points for those reporting severe symptoms. These effects remain significant when restricting the sample to new market entrants, confirming that depression blocks stock market participation.

The findings for **anxiety** are interesting and perhaps counterintuitive at first sight. Mild anxiety is positively and significantly associated with stock market participation (i.e., +1.2 percentage points), while higher levels of anxiety show no significant effects. This inverted-U pattern supports psychological theories (Sweeny & Dooley, 2017) emphasizing the motivational upside of moderate anxiety, which may act as a signal to take proactive steps such as investing. In contrast, severe anxiety may lead to avoidance or cognitive overload, offsetting any motivational benefits.

In contrast to anxiety, self-reported **worry**, even at low levels, is negatively related to stock market participation. Mild and moderate symptoms reduce the likelihood of SMP by roughly 2-3 percentage points, while severe worry is associated with declines of up to 8 percentage points. This pattern also holds for market entry (Columns (3)(4)).

Table 4: Regression Results Disag

This table reports results from linear probability models estimating the relationship between disaggregated mental health symptoms and stock market participation (SMP). The key independent variables are symptom-specific dummy indicators for depression, anxiety and worrying, capturing the intensity of reported symptoms. For each mental health dimension, individuals are grouped into one of four categories: no symptoms (reference group), mild (1 symptom), moderate (2 symptoms), or severe (3 or more symptoms). Coefficients represent the change in the probability of SMP, expressed in percentage points, associated with each symptom level. Columns (1) and (2) report unconditional effects on the overall likelihood of stock ownership. Columns (3)(4) restrict the analysis to individuals who were not stockholders in the previous wave. The sample is restricted to household heads. Standard errors are clustered at the household level. T-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions include demographic controls: gender, age, household income, total wealth, total liabilities, and education.

	SMP		**Becoming SMP**	
Dependent Variable	SMP	SMP	SMP	SMP
	(1)	(2)	(3)	(4)
depression_1	-0.0669***	-0.0227***	-0.0130***	-0.0063*
	(-10.83)	(-3.32)	(-4.20)	(-1.70)
depression_2	-0.1124***	-0.0320**	-0.0260***	-0.0173***
	(-9.65)	(-2.42)	(-4.70)	(-2.65)
depression_3	-0.1365***	-0.0418**	-0.0324***	-0.0051
	(-8.34)	(-2.25)	(-3.99)	(-0.48)
anxious_1	0.0494***	0.0336***	0.0117***	0.0093***
	(8.49)	(5.10)	(4.12)	(2.66)
anxious_2	0.0207*	0.0133	0.0073	0.0050
	(1.85)	(1.05)	(1.36)	(0.76)
anxious_3	0.0459***	0.0272	0.0111	0.0007
	(2.67)	(1.37)	(1.32)	(0.07)
worry_1	-0.0540***	-0.0200***	-0.0197***	-0.0134***
	(-7.97)	(-2.63)	(-5.84)	(-3.29)
worry_2	-0.0726***	-0.0293**	-0.0181***	-0.0111
	(-5.68)	(-2.04)	(-2.92)	(-1.44)
worry_3	-0.0803***	-0.0281	-0.0254***	-0.0247**
	(-4.59)	(-1.48)	(-3.01)	(-2.52)
risk attitude		0.0086***		-0.0012
		(2.83)		(-0.81)
Demographics		Y		Y
Year F.E.	Y	Y	Y	Y
Obs.	38,865	26,541	37,610	26,494
Adj.R-squared	0.0309	0.1820	0.7360	0.7452

4.2 Causal Identification: Evidence from the COVID-19 Shock

The previous analysis documents a robust link between mental health and stock market participation. Are these patterns merely correlational, or can changes in affective states be causally linked to stock market participation?

