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

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July 31, 2025

Abstract

This study examines how affective states, proxied by mental health, shape household stock market participation. Using rich panel data from the German Socio-Economic Panel (SOEP), we show that better mental health significantly increases the likelihood of stock ownership, while symptoms of depression and chronic worry reduce participation. To isolate causal effects, we exploit the COVID-19 pandemic as a natural experiment in a Difference-in-Differences Instrumental Variables (DiD-IV) design. Individuals with weaker pre-crisis social networks experienced larger declines in mental health, which we use to identify exogenous variation. Our results suggest that a one standard deviation increase in mental health predicts approximately 120,000 new stockholding households annually in Germany. We introduce a conceptual framework with three channels: external beliefs, internal beliefs, and preferences to explain how mental health shapes investment behavior. Our results strongly indicate that mental barriers are key constraints to stock market entry.

JEL Classification: D1, G50, G41

*Early stage, please do not distribute.

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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 regardless of risk preferences, standard portfolio choice models predict universal stock market participation to maximize expected returns.(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 probabilistic regression 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]

To address endogeneity concerns, we exploit the COVID-19 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

[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+).

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 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 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 non-monetary 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 contributes to the literature in three key ways. First, we provide novel evidence that mental health conditions are significant and economically meaningful predictors of stock market participation. Second, we argue that ignoring mental health in financial decision-making models introduces omitted variable bias and over-attributing outcomes to traditional economic factors. Third, our findings suggest that conventional policy tools, such as improving financial literacy, may be insufficient to increase stock market participation among individuals facing mental health conditions.

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 influence on financial behavior 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. Section 2 describes the data. Section 3 outlines the empirical strategy and presents the main findings. Section 4 discusses the conceptual framework to interpret the results. Finally, Section 5 concludes.

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

2 Data

2.1 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, and 2020 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 SOEP's 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.

2.2 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 aggregate measures, we include a 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.

2.3 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. 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 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

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
hhgr	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

	(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	1019.936	1773.754	-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	96770.872	279056.912	-182286.04	-23.7
tot liabilities	18164.694	33073.486	-14908.792	-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
hhgr	2.366	2.544	-0.178	-20.284
sociability	3.973	4.502	-0.529	-21.828

Figure 1: Mental health across age groups.

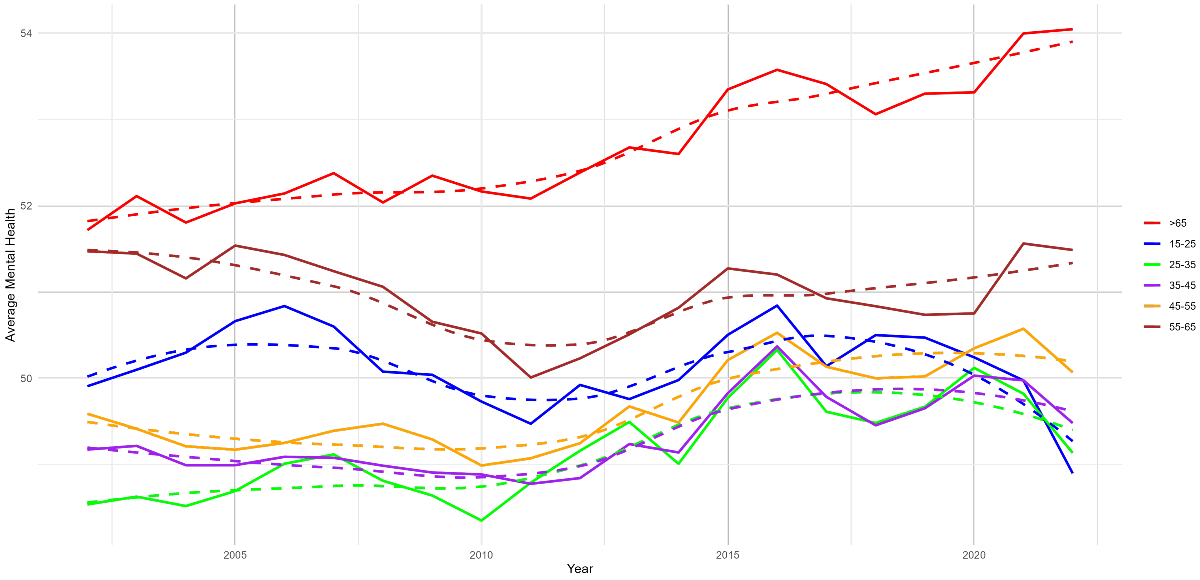


Figure 2: Mental health across gender.

