MACROECONOMICS OF MENTAL HEALTH

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Macroeconomics of Mental Health*

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Abstract

We develop an economic theory of mental health. The theory is grounded in classic and modern psychiatric literature, is disciplined with micro data, and is formalized in a life-cycle heterogeneous agent framework. In our model, individuals experiencing mental illness have pessimistic expectations and lose time due to rumination. As a result, they work less, consume less, invest less in risky assets, and forego treatment which in turn reinforces mental illness. We quantify the societal burden of mental illness and evaluate the efficacy of prominent policy proposals. We show that expanding the availability of treatment services and improving treatment of mental illness in late adolescence substantially improve mental health and welfare.

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1 Introduction

Mental illness is widespread and costly. In the United States, more than 20 percent of adults live with mental illness and approximately 5.5 percent experience serious mental illness (SAMHSA, 2022). Depression and anxiety, the most common mental illnesses, account for 8 percent of all years lived with disability globally (GBD, 2018). Policymakers are increasingly considering policies to improve mental health, for example by expanding access to treatment or by lowering out-of-pocket services costs.

We construct an economic theory of mental illness to study its macroeconomic implications. The theory is grounded in classic and modern psychiatric literature, is disciplined with micro-level data, and is formalized in a dynamic life-cycle heterogeneous agent economy. We show that mental illness alters consumption, savings, portfolio choice, and labor supply. We use this framework to quantify the societal burden of mental illness and to evaluate the efficacy of prominent policy proposals.

Our economic framework of mental health builds on classic and modern psychiatric theories. These theories emphasize three features of mental illness: negative thinking, rumination, and reinforcement through behavior.[1] We model negative thinking as individuals having pessimistic subjective expectations. Rumination, a repetitive and uncontrollable preoccupation with negative thoughts, is represented by a loss of available time. The third central feature is that mental illness reinforces itself through behavior. For example, individuals experiencing mental illness can choose to seek treatment, however, negative thinking about its efficacy and rumination may deter them, perpetuating mental illness. We model treatment decisions, which generate self-reinforcing behavior of mental illness.

Our first result is to quantify the degree of negative thinking and its dependence on mental health. We use micro level economic data to determine the extent of negative thinking among individuals experiencing mental illness. We quantify negative thinking using RAND's American Life Panel (ALP). Negative thinking across individuals is elicited using the classic Ellsberg urn paradox in a module designed by Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2015, 2016, 2021). Our interest is to measure how negative thinking varies by mental health. We do so by merging information on negative thinking with modules on well-being that provide information on the mental health of the respondents. We find that the subjective probability of the worst-case outcome is 4.8 percent higher for individuals experiencing mental illness when faced with the same objective uncertainty. We also show that negative thinking

[1] We model mental illness focusing on depression and anxiety, the most prevalent mental illnesses around the world (GBD, 2018). Our model also captures salient aspects of a variety of other mental conditions, such as impulse control disorders, substance abuse disorders, and PTSD, as they share mechanisms and symptoms with and are comorbid to depression and anxiety (Kessler, Chiu, Demler, and Walters, 2005).

increases with the severity of mental illness. Individuals experiencing mild mental illness have a 3.4 percentage point higher subjective probability of the worst-case outcome, while individuals experiencing serious mental illness have a 6.9 percentage point higher subjective probability of the worst case outcome.

We formalize our economic theory of mental illness in a lifecycle model with heterogenous agents. Individuals choose consumption, labor supply, and the amount to save in risk-free and risky assets. Mental health is a stochastic state variable that affects negative thinking, rumination, and treatment efficacy. We model negative thinking building on the cognitive model of depression (Beck, 1967, 1976, 2002, 2008) and the clinical and neuroscience literature supporting it (see, for example, Clark, Beck, Alford, Bieling, and Segal (2000), Mathews and MacLeod (2005), Disner, Beevers, Haigh, and Beck (2011) and Beck and Bredemeier (2016)). Individuals experiencing mental illness have pessimistic expectations on the realizations of uncertain outcomes. They behave according to the probability distribution that minimizes the continuation value among all distributions within a given distance from the objective probability distribution. Mental illness increases the subjective probability assigned to the worst-case outcome while diminishing the subjective probabilities assigned to the most favorable outcomes. Individuals experiencing mental illness expect lower productivity, lower returns on risky investments, and have a pessimistic view of their mental health evolution. The second aspect of mental illness is rumination (Nolen-Hoeksema, 1991; Just and Alloy, 1997; Nolen-Hoeksema, 2000; Nolen-Hoeksema, Wisco, and Lyubomirsky, 2008; Singer and Dobson, 2007) which we model as losing a portion of available time. The third aspect of mental illness is reinforcement through behavior. In the model, we capture this by modeling the treatment decision of individuals experiencing mental illness. Treatment increases the probability of transitioning into better mental health but is costly. Individuals experiencing mental illness may choose to not seek treatment as they see reduced benefits on the evolution of mental health status due to negative thinking. Mental illness is thus reinforced through the treatment decisions.

We next quantify the model. Following our empirical analysis, we model three mental health states: healthy, mild illness, and serious illness. First, we parameterize the extent of negative thinking for each mental health state. We identify negative thinking by mental health using the observation that differences in the subjective worst-case probabilities in the data directly map into differences in the extent of negative thinking in the model. Using the empirical estimates of the differences in the subjective worst-case probabilities from the ALP, we parameterize the extent of negative thinking to be 3.4 percent for individuals experiencing mild mental illness and 6.9 percent for individuals experiencing serious illness.

Second, we estimate the transition probabilities for individuals who receive treatment and who do not receive treatment. For identification, we use biannual transition probabilities between mental health states from the Panel Study for Income Dynamics (PSID), population shares and treatment propensities across mental health states obtained from the National Institute of Mental Health (NIMH) as well as estimates on the impact of treatment from the medical literature (Ekers, Richards, and Gilbody, 2008; Barth, Munder, Gerger, Nüesch, Trelle, Znoj, Jüni, and Cuijpers, 2016).

We calibrate remaining parameters so that model moments align with the data. The time that individuals lose due to rumination is calibrated to align hours worked by mental health status. With a time loss of 9.3 hours per week for mild mental illness and 12.5 hours per week for serious illness, the hours worked in the model match the empirical hours by group: 37.5 hours per week for mild mental illness and 35.0 for serious illness. We calibrate the utility cost of treatment to match the share of seriously ill who receive treatment. We target the estimate of the NIMH that 65.4 percent of those who are seriously ill receive treatment. We assume treatment is not available to a fraction of individuals who are mildly ill as availability is one of the most commonly cited barriers to treatment.[2] We calibrate availability so that the share of mildly ill receiving treatment is equal to 41.4 percent. This implies that one-thirds of the population does not have access to treatment when mildly ill.[3]

We validate the model by evaluating how it compares to non-targeted moments that describe the relation between mental health and economic outcomes. First, we evaluate the model predictions for average consumption, income, wealth and risky investments by mental health status. The model captures almost perfectly income levels and risky participation rates by mental health group, while somewhat understating the decrease in wealth. Second, the model captures well the distributions of consumption, income, portfolio allocations by mental health. For example, the income distribution among healthy individuals is skewed to the right, while the income distribution among individuals experiencing serious illness is skewed to the left due to working fewer hours. Finally, we validate the model against regression evidence from the PSID. The conditional correlations between individual consumption, labor supply, risky investments and mental health in the model align well with the data, controlling for relevant observables. For example, individuals with mild mental illness consume 3.2 (2.6) percent less and with serious illness consume 6.2 (7.0) percent less than healthy individuals in the model (data).

Having quantified our theory of mental illness, we discuss its implications. We first estimate the societal costs of mental illness. We find an aggregate cost of mental illness equal to 1.7 percent of

[2]See the White House Fact Sheets (www.whitehouse.gov/s1, www.whitehouse.gov/s2, www.whitehouse.gov/s3) and workforce data from the United States Department of Health and Human Services (www.hrsa.gov) and from the American Psychological Association (www.apa.org).

[3]This coincides with estimates of the number of individuals whose treatment needs are not met according to the United States Department of Health and Human Services that we discuss in footnote 32.

consumption annually. The average consumption equivalent cost of mental illness for individuals with serious mental illness is 15.6 percent, and is 10.3 percent for those with mild illness. We show that the welfare costs are larger for younger individuals than for older individuals: individuals below age 55 experience an average welfare cost of 2.4 percent; those above age 55 experience a welfare cost of 1.0 percent. Among individuals below age 55 the welfare costs are largest among the middle class, for whom the welfare cost is 3.4 percent.