To answer this question, we develop and formalize a novel identification strategy within a two-stage DiD-IV framework, exploiting the COVID-19 pandemic as an exogenous shock to mental health. The main idea behind our approach is that mental health impact of the pandemic was not uniform: individuals with weaker pre-crisis social networks were more vulnerable to psychological distress during COVID-related isolation than those with stronger social ties. This heterogeneity in exposure provides the necessary exogenous variation to identify the causal effect of mental health on stock market participation.

The empirical strategy follows two steps. In the first stage, we isolate plausibly exogenous variation in mental health by interacting individual's pre-crisis sociability with a post-crisis indicator in a DiD design:

$$A_{i,t} = \alpha + \beta \; treated \times post + X_{i,t} + \delta_t + \lambda_i + \varepsilon_{t,i}$$

Here, $A_{i,t}$ denotes standardized mental health for individual i in year t, *treated* is an indicator for strong pre-crisis social networks and *post* denotes the post-COVID period. The specification includes time-fixed effects δ_t, social group fixed effects λ_i, and demographic controls $X_{i,t}$.

In the second stage, we use the predicted mental health variation from the first stage, $\hat{A_{i,t}}$, as an instrument to estimate its causal effect on the decision to enter the stock market:

$$SMP_{i,t} = \nu + \beta \hat{A_{i,t}} + X_{i,t} + \delta_t + \lambda_i + \epsilon_{t,i}$$

Figure 4 supports the identification strategy by illustrating diverging mental health trends between treatment and control groups after 2020. When interpreting the plot, it is important to note that mental health is standardized within each survey wave. As a result, post-crisis increases in mental health for the treated group (individuals with strong pre-crisis social networks) reflect relative changes compared to the overall sample mean. The apparent improvement in mental health among the treated group should therefore be interpreted as a relative shift rather than an absolute gain. Individuals with strong social ties appear somewhat protected during the early crisis years, while those with weaker pre-crisis networks closely follow the overall sample trend. By 2023, mental health declines for both groups, but the drop is more pronounced among the socially isolated. This pattern is consistent with our assumption of heterogeneous exposure, as the untreated group, i.e., those with low pre-pandemic social ties, experienced the steepest deterioration in mental health following COVID-19.

However, a natural concern is that the COVID-19 pandemic may have affected economic opportunities directly, not only through the mental health channel linked to social isolation. If these economic effects were more pronounced among individuals with fewer social connections, this could introduce a confounding factor. To address this concern, we examine the evolution of labor income dynamics for treated and untreated individuals. Pre- and post-crisis trends in labor income are displayed in Figure 5. While there is a slight difference in income levels between the two groups, this gap remains stable over time and does not exhibit any sharp divergence following the onset of the pandemic.