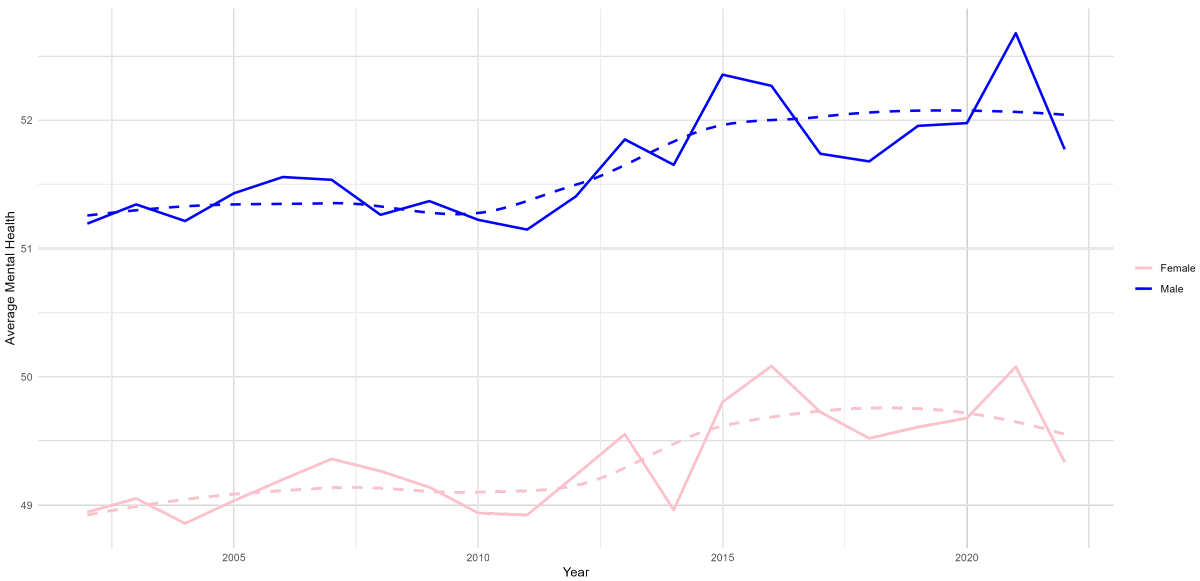
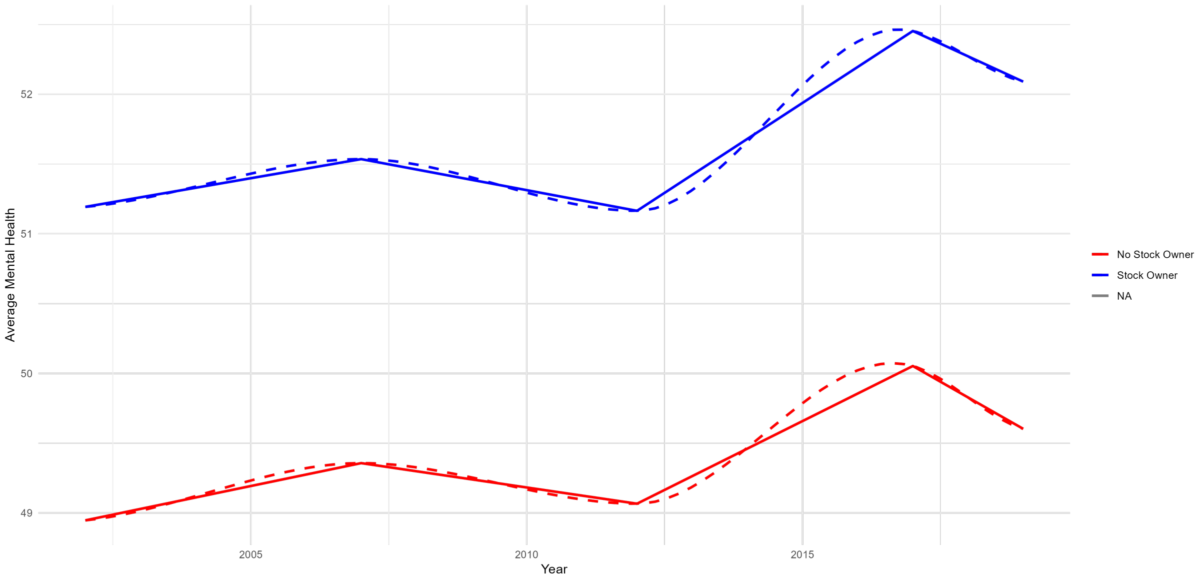