We then evaluate the welfare implications of three widely discussed mental health policies: increasing availability of treatment, lowering out-of-pocket treatment costs, and improving mental health in late adolescence and young adulthood. First, we consider increasing the availability of treatment. We evaluate a policy that makes treatment available to all individuals. Increasing availability of mental treatment services reduces mental illness by 3.1 percentage points. This reduction in mental illness is driven by a strong increase in the treatment share among individuals experiencing mild illness, which almost doubles to 78.9 percent from 41.4 percent. The welfare benefits of providing full access to treatment services is 1.1 percent of aggregate consumption. The welfare gains are largest for individuals who are mildly ill and do not have access to treatment in the benchmark economy. Healthy individuals also experience gains due to the improved access in case they experience mental illness in the future. Second, we consider the implications of a policy under which individuals do not pay out-of-pocket for their treatment. We find that the welfare benefit of reducing out-of-pocket costs is effectively zero. Since the monetary costs of treatment are relatively low in the baseline economy, a further cost reduction does not lead to a significant uptake in treatment, and hence does not reduce mental illness. Third, we consider a policy that improves mental health treatment in late adolescence and young adulthood. We change the initial distribution of mental health assuming all individuals between age 16 and 25 receive treatment when they experience mental illness. Treatment of young adults improves the mental health of 25 year olds, which translates into an aggregate consumption equivalent gain of treatment in young adulthood of 1.7 percent annually.

Finally, we quantify the value of improving the efficacy of mental health treatment, for example due to advances in therapy or anti-depressant medication. We re-estimate the mental health transition matrix when treatment is 10 percent more effective. The aggregate consumption equivalent gain of this improvement in treatment is 0.7 percent, or 78 billion dollars annually. These estimates can be used to evaluate the value of improved treatment technologies and of research programs targeted to improve treatment.

Literature. We build on research on mental health from psychiatry and clinical psychology, and integrate the key insights of these literatures with the quantitative macroeconomics literature. We provide an overview of the mental health literature in Section 2.

Our modeling framework is closest to the literature on consumption, labor supply, and portfolio allocation over the life-cycle (Rios-Rull, 1996; Carroll, 1997; Campbell and Viceira, 1999; Gourinchas and Parker, 2002; Cocco, Gomes, and Maenhout, 2005; Gomes and Michaelides, 2005; Heathcote, Storesletten, and Violante, 2010; Low, Meghir, and Pistaferri, 2010; Huggett, Ventura, and Yaron, 2011; Kaplan and Violante, 2014; Fagereng, Gottlieb, and Guiso, 2017). Individuals choose labor supply, consumption, and how to allocate their savings between safe and risky assets. We incorporate mental health and analyze how mental health affects quantitative economic outcomes.

Our theory of negative thinking is related to the literature on multiple priors and ambiguity aversion (Gilboa and Schmeidler, 1989; Epstein and Schneider, 2003; Ilut and Schneider, 2014; Ilut, Valchev, and Vincent, 2020; Bhandari, Borovička, and Ho, 2022; Ilut and Valchev, 2023). In our model, individuals experiencing mental illness think negatively. That is, they consider a set of multiple priors regarding the distribution of future states and evaluate their choices according to the worst prior in this set. First, using survey data, we document that mental illness is positively associated with negative thinking. Second, we develop an approach to map micro level subjective loss probabilities to structural parameters that govern negative thinking. Third, mental health and, hence, negative thinking in our model is endogenous, stochastic, and heterogeneous.

A rich macroeconomic literature studies models of general health and its macroeconomic and life-cycle implications (Hubbard, Skinner, and Zeldes, 1995; French, 2005; Hall and Jones, 2007; De Nardi, French, and Jones, 2010; French and Jones, 2011; Low and Pistaferri, 2015; De Nardi, French, and Jones, 2016; Cole, Kim, and Krueger, 2019; Ameriks, Briggs, Caplin, Shapiro, and Tonetti, 2020; Fang and Krueger, 2022). Following Grossman (1972) and Ehrlich and Chuma (1990), better physical health improves longevity, well-being, and productivity but requires investment of time and money. Our model is specifically constructed to capture mental health, which is primarily a cognitive disorder. We model mental illness based on the salient features of the psychiatry literature: negative thinking, rumination, and effects of treatment.

Jolivet and Postel-Vinay (2023) develop a life-cycle search model of individual career and mental health dynamics. They focus on the interactions between health and labor market outcomes and quantify the effects of job loss, mental health shocks and job stress shocks. As in the health economics literature, in their model poor health affects employment, and working in a stressful job negatively affects health (see Currie and Madrian (1999)). Cronin, Forsstrom, and Papageorge (2023) analyze a structural model of dynamic treatment choices where mental illness is modeled akin to physical illness. We develop a life-cycle heterogeneous agent consumption, savings, and labor supply model of mental health built on the classic and modern psychiatric theories and study the consequences of mental health on consumption, savings, income, and portfolio allocation. De Quidt and Haushofer (2016) is a stylized model of static actions of how depression affects food, non-food, and sleep consumption through pessimistic beliefs and leads to overeating and undersleeping. We propose a rich dynamic stochastic model with forward looking individuals suited for quantitative work and welfare analysis.

Finally, by evaluating the welfare costs of mental illness in the United States, our paper contributes to the epidemiological literature that quantifies the societal costs of mental disorders (Greenberg, Kessler, Birnbaum, Leong, Lowe, Berglund, and Corey-Lisle, 2003; Kessler, Aguilar-Gaxiola, Alonso, Chatterji, Lee, Ormel, Üstün, and Wang, 2009; Greenberg, Fournier, Sisitsky, Pike, and Kessler, 2015). According to these studies, the annual cost of mental disorders is 217 billion dollars (in 2015 dollars). Our results suggest that these estimates, which are frequently cited by policymakers to provide justification for increasing funding for mental health services, are downward biased. The epidemiological literature focuses primarily on the static income penalty associated with mental illness and the monetary costs associated with treating mental illness. By developing an economic model of mental health, we are able to quantify not only these costs, but also how mental health affects consumption, job choice, savings and portfolio choice, how this dynamically translates to improved lifetime trajectories, and how individuals value better mental health. Our estimates imply that the annual cost of mental illness in the United States are 282 billion dollars, 30 percent larger than the estimate from the epidemiological literature.

2 Psychiatric Literature

This section summarizes theories of mental illness that provide the foundation for our economic approach to mental illness. We model mental illness as having three main components emphasized by the psychiatric literature − negative thinking, time loss through rumination, and self-reinforcing behavior.

Negative Thinking. The first key feature in the psychiatric literature on mental illness is negative thinking. The predominant psychiatric theory of depression is Beck's cognitive model of depression. Beck's theory posits that depression is a cognitive disorder characterized primarily by negative thinking (Beck, 1967, 1976, 2002, 2008). Depressed patients show the negative cognitive triad − a negative view of the self, the future, and the past. These negative thoughts are responsible for the observed symptoms of depression. The symptoms such as inaction, sadness, hopelessness, and loss of initiative are thus due to systematic negative expectations. Negative thinking is viewed as the fundamental cognitive bias not only of depression but also of anxiety disorders, PTSD, and psychosis (Beck, Emery, and Greenberg, 1985; Eysenck, 2014; Ehring and Watkins, 2008; Beck and Clark, 1991).

Clinical research in psychology provides extensive empirical support for the cognitive model of depression (see Clark, Beck, Alford, Bieling, and Segal (2000), Mathews and MacLeod (2005), and Beck (2008) for reviews). Depressed and anxious patients negatively interpret ambiguous stimuli, suffer from repetitive negative thinking, selectively attend to negative aspects of experiences, and overgeneralize and self-attribute negative realizations. A recent literature in behavioral genetics and cognitive neuroscience has provided further support for the cognitive model. Due to advances in genetics and neuroimaging, this literature identified a number of neurobiological correlates of depression that associate with negative thinking (see Disner, Beevers, Haigh, and Beck (2011) and Beck and Bredemeier (2016) for reviews). Guided by the cognitive model of depression and the clinical and neuroscience literature that supports it, we model negative thinking as a main feature of mental illness.

Rumination. The second main feature of mental illness is rumination. Psychiatric theory (Nolen-Hoeksema, 1991; Nolen-Hoeksema, Wisco, and Lyubomirsky, 2008) posits that depression is characterized by rumination, which is defined as an uncontrollable and repetitive preoccupation with one's negative thoughts. Depressed patients spend excessive amounts of time ruminating on their negative mood. Rumination in turn disrupts behavior and decision making and is recognized as a main driver of the symptoms of depression. We thus model rumination as a feature of mental illness that leads to time loss.

A large body of work provides empirical support for the key role of rumination in depression. Research in clinical psychology has connected rumination with the onset and duration of depression (see, for example, Just and Alloy (1997), Nolen-Hoeksema (2000), Singer and Dobson (2007)). Individuals who ruminate more about their negative mood experience longer and more severe depression spells. Rumination has also been shown to predict the severity of anxiety symptoms and the duration of anxiety spells. Recent advances in cognitive neuroscience provide further empirical evidence for the connection between rumination and depression. For example, rumination is strongly associated with neurobiological correlates of depression (Disner, Beevers, Haigh, and Beck, 2011).

More recent psychiatric theories of cognitive control also support the link between rumination and depression. Rumination is regarded as a maladaptive emotion regulation strategy that is due to deficits in cognitive control (Gotlib and Joormann, 2010; Le Moult and Gotlib, 2019). Depressed patients experience difficulties in controlling the content of their working memory − a cognitive system with a limited capacity that is important for reasoning and behavior. Instead of disengaging from negative information, depressed patients spend their time ruminating on it. Importantly, the theory emphasizes that depressed patients do not experience a generalized cognitive deficit or a lack of cognitive resources, but rather specific deficits in cognitive control or rumination (Hertel, 2004; Gotlib and Joormann, 2010).[4] Similar impairments in cognitive control that manifest through rumination are observed in other psychological disorders, such as anxiety, schizophrenia, and personality disorders (Burt, Zembar, and Niederehe, 1995).