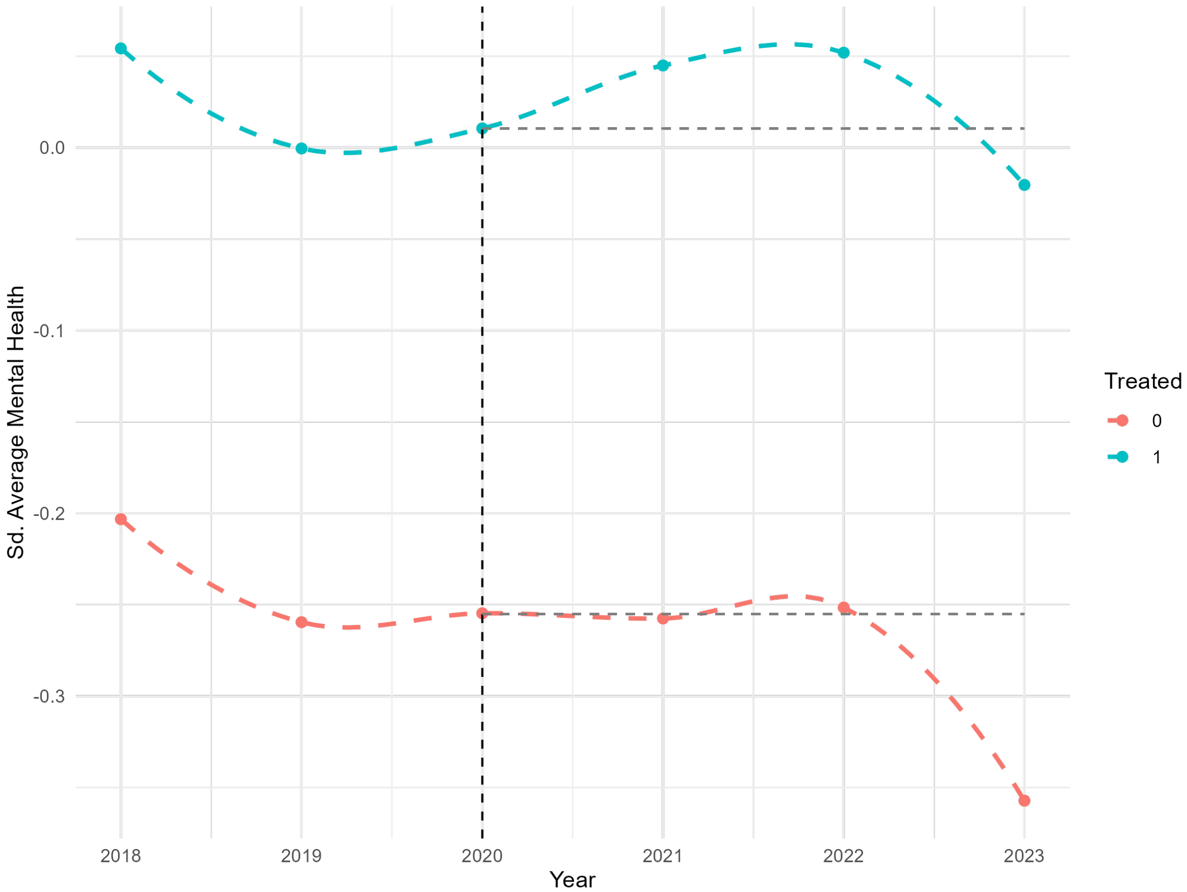
Instrument strength is supported by the first-stage F-statistics reported in Table 5. For the exclusion restriction, we argue that while the COVID-19 pandemic, including stay-at-home policies and broader social isolation, may have affected both mental health and financial behavior, these effects were common to both groups. Our identification strategy relies on heterogeneity in the intensity of the mental health shock: individuals with weaker pre-crisis social networks experienced a disproportionately larager decline in mental health. Importantly, alternative channels, such as changes in free time or opportunity to engage in stock market activities (Meister et al., 2024) should affect both groups similarly and therefore do not threaten the exclusion restriction. Our instrument thus isolates exogenous variation in stock market participation that arises specifically through the heterogeneous impact of the pandemic on mental health.

The results in Table 5 indicate a clear and statistically significant positive relationship between mental health and the likelihood of stock market entry. Individuals who experienced relatively less mental health distress during the pandemic, due to stronger pre-crisis social networks, are more likely to begin participating in the stock market in subsequent years. The estimates remain robust to the inclusion of demographics. The first-stage

F-statistics exceed conventional thresholds, confirming the strength of the instrument.[6]

Figure 4: Pre- and Post-Crisis Trends in Average Mental Health

This plot displays pre- and post-crisis trends in average mental health for the treatment and control groups used in the DiD-IV strategy. The treatment group consists of individuals reporting strong pre-crisis social networks, while the control group includes individuals reporting weak pre-crisis social networks. The vertical line indicates the onset of the COVID-19 crisis. Mental health is standardized, and values reflect average scores by wave. The sample is restricted to household heads.



[6] The relatively large magnitude of the second-stage coefficients is a common feature of IV regressions. When the instrument is strong (e.g., high first-stage F-statistic) and plausibly satisfies unconfoundedness and the exclusion restriction, an IV estimate exceeding the corresponding OLS coefficient is not problematic. See Lal, Lockhart, Xu, and Zu (2024) for details.