Figure 3: Mental health across stock owners and non-stock owners.



3 Methodology and Results

3.1 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 raging 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.	113381.0000	83871.0000	112476.0000	83760.0000	88006.0000	64866.0000
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.	143290.0000	84905.0000	137775.0000	84846.0000	109912.0000	65639.0000
Adj.R-squared	0.0112	0.1742	0.7358	0.7466	0.0028	0.0310

3.1.1 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 worry, 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.	38865.0000	26541.0000	37610.0000	26494.0000
Adj.R-squared	0.0309	0.1820	0.7360	0.7452

3.2 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 weak 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 $X_{i,t}$.

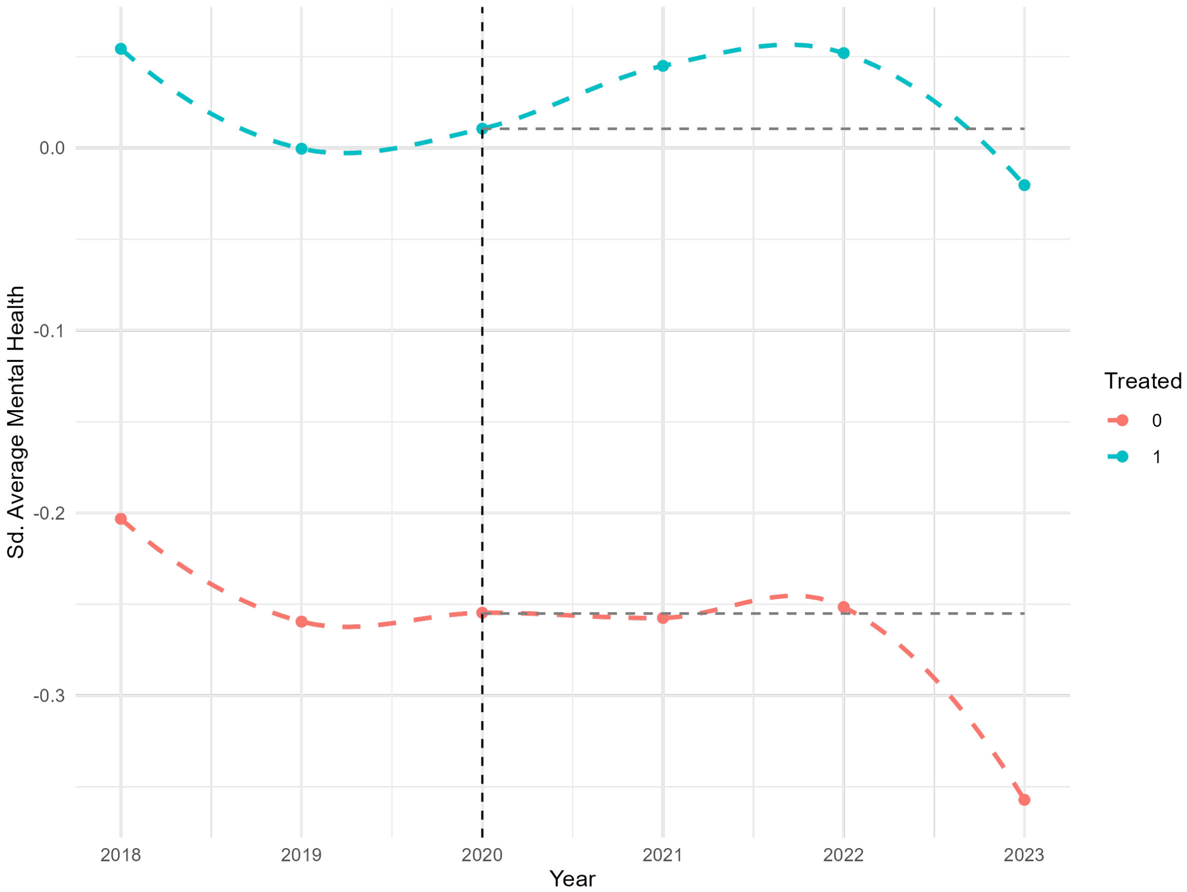
In the second stage, we use the predicted mental health variation from the first stage, $\hat{A_{i,t}}$, as an instrument to estimate its causal effect on the decision to enter the stock market:

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

Figure 4 supports the identification strategy by illustrating diverging mental health trends between treatment and control groups after 2020. The treatment group, i.e., those with low pre-pandemic sociability, experienced a marked deterioration in mental health post-COVID, validating the assumption of heterogeneous treatment exposure.

Figure 4: Mental health across age groups.

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 weak pre-crisis social networks, while the control group includes individuals reporting strong 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.



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.[4]

[4]The estimated second-stage coefficients are large in magnitude, a common feature of IV regressions

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.

Dependent Variable	Becoming SMP 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

when the instrument isolates local average treatment effects or when there is measurement error in the endogenous regressor. We focus on the direction and robustness of the effect rather than its precise size.

3.3 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 sock 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

3.4 Channels: How Does Mental Health Affect Participation?

To conceptualize a framework for our empirical findings, we consider the following simple framework following Jiang et al. (2024); Markowitz (1952); Merton (1969). In this framework, investor i's portfolio choice is shaped not only by expected returns and risk but also by non-pecuniary factors, such as self-perception, emotional stability, and perceived cost of investing, that are likely influenced by an individual's affective state.

The objective function can be written as:

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

The first component reflects the standard mean-variance optimization problem: γ_i denotes 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 term introduces a penalty for deviations from the target portfolio w_i^*, which may be reflecting internal or social motivations. The parameter $\alpha \in [0,1]$ represents how much weight the investor assigns to these non-pecuniary factors. When $\alpha = 0$, the decision is purely rational and driven by risk-return trade-offs. In contrast, when $\alpha = 1$, choices are entirely shaped by factors beyond standard utility maximization.

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

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

This expression shows that investment decisions are jointly determined by beliefs ($E_i[r]$ and $Var_i[r]$), preferences towards risk (γ_i), and non-pecuniary factors summarized by w_i^*.

This framework provides a useful lens for interpreting how affective states, proxied by mental health, can influence stock market participation. We argue that mental health may affect investment decisions through three channels: First, by shaping risk preferences. Individuals exhibiting poorer mental health may perceive higher risks and exhibit greater loss aversion, raising their effective risk aversion parameter γ_i. Second, by affecting external beliefs about future outcomes. Pessimism and diminished reward anticipation can lead individuals to form systematically lower expectations about returns $E_i[r]$ or higher perceived risk $Var_i[r]$. Finally, mental health may alter investment decisions through its effect on the subjective target portfolio w_i^*. This captures internal beliefs, such as self-efficacy or confidence in one's ability to participate in the stock market.

In what follows, we test these three channels empirically using a two-step approach. First, we examine whether mental health predicts variation risk attitudes, optimism, and self-esteem, used as proxies for the three conceptual channels described above.[5] In a second step, we investigate whether these variables, in turn, predict stock market participation. his approach allows us to identify potential channels through which mental health translates into financial behavior.

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 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,

[5]For question wordings and scales of the proxies used for each channel, see Appendix Table A.1.

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.		102304	114507	114507
Adj.R-squared		0.0721	0.3345	0.5065

Panel B: Beeing 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)

(continued)				
Selfesteem			0.0215***	0.0036
			(4.97)	(0.79)
Demographics	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
Obs.	189365	229099	229099	189365
Adj.R-squared	0.1721	0.1747	0.1738	0.1735

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.	189188	227173	227173	189188
Adj.R-squared	0.7425	0.7420	0.7420	0.7426

4 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.

Acknowledgements

The authors declare that they have not received any financial support, funding, or research grants for this study. There are no financial relationships or potential conflicts of interest to disclose.

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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