Reinforcement Through Behavior. The third main feature of psychiatric theories of mental illness is that mental illness reinforces itself through behavior. In Beck's cognitive model of depression and in theories of rumination, individuals experiencing mental illness exhibit reduced motivation to engage in goal-directed or problem-solving activities. Negative expectations of the outcome of an action that might improve mental health discourages individuals to take such actions. In theories of rumination, excessive elaboration on one's negative thoughts similarly discourages individuals from taking action that might benefit their mental health. For example, depressed individuals may not seek treatment because they are pessimistic about its efficacy and because ruminating preoccupies their time, thereby reinforcing mental illness. This sustains mental illness.

Reinforcement through behavior is also at the center of computational psychiatry. This interdisciplinary field combines computational and mathematical tools with neuroimaging and clinical data to study mental illness (see Adams, Huys, and Roiser (2015), Huys, Maia, and Frank (2016) and Bishop and Gagne (2018) for reviews). In computational psychiatry, mental illness is characterized as an array of distortions in the evaluation of costs and benefits of actions that persist through self-reinforcement. Depressed and anxious patients hold pessimistic expectations of future outcomes – they underestimate the likelihood of positive outcomes and overestimate the likelihood of negative outcomes. This leads to inaction which in turn implies that pessimism is reinforced.

Guided by these classic and modern theories, in our model mental illness reinforces itself through inaction. Individuals experiencing mental illness can choose to seek treatment but may choose not to. Pessimistic beliefs about the potential success of treatment and about the benefits of being healthier, together with rumination, may deter individuals from seeking treatment.

Treatment. Cognitive behavioral therapy (CBT), the current standard in psychotherapy, is grounded

[4] A generalized cognitive deficit would imply that an individual would experience lower productivity. However, individuals with depression perform on par with healthy individuals once their attention is controlled and they cannot ruminate (Hertel, 2004).

in Beck's cognitive model and in theories of rumination. CBT aims to change negative thinking patterns by helping patients understand their thinking and behavior, and by providing tools to change distorted beliefs (Beck, 1976; Dobson and Dozois, 2019). Treatment guides them to disengage from negative information and regain cognitive control. Consistent with CBT, treatment in our model, if successful, reduces negative thinking and excessive rumination. A vast medical literature estimates the effects of different treatments on mental health using randomized trials. The effect sizes are typically standardized to facilitate comparison across different studies. Specifically, they are reported in terms of the standardized mean difference (SMD).[5] Meta-analysis by Ekers, Richards, and Gilbody (2008) reports an average SMD of -0.70 for behavioral psychotherapy, while the meta-analysis of Turner, Matthews, Linardatos, Tell, and Rosenthal (2008) shows and average SMD of -0.37 for antidepressants.

3 Empirical Evidence

We provide quantitative evidence on the relationship between mental illness and negative thinking. Our main finding in this section is that individuals experiencing mental illness show higher levels of negative thinking. These micro-level estimates of negative thinking directly map to the key parameters that discipline negative thinking in our quantitative model.

3.1 Negative Thinking

To quantify the relationship between negative thinking and mental illness, we use the RAND American Life Panel (ALP), a nationally representative survey of U.S. adults. Specifically, we merge two different ALP modules. The first module, implemented between March and April 2012, was designed by Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2015, 2016, 2021). This module, which we refer to as the Ellsberg module, elicits respondents' subjective loss probability when facing a lottery with unknown odds. It does so by presenting them with the classic Ellsberg urn problem (Ellsberg, 1961).

Our measure of negative thinking is this subjective loss probability of losing a gamble on an unknown urn.[6] The Ellsberg module elicits an individual's point of indifference between a gamble on an unknown urn and a gamble on a known urn with an objective losing probability q. To illustrate, let w_2 denote the value when winning, and let w_1 denote the value when losing, where $w_2 > w_1$.[7] Consider an individual i. The expected value from a gamble on the outcome of the known urn is given by $(1-q)w_2 + qw_1$. A

[5] See Appendix C for details.

[6] We provide further details in Appendix A.

[7] While the utility from winning a gamble may differ by individual i, we suppress the notation since preference heterogeneity does not affect our measurement.

gamble that yields w_2 when the individual wins and w_1 if the individual does not win with subjective loss probability p_i is evaluated as $(1-p_i)w_2 + p_i w_1$. The elicited indifference probability q is such that the individual is indifferent between the gamble on the known urn with objective probability of losing q, and a gamble on the unknown urn, or $(1-q)w_2 + qw_1 = (1-p_i)w_2 + p_i w_1$. The elicited indifference probability q is exactly the individual's subjective loss probability when facing a gamble on the unknown urn: $p_i = q$. An individual thinks more negatively if the subjective loss probability for the unknown urn is higher. Faced with the same objective uncertainty, an individual who thinks more negatively has lower expectations of winning. Our measure of negative thinking is this subjective loss probability. As we discuss in Section 4, the subjective loss probability can be directly mapped to parameters that govern negative thinking in dynamic optimization problems. It is also an intuitive measure of negative thinking: individuals who have higher subjective loss probabilities hold more pessimistic expectations on future outcomes.

The Ellsberg module does not contain information on mental health. We merge it with the second ALP module that asks respondents about their mental health. This module, which we refer to as the well-being module, consists of two ALP surveys between May and July 2012 and between May and August 2012, in close proximity to the Ellsberg module. We merge the Ellsberg module with the well-being module, exploiting the structure of the ALP which allows identifying respondents across ALP surveys. By combining these modules, we quantify the extent of negative thinking as a function of mental health.

The well-being module contains three questions about respondents' mental health. First, respondents are asked whether they experienced depression. Our first measure of mental illness is a dummy variable that takes the value of one if the answer to this question is yes, and zero otherwise. We refer to this indicator as Depression Indicator I. Second, respondents are asked whether they felt depressed, and can reply not at all, a little, somewhat, quite a bit, or very. Our second measure of mental illness is a dummy variable that takes the value of one if the respondents answered quite a bit or very depressed, and zero otherwise. We refer to this indicator as Depression Indicator II. Both depression related questions are asked only to subsamples of the well-being surveys. Third, respondents are asked to describe how anxious they feel on a scale from 0 to 10, where 0 corresponds to not anxious at all and 10 corresponds to completely anxious. Our third measure of mental illness is a dummy variable that takes the value of one if the answer to this question exceeds 5. We refer to this indicator as the Anxiety Indicator. The question on anxiety is fielded to all survey respondents.

To assess the relationship between mental illness and negative thinking, we first estimate the following regression. Let p_i be the subjective loss probability of individual i, elicited from the Ellsberg module.

Table 1: Negative Thinking and Mental Illness Indicators

	Depression Indicator I	Depression Indicator II	Anxiety Indicator
κ	4.8	3.9	4.1
	(1.5)	(2.0)	(1.1)
Observations	1,636	1,651	2,974
R^2	0.09	0.06	0.06
Mean	47.3	47.3	47.4

Table 1 displays regression coefficients on indicator variables of mental illness with respect to negative thinking in equation (1). The dependent variable across all specifications is the subjective loss probability. Columns correspond to different regression specifications that vary by the independent dummy variable D. Standard errors are reported in parenthesis in the second row. The control variables include education, age, sex, race, income, employment, and risk aversion.

Let D_i be one of our three mental illness indicators. We consider the following regression:

$$p_i = \kappa D_i + \kappa_x X_i + \varepsilon_i, \tag{1}$$

where X_i are controls, such as age, sex, education, race, risk aversion, household income, employment status, and a constant. The regression coefficient κ captures how the subjective loss probability varies with mental health.

Table 1 shows that individuals experiencing mental illness think more negatively. Across different measures of mental illness, represented by the different columns, we find that mental illness is associated with a higher subjective loss probability. Quantitatively, the subjective loss probability is 4 to 5 percentage points higher for individuals experiencing mental illness, when faced with the same objective uncertainty.

We now evaluate how negative thinking varies with the severity of mental illness. We construct a new categorical variable indicating whether an individual is healthy, experiences mild mental illness, or experiences serious mental illness. We do so using the anxiety question that is fielded to all survey respondents.[8] We classify an individual as experiencing serious mental illness if the reported anxiousness exceeds an upper threshold a_s in both the well-being surveys. We choose the threshold a_s such that the proportion of individuals classified as experiencing serious mental illness aligns with the proportion of adults experiencing serious mental illness. We classify an individual as experiencing mild mental illness if

[8]The anxiety question is a part of a block of questions that is fielded to all ALP respondents. The depression questions are fielded only to subsets of the respondents.