Figure 5: Pre- and Post-Crisis Trends in Economic Conditions

This plot displays pre- and post-crisis trends in average labor income for the treatment and control groups used in the DiD-IV strategy. The treatment group consists of individuals reporting strong pre-crisis social networks, while the control group includes individuals reporting weak pre-crisis social networks. The vertical line indicates the onset of the COVID-19 crisis. Labor income is indexed to the base year 2016 to evaluate relative income growth over time. The sample is restricted to household heads.

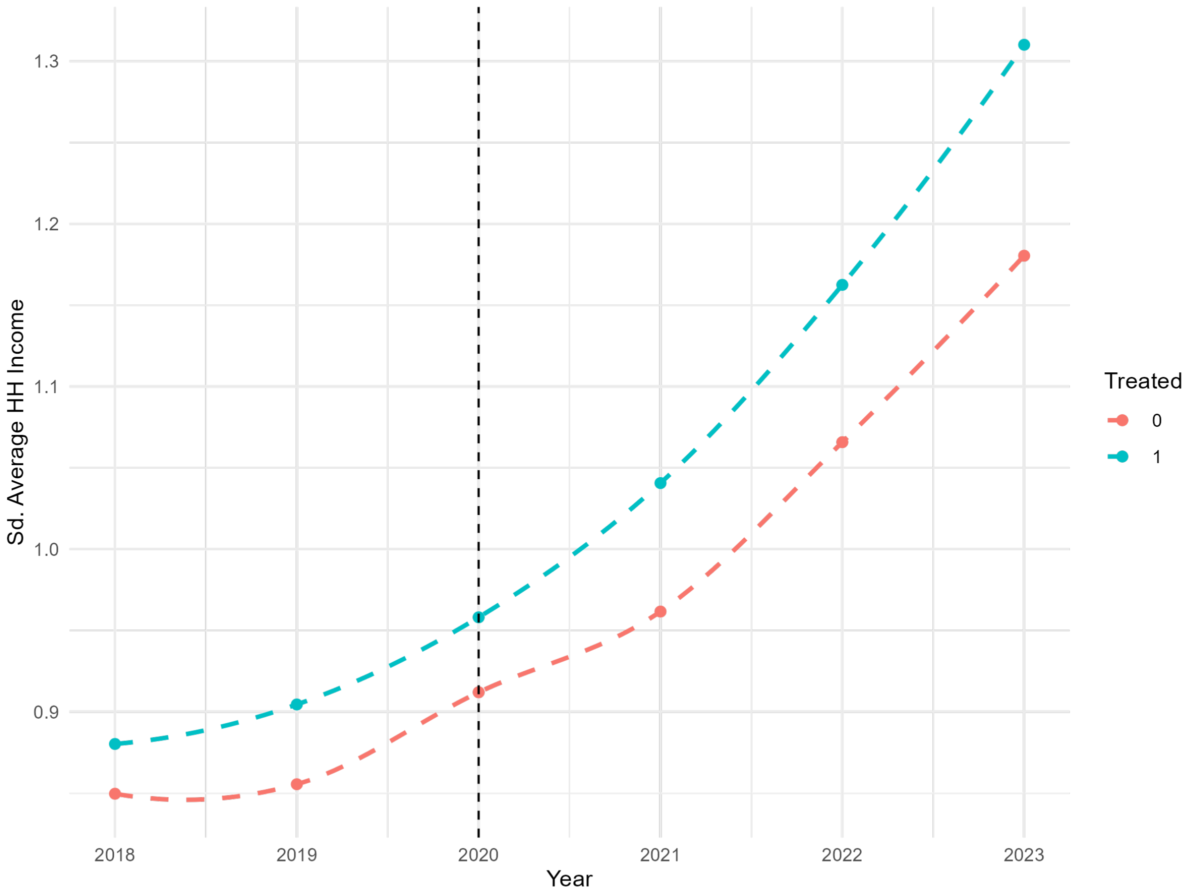


Table 5: Regression Results: Identification

This table reports results from a Difference-in-Differences Instrumental Variables (DiD-IV) strategy that exploits the COVID-19 pandemic as a plausibly exogenous shock to mental health. Identification relies on the assumption that individuals with weaker pre-crisis social networks experienced a stronger mental health impact from pandemic-related social isolation compared to those with stronger pre-crisis networks. In the first stage, we estimate a quasi-Difference-in-Differences model to isolate the component of mental health variation driven by the COVID-19 shock among socially less connected individuals. In the second stage, we use this predicted variation as an instrument for observed mental health to estimate its causal effect on stock market participation (SMP). The sample is restricted to household heads. Standard errors are clustered at the household level. T-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions include demographic controls: gender, age, household income, total wealth, total liabilities, and education.

	Becoming SMP	
Dependent Variable	SMP	
	(1)	(2)
Mental Health	0.1002**	0.1452*
	(2.10)	(1.78)
old_SMP	0.9035***	0.8836***
	(150.34)	(151.02)
Social FE	Y	Y
Time FE	Y	Y
Demographics		Y
Obs.	21,602	19,222
First-stage R-squared	0.0272	0.0655
First-stage F	113.79	87.81

4.3 Robustness Check: Reverse Causality

A potential concern is that the observed relationship between mental health and stock market participation may be driven by reverse causality, that is, deteriorating market conditions might affect individuals' affective states. To address this, we regress individual-level mental health on lagged log DAX returns:

$$A_{it} = \alpha \; DaxReturn_t + \beta X_{i,t} + \varepsilon_{i,t}$$

Table 6 reports the results using both aggregate and individual level data, with and without demographic controls. Across all specifications, the estimated coefficients are small and statistically insignificant, indicating no meaningful association between stock market returns and mental health conditions.

These findings suggest that reverse causality is unlikely to explain the main result and support the interpretation that mental health drives households' investment decisions.