Table 2: Negative Thinking and Mental Illness Severity

Mild κ_1	3.4	3.3	3.4	3.4	3.2
	(1.3)	(1.3)	(1.0)	(1.3)	(1.3)
Serious κ_2	6.4	6.9	6.9	6.9	7.0
	(2.2)	(2.2)	(2.2)	(2.2)	(2.2)
Observations	2,974	2,974	2,974	2,974	2,974
Controls	None	+ Income, Age	+ Education	+ Race, Gender	All
R^2	0.02	0.03	0.03	0.04	0.06
Mean	47.4	47.4	47.4	47.4	47.4

Table 2 displays the regression coefficients κ_1 (first row) and κ_2 (third row) estimated from equation (2) as well as their corresponding standard errors (in rows 2 and 4). The control variables include income, age, education, race, gender, employment, and risk aversion. Table 2 shows how negative thinking varies with mental health. From the first to the final column, we incorporate additional control variables. All numbers are statistically significant as implied by the standard errors, which are reported in parentheses below the regression coefficients.

the reported anxiousness exceeds a lower threshold a_m in both the well-being surveys, and the individual is not classified as experiencing serious illness. We select the threshold a_m so that the proportion of individuals classified as experiencing mild mental illness is closest to their proportion in the population reported by the NIMH.[9]

In order to evaluate how negative thinking varies with the severity of mental illness, we estimate the following regression:

$$p_i = \kappa_1 D_{1i} + \kappa_2 D_{2i} + \kappa_x X_i + \varepsilon_i, \tag{2}$$

where p_i is the subjective loss probability of individual i, D_{1i} is a dummy variable taking the value one when individual i is classified as experiencing mild illness, and D_{2i} is a dummy variable taking the value one when individual i is classified as experiencing serious illness.

Table 2 shows how negative thinking varies with mental health. Each column corresponds to a

[9]The Substance Abuse and Mental Health Services Administration's 2012 National Survey on Drug Use and Health reports that 13.9 percent of adults in the US experience mild illness, and 4.1 percent of adults experience serious mental illness. We classify individuals with an anxiety score greater than or equal to $a_s = 7$ as experiencing serious mental illness, and individuals with an anxiety score of 5 or 6 as experiencing mild mental illness, $a_m = 5$. With these cutoffs, 10.0 percent of ALP respondents experience mild mental illness and 3.1 percent of adults experience serious mental illness.

regression that differs in the controls that are included. From the first to the fifth column, we add control variables. For example, the first column shows that without controls, we find that individuals experiencing mild mental illness have a subjective loss probability that is 3.4 percentage point higher relative to healthy individuals (first row), while individuals experiencing serious mental illness have a subjective loss probability that is a 6.4 percentage point higher (third row). The final column shows that this finding is robust to the inclusion of all control variables. Individuals with mild (serious) mental illness have a subjective loss probability that is 3.2 (7.0) percentage point higher relative to healthy individuals. In sum, individuals experiencing mental illness tend to think more negatively, and the extent of negative thinking increases with the severity of mental illness.[10]

4 Model

We formalize our economic theory of mental health in a lifecycle model with heterogeneous agents.

Demographics. We consider an infinite horizon economy populated by overlapping generations, each of mass one. Individuals live for T years. Time is discrete. Age is denoted by $t = 1, 2, \ldots, T$.[11]

Preferences. Individuals derive flow utility $u(c, \ell)$ from consumption c and leisure ℓ. Individuals have preferences which are separable in time and discount the future with a constant discount factor β. Total time each period is normalized to one.

Productivity. Individuals can work for the first T_w years of life and are retired for the remaining years. During retirement, individuals receive a constant pension income y_t^p. During working life, individuals face idiosyncratic productivity risk. As in French (2005) and Bick, Blandin, and Rogerson (2022), the logarithm of labor productivity is

$$\log z_t = \log \zeta_t + \theta(n_t) \log n_t + \Phi(n_t) + \log \nu_t. \tag{3}$$

The first component, $\log \zeta_t$, is a deterministic life-cycle component. The component $\theta(n_t)$ captures the elasticity of labor productivity with respect to hours worked, which varies with hours worked. We follow Bick, Blandin, and Rogerson (2022) and specify $\theta(n_t)$ as a step function so the relationship between labor productivity and hours is piecewise log-linear. The function $\Phi(n_t)$ preserves continuity of labor

[10] In Appendix A, we show that risk aversion does not vary systematically with mental illness. In line with the psychiatric theory (Beck, 1967, 2008), our estimates indicate that differences in negative thinking rather than differences in risk aversion is a key feature of mental illness.

[11] We consider a stationary economy, hence, time is left implicit and variables are indexed only by age t.

productivity with respect to hours worked despite the discontinuity in the step function $\theta(n_t)$. The idiosyncratic persistent component $\log \nu_t$ follows a discretized AR(1) process with persistence ρ_ν and variance of innovations σ_ν^2. Denote by Ω_ν the finite set of realizations that ν_t takes and by Γ_ν the corresponding transition probability matrix.[12]

Labor Supply. Each period, individuals choose a job j before their labor productivity is realized. After choosing a job, productivity is realized, and individuals choose the amount of hours to work. A job j is described by an up-to-task production technology which is parameterized by a job-specific up-to-task requirement y_j. Consider an individual who chooses a job j. If the individual's effective labor input, which is the product of productivity z and working hours n, exceeds the job requirement y_j, then the worker is up to the task and income is equal to y_j. If the individual's effective labor input is less than the job requirement y_j, then the worker is not up to the task and income is zero. The individual's income y is therefore a function of effective labor input and the job requirement:

$$y(zn, j) = \begin{cases} y_j & \text{if } zn \geqslant y_j. \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Given the up-to-task production technology, a worker in job j either works zero hours ($n = 0$), or chooses hours to exactly meet the job requirement y_j. In the latter case, the worker's income equals $y_j = zn$. That is, whenever individuals work a positive amount of hours, the hourly wage y_j/n is equal to labor productivity z. Going forward, we refer to z as the hourly wage and as labor productivity interchangeably.[13]

We use the up-to-task production technology (4) and assume that jobs are chosen before productivity is realized to introduce a mechanism through which negative thinking lowers working hours.[14] Negative

[12] We assume mental illness does not directly affect labor productivity. The psychiatric literature emphasizes that depression is characterized by impaired cognitive control rather than by cognitive deficits (Gotlib and Joormann, 2010). Specifically, individuals experiencing depression have difficulties in controlling the content of their working memory because they ruminate on their negative thoughts. Importantly, individuals with depression perform on par with healthy individuals once their attention is controlled and they cannot ruminate (Hertel, 2004).

[13] The specification of the up-to-task labor technology (4) follows two strands of literature. Similar to the search and matching literature (Shi, 2002; Albrecht and Vroman, 2002; Jarosch and Pilossoph, 2019; Braxton and Taska, 2023), our technology (4) specifies that worker inputs need to meet the standards to generate income and output. Different from these papers, the worker input, zn, is endogenous in our framework due to the worker's labor supply decision. Similar to Goldin (2014), an individual's hours choice determines whether the standards for a given job j are met.

[14] The up-to-task production technology introduces the psychiatric notion of inaction into our modeling of labor supply. Inaction is an important symptom highlighted in theories of mental illness (Beck, 1967, 2008; Huys, Maia, and Frank, 2016). The mechanism is that negative thinking induces low valuation of future rewards which in turn deters individuals from taking an action. In our setting, individuals do not pick demanding jobs since they think they will not be able to fulfill the job requirements.

thinking means that individuals hold a pessimistic expectation of their future productivity. Expecting that their productivity may not be high enough to fulfill the requirements of jobs with high up-to-task requirements, individuals with negative thinking select into jobs with lower up-to-task requirements. In other words, individuals may chose less demanding jobs as they may underestimate their capabilities.[15]

Assets. Individuals can save in risk-free and risky assets. The risk-free asset is a one-period bond that earns a gross return R_f. Denote by $r_f = \log R_f$ the log return on the risk-free asset. The log return on the risky asset is given by:

$$r_t = r_f + r_p + \upsilon_t, \tag{5}$$

where r_p is the risk premium over the risk-free asset, and υ_t is an innovation drawn from a discretized normal distribution $\mathcal{N}(0, \sigma_\upsilon^2)$. Denote the finite set of aggregate realizations that υ_t can take by Ω_υ. Denote the risky asset's gross return by $R_t = \exp(r_t)$.

Individuals choose savings s_t and how to allocate savings between risk-free and risky assets. To invest in risky assets, individuals incur a per-period fee φ_k. Denote by $k_t \in [0, 1]$ the share of savings invested in risky assets. Given a savings choice s_t, a portfolio choice k_t and a realized return on risky assets R_t, an individual's wealth at the beginning of period $t+1$ is given by

$$a_{t+1} = s_t R_t^s(k_t), \tag{6}$$

where $R_t^s(k_t) = k_t R_t + (1 - k_t) R_f$. Individuals can borrow up to an amount $\underline{s}$, that is $s_t \geqslant \underline{s}$.

Timing Within a Period. The state of an individual at the beginning a period is age t, wealth a_t, lagged idiosyncratic labor productivity component ν_{t-1}, mental health state m_t. Within a period individuals choose job j_t before idiosyncratic productivity ν_t realizes. After idiosyncratic productivity realizes, individuals choose consumption c_t, labor supply n_t, and allocate savings s_t towards risky and risk-free assets as well as decide whether to go into treatment. At the end of the period, returns on risky assets R_t realize, determining next period wealth, and next period mental health m_{t+1} realizes. The timing of decisions and stochastic realizations within a period are depicted in Figure 1.

Mental Health. Mental health is denoted by $m \in \mathcal{M}$, where $\mathcal{M}$ is a finite set. In particular, we consider a specification with three mental health states: a healthy state m_0, a mild illness state m_1, and a serious

[15]To illustrate this mechanism, consider an individual who chooses a job with requirement y_j prior to the realization of productivity z to maximize $\mathbb{E}\big[\log c - \frac{1}{2}n^2\big]$ subject to a budget constraint $c = y$ and up-to-task production technology (4). The optimal job choice is characterized by $y_j = (\mathbb{E}\big[\frac{1}{z^2}\big])^{-\frac{1}{2}}$. Under negative thinking, the subjective probability of low productivity realizations is higher and the subjective probabilities for high realizations is lower, thus increasing $\mathbb{E}\big[\frac{1}{z^2}\big]$ and lowering the job requirement, income, and hours $n = y_j/z$.

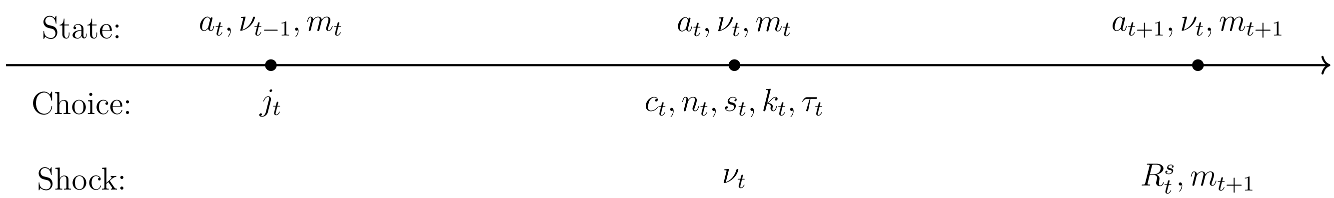

Figure 1: Timing Within a Period

Figure 1 displays the timing within a given period. Individuals choose job j_t before their idiosyncratic productivity component ν_t realizes. After productivity realizes, individuals choose consumption c_t, hours n_t, savings s_t, and portfolio allocation k_t, and decide whether to go into treatment τ_t. Finally, returns on risky assets R_t realize, which determines next period wealth, and the next period mental health state m_{t+1} realizes.

illness state m_2. Individuals draw their initial mental health state from a distribution π_m. Mental health evolves according to a first-order Markov chain with conditional transition probabilities $\Gamma_m(\tau_t)$ that depend on the individual's treatment choice τ_t. An individual's mental health governs negative thinking, rumination, and the efficacy of treatment.

Rumination. Time available for work and leisure varies with mental health. As discussed in Section 2, a main feature of mental illness is rumination. We model rumination as a reduction of time available for work and leisure. Specifically, individuals with mental health m lose $n_r(m)$ hours due to rumination. Available time for work, leisure, and treatment is $1 - n_r(m)$.

Treatment. Individuals decide whether to go into treatment. We denote by $\tau_t = 0$ if the individual does not get treatment, and by $\tau_t = 1$ if the individual goes to treatment. Treatment increases the probability of transitioning into better mental health states. An individual going into treatment incurs a time cost n_τ, a financial cost φ_τ, and a utility costs ξ_τ. As a result, time available for leisure and work is $\bar{n}(m_t, \tau_t) = 1 - n_r(m_t) - \varphi_\tau \tau_t$. We introduce a utility costs ξ_τ to model stigma. The psychiatric literature identifies stigma as an important factor contributing to low treatment rates of mental illness despite the efficacy of treatment (see, for example, Corrigan (2004) and Clement, Schauman, Graham, Maggioni, Evans-Lacko, Bezborodovs, Morgan, Rüsch, Brown, and Thornicroft (2015)).[16]

A fraction ω_τ of all individuals has access to treatment when experiencing mild illness. This captures the fact that access to mental health services is an important barrier to treatment. Let $\omega = 1$ denote that an agent has access to treatment when experiencing mild illness, and $\omega = 0$ otherwise. All individuals have access to treatment when experiencing serious illness.

[16]The National Survey on Drug Use and Health for 2021 conducted by the Substance Abuse and Mental Health Services Administration reports that 47.2 percent of American adults experiencing mental illness receive treatment.

Negative Thinking. Guided by the cognitive model of mental illness in Section 2, we model negative thinking so that an individual may have a different, and potentially more pessimistic, subjective probability distribution over random outcomes.

We illustrate our modeling of negative thinking by considering the individual's job choice. The individual chooses a job j_t before idiosyncratic productivity realizes. Let the value of working in job j_t with wealth a_t, idiosyncratic productivity ν_t, and mental health m_t for an individual with access to treatment ω be given by $w_t(j_t, a_t, \nu_t, m_t, \omega)$. The indirect utility associated with the optimal job choice is denoted $v_t(a_t, \nu_{t-1}, m_t, \omega)$ and is given by:

$$v_t(a_t, \nu_{t-1}, m_t, \omega) = \max_{j_t} \min_{p_t} \mathbb{E}_{p_t} w_t(j_t, a_t, \nu_t, m_t, \omega) = \max_{j_t} \min_{p_t} \sum_{\nu_t \in \Omega_\nu} p_t(\nu_t) w_t(j_t, a_t, \nu_t, m_t, \omega) \tag{7}$$

where the subjective probabilities p_t are constrained to be less than $\kappa(m_t)$ from the objective probability q_t in total variation distance:[17]

$$\frac{1}{2} \sum_{\nu_t \in \Omega_\nu} \left| p_t(\nu_t) - q_t(\nu_t) \right| \leqslant \kappa(m_t), \tag{8}$$

where $q_t(\nu_t)$ is the objective conditional probability of idiosyncratic productivity realization ν_t given ν_{t-1}.

An individual selects a job j_t together with the probability distribution p_t that minimizes the expected payoffs in that job among the probability distributions that are within a distance $\kappa(m_t)$ from the objective probability distributions. This minimization problem over probability distributions represents negative thinking, as the solution increases the subjective probability of the worst-case outcome by $\kappa(m_t)$ while reducing the subjective probabilities of the most favorable outcomes.

Example. Consider an example with values w_1 and w_2 such that $w_2 > w_1$, where the objective probability of the low outcome is equal to q.[18] Negative thinking is modeled as selecting a subjective probability p which solves $\min_p (1-p)w_2 + pw_1$ subject to $|p - q| \leqslant \kappa$. Individuals put a higher subjective probability on the worst possible outcome, $p^* = q + \kappa$. The parameter κ, the total variation budget, represents the degree to which the subjective probability of the worst state exceeds the corresponding objective probability, which is the extent of negative thinking.

Consider two individuals who face identical objective probabilities q and $1-q$ for the low and high outcome. The extent to which individuals i and i' differ in negative thinking κ is reflected in the subjective

[17] The total variation distance between probability measures P and Q is $\delta(P, Q) = \max |P(A) - Q(A)|$, that is, the largest possible difference between the probabilities that the two probability measures assign to some event A. For our discrete domain, this is equivalent to half of the taxicab distance between the probability mass functions.

[18] This setup is similar to the Ellsberg setting of Section 3.

probabilities of the worst case outcome:

$$p_i - p_{i'} = \kappa_i - \kappa_{i'}. \tag{9}$$

Equation (9) shows how we identify κ by mental illness status using the observation that subjective worst-case probabilities directly map into differences in the extent of negative thinking. Equation (9) shows that differences in the extent of negative thinking are identical to differences in the subjective worst-case probabilities whenever the objective probabilities are identical. In Section 3, we measured the differences in the subjective worst-case probabilities using regression equation (2), and hence we quantified the differences in negative thinking between mental health states. Specifically, Table 2 shows that the extent of negative thinking is about 3.4 percent for individuals experiencing mild mental illness and about 6.9 percent for individuals experiencing serious mental illness.

The general negative thinking problem is solved identically. For any set of N ordered values associated with events e, $w_1 < w_2 < \cdots < w_N$, consider choosing a probability distribution $(p_1, p_2, \ldots, p_N)$ satisfying total variation constraint (8) that minimizes the expected value $\sum p_e w_e$. The solution to this program, negative thinking, consists of two parts. First, negative thinking maximally increases the subjective worst-case probability, that is, $p_1 = q_1 + \kappa$. Second, negative thinking sequentially decreases the probabilities associated with the best outcomes. Specifically, negative thinking first decreases the probability of the best outcome by δ_N such that $p_N - \delta_N \geqslant 0$, then decreases the subjective probability of the second best outcome by δ_{N-1} such that $p_{N-1} - \delta_{N-1} \geqslant 0$, and so on until the total variation constraint binds, $\delta_N + \delta_{N-1} + \cdots = \kappa$. Importantly, a powerful feature of this approach is that it does not require the underlying dimension of uncertainty to be unidimensional as it can be applied to any joint distributions over outcomes. We exploit this feature in the decision problem where the individuals face uncertainty about returns on risky assets and the mental health evolution. Similarly, the observation that differences in negative thinking are identified by differences in subjective probabilities of the worst outcomes also applies to the general case with N possible random outcomes.