Table 6: Dax Returns and Mental Health

This table reports results from linear regression models estimating the relationship between stock market returns and mental health to assess potential reverse causality. Coefficients indicate the change in mental health associated with a one-unit increase in log DAX returns. Columns (1) and (2) use aggregated data, where mental health is averaged across all individuals in each wave. Columns (3) to (6) use individual-level data. Columns (2), (5), and (6) restrict the sample to stockholders, while Columns (1), (3), and (4) are based on the full sample of household heads. The sample is restricted to household heads. Standard errors are clustered at the household level. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions include demographic controls: gender, age, household income, total wealth, total liabilities, and education.

	Average Mental Health		Mental Health			
	Full Sample	Owners	Full Sample		Owners	
	(1)	(2)	(3)	(4)	(5)	(6)
Dax Returns	0.040	-0.081	0.052	0.060	-0.110	-0.016
	(0.047)	(0.092)	(0.035)	(0.039)	(0.067)	(0.070)
Demographics				Y		Y
Obs.	20	20	216,611	184,063	56,789	52,194
Adj. R^2	-0.050	-0.050	0.00001	0.052	0.00003	0.064

4.4 Channels: How Does Mental Health Affect Participation?

Building upon our conceptual framework, we now empirically examine the specific mechanisms through which mental health influences stock market participation. As outlined previously, our theoretical model identifies three distinct but interrelated channels: risk preferences, external beliefs, and internal beliefs.

To operationalize and empirically test these channels, we employ a two-step empirical strategy. First, we examine whether mental health predicts variation in key psychological and attitudinal variables serving as empirical proxies for the theoretical channels. Specifically, we proxy risk preference through reported risk attitudes, capturing an individual's willingness to accept financial uncertainty and risk (represented by the risk aversion parameter γ_i in our model, Eq. 1). External beliefs are proxied by levels of optimism regarding future outcomes, directly influencing subjective expectations $E_i[r]$ and perceived market risk $Var_i[r]$. Internal beliefs are proxied by measures of self-esteem, reflecting investors' confidence and perceptions of their capability to engage in stock market investing, captured by the target portfolio w_i^*.[7]

In a second step, we investigate whether these empirically derived proxies - risk attitudes, optimism, and self-esteem - subsequently predict stock market participation. This approach allows us to identify and validate the potential channels through which mental health translates into financial decision-making, ultimately influencing participation in stock markets.