Decision Problem. The budget constraint is:

$$c_t + \varphi_\tau \tau_t + \varphi_k \mathbf{1}_{k_t} + s_t \leqslant a_t + y_t(z_t n_t, j_t). \tag{10}$$

The individual pays a fixed cost φ_τ when undergoing treatment. If the individual allocates a positive part of savings to risky assets at date t, there is a fixed cost φ_k – the indicator variable $\mathbf{1}_{k_t}$ takes the value one if $k_t > 0$, and takes the value zero otherwise.

The problem of an individual with job j_t, wealth a_t, productivity ν_t, mental health m_t, and access to treatment ω is to choose consumption c_t, hours worked n_t, treatment τ_t, savings s_t, and portfolio share $k_t \in [0,1]$ to solve the individual's decision problem:

$$w_t(j_t, a_t, \nu_t, m_t, \omega) = \max_{c_t, n_t, \tau_t, s_t, k_t} \Big\{ u\big(c_t, \bar{n}(m_t, \tau_t) - n_t\big) - \xi_\tau \tau_t + \beta \min_{p_t} \mathbb{E}_{p_t} v_{t+1}(a_{t+1}, \nu_t, m_{t+1}, \omega) \Big\} \quad (11)$$

subject to the asset accumulation equation (6), the budget constraint (10), the borrowing condition $s_t \geqslant \underline{s}$, and to negative thinking:

$$\frac{1}{2} \sum_{\Omega_v \times \Omega_m} \big| p_t(a_{t+1}, m_{t+1}) - q_t(a_{t+1}, m_{t+1}) \big| \leqslant \kappa(m_t), \quad (12)$$

where $q_t(a_{t+1}, m_{t+1})$ is the objective conditional probability of state (a_{t+1}, m_{t+1}) induced by the distribution of return risks and the mental health transition matrix on $\Omega_m \times \Omega_v$. The continuation value $v_{t+1}(a_{t+1}, \nu_t, m_{t+1}, \omega)$ is the value of choosing a job at the beginning of $t+1$ with wealth a_{t+1}, productivity ν_t, and mental health m_{t+1} described by (7). The mental health status determines the degree of negative thinking $\kappa(m_t)$ in (12). Negative thinking in this consumption and saving problem is with respect to joint uncertainty over the returns on the risky investment and the future mental health status. That is, individuals experiencing mental illness are jointly pessimistic about both returns on risky investments and their mental health evolution. Also, individuals experiencing mental illness are pessimistic about benefits of treatment in terms of the evolution of mental health and thus may not seek treatment.

5 Model Quantification and Validation

This section quantifies the model.

5.1 Exogenous Parameters

We begin by describing the parameters that are exogenously calibrated based on direct empirical evidence or existing literature.

Demographics. Individuals start adult life at age 25 and can choose to work up to the normal retirement age $T_w = 65$. Individuals die deterministically at age $T = 84$, which is the average life expectancy conditional on reaching the normal retirement age.

Productivity and Labor Supply. One unit of time corresponds to 100 hours per week. We calibrate the dependence of wages on hours worked, $\theta(n_t)$, using data from the CPS-ORG documented in Bick, Blandin,

Table 3: Exogenous General Parameters

Parameter	Target	Value
	Demographics	
Retirement age T_w	Normal retirement age	65
Terminal age T	Life expectancy	84
	Labor Markets	
Wage elasticity for short hours θ_S	Bick, Blandin, and Rogerson (2022)	0.40
Wage elasticity for medium hours θ_M	Bick, Blandin, and Rogerson (2022)	0.58
Wage elasticity for long hours θ_L	Bick, Blandin, and Rogerson (2022)	-0.76
Frisch elasticity of labor supply η	Chetty, Guren, Manoli, and Weber (2012)	0.284
Persistence of productivity ρ_ν	Persistence of residual wages	0.960
Variance of productivity σ_ν^2	Variance of innovation in residual wages	0.138
Retirement income y^p in dollars	Average retirement income	14,700
	Asset Markets	
Risk-free rate r_f	Return on safe assets	0.0192
Standard deviation of risky returns σ_υ	Standard deviation on risky assets	0.0791
Risk premium r_p	Risk premium for risky assets	0.0244
Borrowing constraint $\underline{s}$		0

Table 3 presents the values of model parameters that are set exogenously. The first columns shows the parameters. The second column describes the empirical moment that directly informs the parameter value. The third column shows the parameter value.

and Rogerson (2022). We consider three regions for the wages elasticity: θ_S for short hours (less than 40 hours per week, or $n_t \leqslant 0.4$), θ_M for medium hours (between 40 and 50 hours per week, or $0.4 < n_t \leqslant 0.5$), and θ_H for long hours (exceeding 50 hours per week, or $n_t > 0.5$). Using the data underlying Figure 3 of Bick, Blandin, and Rogerson (2022), we estimate the corresponding wage elasticities and obtain $\theta_S = 0.40$, $\theta_M = 0.58$, and $\theta_L = -0.76$. We set the step function $\Phi(n_t)$ in equation (3) by choosing $\Phi_M = -\theta_M \log(0.4)$ such that there is no wage penalty when individuals work full-time, and select Φ_L and Φ_H to ensure continuity of the wage penalty $\theta(n_t)\log n_t + \Phi(n_t)$.[19]

We specify the productivity process by analyzing residual wages of individuals in the PSID sample.[20] Consistent with the wage equation (3), we regress logarithmic hourly wages on log hours worked, where the elasticity of wages to hours as well as the intercept may vary by the short, medium, and long hours regions.

We extract a deterministic life-cycle profile ζ_t by fitting a third-degree polynomial through the age effects on the remaining variation, and estimate the persistence ρ_ν and the variance of productivity shocks σ_ν^2 to align the model-implied and empirical auto-covariation between residual wages. We find $\rho_\nu = 0.960$ and $\sigma_\nu^2 = 0.138$. Retirement income y^p is equal to 0.226, which is the average retirement benefits relative to average income.

Preferences. Individuals have flow utility over consumption c and leisure ℓ given by:

$$u(c, \ell) = \log c + \psi \frac{\ell^{1-\frac{1}{\eta}} - 1}{1 - \frac{1}{\eta}}\ , \tag{13}$$

where $\eta \geqslant 0$ governs the curvature with respect to leisure hours, and $\psi \geqslant 0$ governs the value of leisure.[21] We choose the parameter η so that the Frisch elasticity of labor supply for an average healthy worker, who works $\bar{n} = 0.405$ hours, equals 0.55 following Chetty, Guren, Manoli, and Weber (2012). To align with the Frisch elasticity of labor supply for these workers in the model, we require $\eta = \frac{\bar{n}}{1-\bar{n}} \frac{1}{\frac{1}{0.55} + \theta_M} = 0.284$.[22]

[19] To illustrate the identification, evaluate earnings growth in Bick, Blandin, and Rogerson (2022) between 20 and 40, between 40 and 50, and between 50 and 80 hours. This gives elasticities $\frac{0.81}{\log(35/20)} - 1 = 0.45$, $\frac{0.19}{\log(45/40)} - 1 = 0.59$ and $\frac{0.10}{\log(80/50)} - 1 = -0.79$.

[20] Data on consumption, labor supply, savings and portfolio choice, and mental health, is obtained from the PSID. We discuss the construction of our sample in Appendix B.

[21] According to the psychiatric literature, the depressed mood is not due to the deficit in primary utility. Rather, expected utility is low due to the biased probability distribution over future outcomes (Amsterdam, Settle, Doty, Abelman, and Winokur, 1987; Berlin, Givry-Steiner, Lecrubier, and Puech, 1998; Clepce, Gossler, Reich, Kornhuber, and Thuerauf, 2010; Dichter, Smoski, Kampov-Polevoy, Gallop, and Garbutt, 2010; Huys, Daw, and Dayan, 2015). In line with this evidence, we do not incorporate a flow utility penalty associated with mental illness. The expected utility for individuals experiencing mental illness is low due to negative thinking.

[22] Using the first-order conditions for labor supply, we express the Frisch elasticity for workers working $\bar{n} = 0.405$

Table 4: Exogenous Mental Health Parameters

Parameter	Target	Value
Negative thinking, mild $\kappa(m_1)$	Ambiguity index regressions, mild	0.035
Negative thinking, serious $\kappa(m_2)$	Ambiguity index regressions, serious	0.062
Monetary cost of treatment φ_τ in dollars	Cronin, Forsstrom, and Papageorge (2023)	1,250
Time cost of treatment n_τ	Two one-hour sessions per week	0.020

Table 4 presents the values of the model parameters for mental health that we set without solving the model. The first column shows the parameters. The second column describes the empirical moment that directly informs the parameter value. The third column shows the parameter value.

Assets. We set the log return on the risk-free asset to $r_f = 0.0192$, which corresponds to the log annual real returns on safe assets reported by Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019) between 2001 and 2020. The risk premium is set to $r_p = 0.0244$ per year, which is the observed log return differential between risky assets and government bonds. We set $\sigma_v = 0.0791$, which is the standard deviation of log risky returns.[23] The borrowing constraint is set so that individuals cannot borrow, $\underline{s} = 0$.

Mental Health. For each mental health state, we need to specify the total variation budget $\kappa(m)$. We quantify the differences in negative thinking between mental health states using that differences in the subjective probability of the worst-case outcome directly map into differences in the extent of negative thinking κ as explained by (9). Table 2 shows that the extent of negative thinking is 3.4 percent for individuals experiencing mild mental illness and 6.4 percent for individuals experiencing serious mental illness. Normalizing the extent of negative thinking to zero for individuals who are healthy, or $\kappa(m_0) = 0$, these empirical estimates thus determine the total variation budget for individuals who experiences mild illness $\kappa(m_1)$, and for individuals who experience serious illness $\kappa(m_2)$.

We now describe how to quantify the transition matrix for individuals who receive treatment $\Gamma_m(1)$ and who do not receive treatment $\Gamma_m(0)$.[24] The mental health transition matrices with and without treatment require the identification of 12 transition probabilities, that is, six transition probabilities in each matrix. We assume treatment does not benefit healthy individuals, that is, the transition probabili-

hours as $1/\big(\frac{\bar{n}}{1-\bar{n}}\frac{1}{\eta} - \theta(n)\big)$. Given that an average healthy individual works $\bar{n}$ hours, we obtain a Frisch elasticity for healthy individuals working average hours equal to 0.55 when $\eta = \frac{\bar{n}}{1-\bar{n}}/\big(\frac{1}{0.55} + \theta_M\big) = \frac{0.405}{1-0.405}/\big(\frac{1}{0.55} + 0.58\big) = 0.284$.

[23]The returns on risky assets are distributed with a lognormal distribution. The mean returns on the risky assets in logarithms is set equal to $r_p + r_f - \sigma_v^2/2$.

[24]We provide the details in Appendix C.

Table 5: Mental Health Transition Matrix

No Treatment	Healthy	Mild	Serious	*Treatment*	Healthy	Mild	Serious
Healthy	0.949	0.045	0.006	Healthy	0.949	0.045	0.006
Mild	0.215	0.667	0.117	Mild	0.574	0.356	0.070
Serious	0.040	0.126	0.833	Serious	0.154	0.343	0.502

Table 5 presents the mental health transition matrix for individuals who receive treatment and who do not receive treatment.

ties for healthy individuals are independent of treatment, such that ten transition probabilities remain to be identified. This assumption is motivated by the finding that healthy individuals in the MEPS rarely receive treatment (Cronin, Forsstrom, and Papageorge, 2023).

The moments that we use for identification are unconditional biannual transition probabilities between the three mental health states obtained from the PSID (six moments), population shares across mental health status from the NIMH (two moments), and estimates of the efficacy of treatment from the medical literature (two moments). Estimates of the efficacy of treatment are typically reported by the medical literature in terms of the pooled standardized mean difference (SMD). The more negative is the SMD, the larger is the drop in a mental illness indicator in terms of its pooled standard deviation among the treated group relative to the control group, or in other words the more effective is treatment. Meta-analysis by Ekers, Richards, and Gilbody (2008) reports an average SMD of -0.70 for behavioral psychotherapy. Table 5 presents the results for the mental health transition matrix for the individuals who receive and do not receive treatment. The results show that treatment is effective. For example, the probability of becoming healthy when mildly ill increases by about 36 percentage points from 22 to 57 percent when receiving treatment.

We set the monetary cost of treatment based on Cronin, Forsstrom, and Papageorge (2023), who report an out-of-pocket expenditure on psychotherapy of 24 dollars per visit. The total expenditure, including both out-of-pocket payments and insurer payments, is reported to be 126 dollars. Individuals from the 1996 to 2011 cohorts of the Medical Expenditure Panel Survey (MEPS) thus pay about $\frac{24}{126} = 0.19$ of the treatment costs out-of-pocket and 0.81 is covered by insurance. We consider an average of one visit per week per year to arrive at an annual monetary cost of treatment φ_τ of 1,250 dollars. We calibrate the time cost to two hours per week $n_\tau = 0.02$. Monetary and time costs do not vary by mental health.

Table 6: Endogenous Parameters

Parameter	Value	Moment (mean of)	Data	Model
Discount factor β	0.958	Wealth in dollars	294,000	294,000
Risky investments costs φ_k	700	Risky investment share	0.554	0.555
Disutility from work ψ	0.280	Hours worked	0.401	0.401
Rumination, mild $n_r(m_1)$	0.093	Hours worked, mild	0.375	0.376
Rumination, serious $n_r(m_2)$	0.125	Hours worked, serious	0.349	0.349
Utility cost of treatment ξ_τ	0.050	Treatment share, serious	0.654	0.658
Availability ω_τ	0.667	Treatment share, mild	0.414	0.414

Table 6 presents the parameter values set to match model-generated moments to their data analog. The first three columns present the parameters and their values. The fourth column describes a moment that informs the parameter value. The fifth and sixth column present the model-generated moment and the data-equivalent.

5.2 Endogenous Parameters

We next choose parameters so that the model matches data moments related to labor supply, savings and portfolio choice, and to mental health treatment. Table 6 summarizes the endogenous parameters and data moments. Parameters are paired to the data targets they affect most quantitatively. To illustrate which moments structurally identify which parameters, we conduct a parameter sensitivity analysis following Andrews, Gentzkow, and Shapiro (2017) in Appendix D.

We set the discount factor β to 0.958 to match average wealth in the data, which is 294 thousand dollars. The annual participation fee required for investing in the risky asset, φ_k, is estimated to be 700 dollars. It is identified from the mean share of savings invested in risky assets in the data, which is 0.555.

We set the disutility from work to $\psi = 0.28$ to match average hours worked, which is about 40 hours per week. The time that individuals lose due to rumination is calibrated to match the average hours worked by mental health state. In the data, individuals with a mild illness work on average 37.5 hours per week, while individuals with a serious illness work 35 hours per week. With rumination of 9.3 hours per week for mild mental illness, and 12.5 hours per week for serious mental illness, the hours worked in the model match these moments.

We calibrate the utility cost of treatment ξ_τ so that the model matches the share of individuals with severe illness who receive treatment in the data. According to the National Institute of Mental Health (NIMH), 65.4 percent of those who are seriously ill receive treatment during the year. We obtain an estimate of $\xi_\tau = 0.05$. Similarly, we calibrate the share of individuals who have access to treatment when experiencing mild illness ω_τ so that the model matches the share of individuals with mild illness who receive treatment in the data. We find that with $\omega_\tau = \frac{2}{3}$, the share of individuals with mild illness who get treated is equal to 0.414, which matches the share reported by the NIMH.[25]

5.3 Model Validation

Having quantified the model, we next evaluate its fit to non-targeted moments. We first show that the model matches average consumption, income, wealth, risky investment share, and risky participation rate by mental health status.[26] The first three columns of Table 7 show the non-targeted averages in the PSID data, and the final three columns show the model generated averages. The model matches almost perfectly average consumption, average income as well as the average risky investment share within each of the mental health groups. The model somewhat understates the decrease in wealth by mental health. The model correctly captures the risky participation rate, which we define as the share of individuals who invest more than half of their savings in risky assets. We choose this threshold since in the model it is only worth paying the fixed cost of participation φ_k if the risky assets $k_t s_t$ are sufficiently large upon participation.

We next assess the ability of the model to fit the observed distributions of these variables by mental health status. Figure 2 displays the distribution of consumption by mental health status in the model and in the data. The histogram displays the within-group percentage of individuals that consumes a given level, displayed on the horizontal axis in hundred thousand dollars. The figure shows that the model captures the consumption patterns in the data. For example, healthy individuals are overrepresented at high consumption levels, and individuals with serious mental illness tend to be concentrated at low levels of consumption.

We next assess the ability of the model to generate distributions of choice variables by mental health status. Figure 3 shows the distribution of savings by mental health status in the model and in the data. The histogram displays the within-group percentage of individuals that holds a given level of savings,

[25] The National Survey on Drug Use and Health for 2021 reports that 22.8 percent of adults in the United States experience any mental illness, for which 47.2 percent receives treatment. Furthermore, 5.5 percent of adults experience a serious mental illness, for which 65.4 percent receives treatment. As a consequence, 41.4 percent of adults experiencing a mild illness receives treatment as $\frac{5.5}{22.8} \times 65.4 + (1 - \frac{5.5}{22.8}) \times 0.41 = 47.2$.

[26] We scale nondurables expenditures in the PSID by a constant factor such that aggregate personal expenditures in our model align with aggregate consumption expenditures in the national accounts.

Table 7: Validation: Averages

	Data			Model		
	Healthy	Mild	Serious	Healthy	Mild	Serious
Consumption	63	53	49	63	58	52
Income	67	58	49	66	59	52
Wealth	308	234	207	296	289	276
Risky investment share	0.578	0.502	0.453	0.566	0.492	0.465
Risky participation rate	0.659	0.565	0.439	0.625	0.566	0.536

Table 7 displays average consumption, income, wealth, and risky investment by mental health status. Consumption, income, and wealth holdings are in thousands of dollars. The risky investment share is the average share of total assets invested in risky assets. The risky participation rate measures the share of the population that holds more than half of their portfolio in risky assets.