Panel A of Table 7 confirms that mental health is strongly correlated with all three proposed channels: individuals with better mental health report higher willingness to take risks, greater optimism, and more positive self-esteem. These results suggest that affective states significantly impact both internal and external beliefs, and preferences.

Panel B then examines how each of these variables predicts stock market participation. We find that risk tolerance and optimism are both strong and economically meaningful predictors: individuals with greater willingness to take risks and a more optimistic outlook are more likely to hold stocks. A one standard deviation increase in risk tolerance is associated with a 0.5 percentage point increase in the probability of stock market

[7]For detailed information on the specific question wordings and scales used for each proxy, see Appendix Table A.1.

participation, while a one standard deviation increase in optimism is associated with a substantially larger 3.8 percentage point increase. When included jointly (Column (4)), both remain significant. Self-esteem has also has some explanatory power, but it weakens when controlling for the other two channels.

Panel C shows results for the restricted sample: entry into the stock market among individuals who were previously not participants. Here, optimism remains the strongest predictor of becoming a stockholder, followed by risk attitudes. Optimism remains the strongest predictor: a one standard deviation increase in optimism is associated with a 0.77 percentage point higher likelihood of entering the market. Risk attitudes also matter, though the effect is more modest at 0.07 percentage points. When all three channels are included simultaneously, optimism and risk attitudes remain significant, while self-esteem becomes insignificant. These findings suggest that both external beliefs (expectations about future returns) and preferences (risk tolerance) shape entry decisions, consistent with the mean-variance model: higher expected returns and lower perceived variance increase optimal risky asset holdings. In contrast, internal beliefs, as proxied by self-esteem, appear less important for the restricted sample, possibly because they matter more for confidence in managing investments rather than the initial decision to participate.

Table 7: Regression Results: Channels

This table reports results from linear probability models examining the role of potential channels (risk attitude, optimism, and self-esteem) in the relationship between mental health and SMP. Panel A presents estimates from regressions where mental health is used to predict each potential channel. Coefficients indicate the change in the outcome variable (standardized risk attitude or the probability, in percentage points, of being highly optimistic or having high self-esteem) associated with a one-standard deviation increase in mental health. Panel B estimates the relationship between each channel and the overall likelihood of stock market participation. Panel C restricts the sample to individuals who were not previously invested in the stock market and examines how each channel predicts the probability of entering the market (i.e., becoming SMP). The sample is restricted to household heads. Standard errors are clustered at the household level. T-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions include demographic controls: gender, age, household income, total wealth, total liabilities, and education.

Panel A: Channels

Dependent Variable		Risk Attitude	Optimism	Self-Esteem
	(1)	(2)	(3)	(4)
Mental Health		0.0903***	0.0628***	0.0352***
		(20.22)	(37.22)	(25.59)
Demographics		Y	Y	Y
Year F.E.		Y	Y	Y
Obs.		102,304	114,507	114,507
Adj.R-squared		0.0721	0.3345	0.5065

Panel B: Being SMP

Dependent Variable		**SMP**		
	(1)	(2)	(3)	(4)
Risk Attitude	0.0054***			0.0049***
	(6.83)			(6.17)
Optimisim		0.0379***		0.0366***
		(10.02)		(9.08)
Selfesteem			0.0215***	0.0036
			(4.97)	(0.79)
Demographics	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
Obs.	189,365	229,099	229,099	189,365
Adj.R-squared	0.1721	0.1747	0.1738	0.1735

(continued)				
Panel C: Becoming SMP				
Dependent Variable	SMP			
	(1)	(2)	(3)	(4)
Risk Attitude	0.0007***			0.0006**
	(2.62)			(2.43)
Optimisim		0.0077***		0.0054***
		(6.19)		(4.04)
Selfesteem			0.0039***	-0.0025
			(2.77)	(-1.60)
old_SMP	0.8892***	0.8891***	0.8894***	0.8889***
	(646.57)	(698.83)	(700.67)	(644.18)
Demographics	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
Obs.	189,188	227,173	227,173	189,188
Adj.R-squared	0.7425	0.7420	0.7420	0.7426

5 Conclusion

Why do many households choose not to participate in the stock markets, even when they have the means and knowledge to do so? This study provides novel evidence that affective states, proxied by mental health, are important forces behind investment decisions beyond traditional factors. Using longitudinal data from the German Socio-Economic Panel (SOEP), we find that individuals with better mental health are significantly more likely to invest in stocks. In contrast, symptoms of depression and chronic worry are strongly associated with non-participation. These patterns are not merely correlational: to identify a causal effect, we exploit variation in psychological distress induced by the COVID-19 pandemic. Our difference-in-differences instrumental variable strategy isolates heterogeneity in individuals pre-crisis social networks: those with weaker social ties experienced greater declines in mental health during the pandemic, providing a source of exogenous variation.

The results suggest that mental health is not just a background condition, but an active gatekeeper that affects whether individuals act on their financial intentions. A one standard deviation improvement in mental health increases the likelihood of stock market participation by 3-5 percentage points, translating into roughly 120,000 additional participating households per year in Germany.

To explain how mental health alters participation, we develop a conceptual framework based on an extended mean-variance utility function, where traditional beliefs and preferences interact with non-pecuniary influences. Mental health affects participation through three channels: (i) it shapes external beliefs about returns and risk (optimism), (ii) it influences internal beliefs about self-worth and perceived capability (self-esteem), and (iii) it alters preferences, particularly risk tolerance. We show empirically that mental health significantly predicts variation in each of these three proxies, and that these channels, in turn, explain substantial heterogeneity in stockholding.

Taken together, our findings call for a rethinking of standard household finance models. Psychological barriers, rather than purely informational or economic constraints, can prevent individuals from entering financial markets. Ignoring this leads to omitted variable bias and overestimates the role of education or income. Given rising mental health concerns globally, especially among the young, this has first-order implications for policy and financial advice. Addressing affective constraints through behavioral interventions, mental health support, or targeted confidence-building tools may prove more effective than traditional financial literacy programs alone.

By recognizing that stock market participation is shaped by both cognition and affect, this study contributes to a more comprehensive understanding of financial decision-making.

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Data Availability Statement

The data that support the findings of this study are subject to third-party restrictions. Microdata from the German Socio-Economic Panel (SOEP) are provided by the German Institute for Economic Research (DIW Berlin (Goebel et al., 2022)). Access to the SOEP data is granted to researchers upon application and completion of a data use agreement with DIW Berlin (https://www.diw.de/en/diw_01.c.678568.en/research_data_center_soep.html).

A Appendix

A.1 Questions Mental Health

Questions used for mental health scores:

- MH1: During the last 4 weeks, how much of the time did you feel calm and peaceful?
- MH2: During the last 4 weeks, how much of the time did you feel downhearted and blue?
- RE1: Did you accomplish less than you would like due to emotional problems?
- RE2: Did you work less carefully than usual due to emotional problems?
- VT: Did you have a lot of energy?
- SF: Did emotional problems interfere with your social life?

A.2 Questions Channels

Table A.1: Question Wording and Scales for Channel Proxies

Channel	**Survey Question**	**Scale**
Risk Preferences (Risk Aversion)	Are you generally a person who is willing to take risks?	0 = not at all willing to 10 = very willing
External Beliefs (Optimism)	When you think about the future, are you	1 = optimistic to 7 = pessimistic
Internal Beliefs (Self-Esteem)	I have a positive attitude toward myself.	1 = not at all to 7 = completely