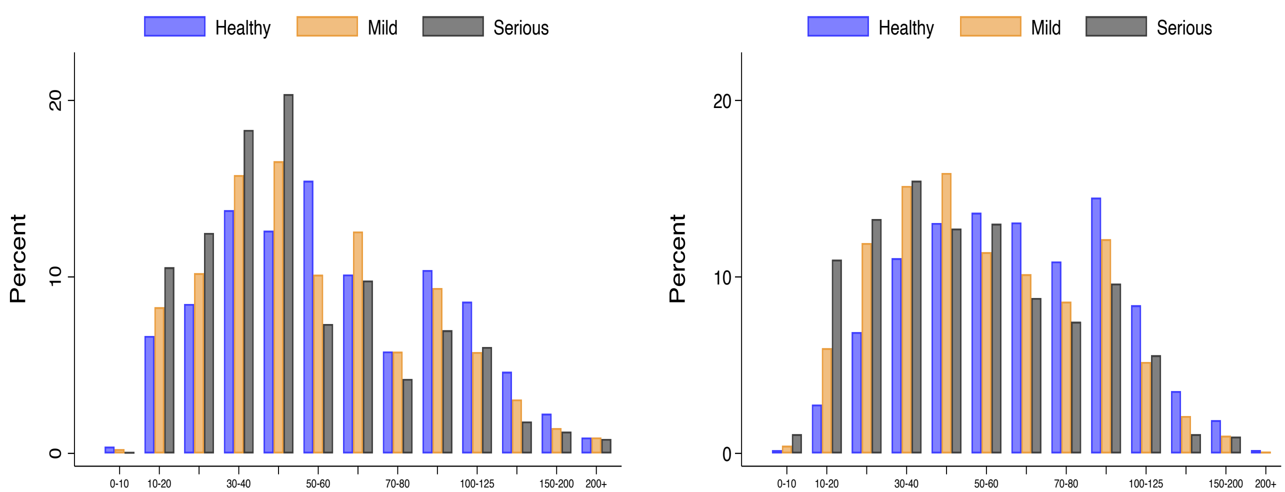

Figure 2: Consumption by Mental Health in the Model and the Data

Figure 2 shows the distribution of consumption by mental health status in the model (left panel) and in the data (right panel). The height of the bars capture the fraction of individuals consuming a particular amount within each mental health status – healthy (blue), mild illness (orange), and serious illness (black).

displayed on the horizontal axis in hundred thousand dollars. Both in the model and in the data, the savings distribution of healthy individuals is more skewed to the right and the savings distribution of individuals experiencing serious illness is more skewed to the left. The fraction of individuals with mild mental illness lies in between the fraction of individuals with serious mental illness and healthy individuals

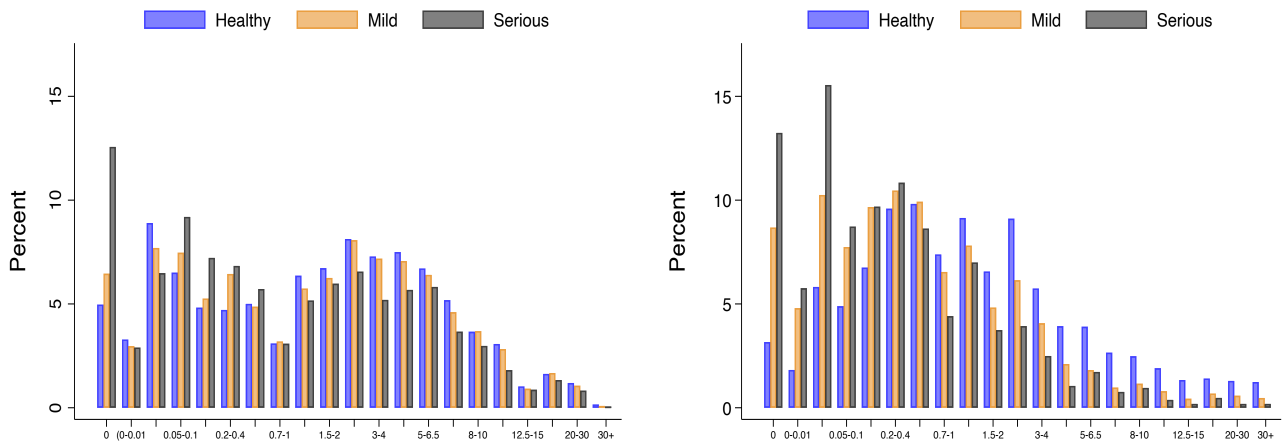

Figure 3: Savings in the Model and the Data

Figure 3 shows the distribution of savings by mental health status in the model (left panel) and in the data (right panel). The height of the bars captures the fraction of individuals holding a particular amount of savings within each mental health status − healthy (blue), mild illness (orange), and serious illness (black).

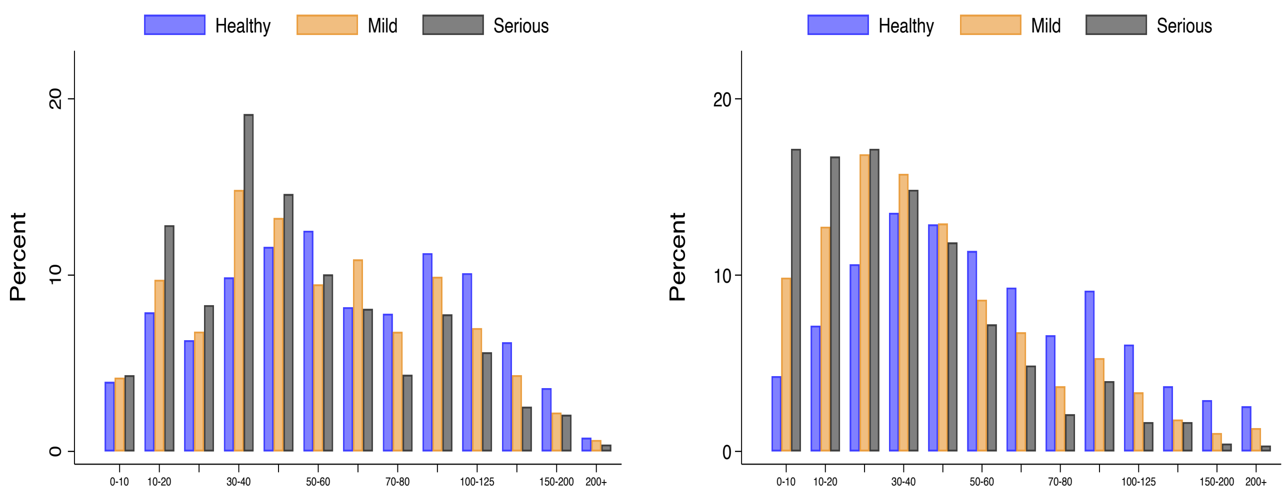

Figure 4: Income by Mental Health in the Model and the Data

Figure 4 shows the distribution of labor income by mental health status in the model (left panel) and in the data (right panel). The height of the bars capture the fraction of individuals earning a particular income within each mental health status − healthy (blue), mild illness (orange), and serious illness (black).

at nearly all wealth levels in the data as in the model.

Figure 4 reports the distribution of income by mental health status. It shows that the model captures the qualitative patterns of the empirical income distribution. As in the data, healthy individuals are overrepresented in the top categories, while individuals experiencing serious illness earn less.

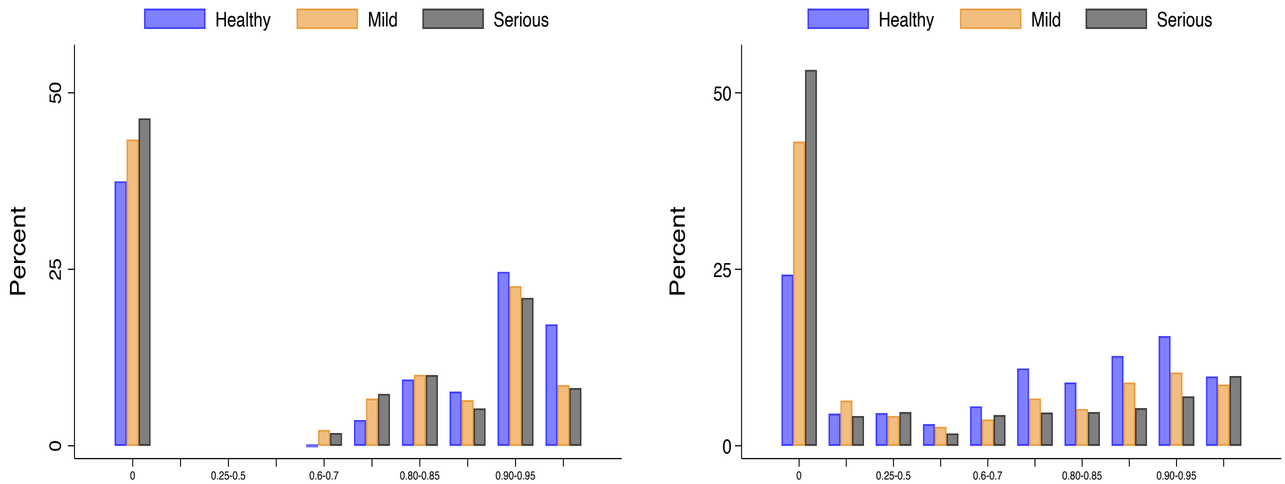

Figure 5: Risky Investment Share in the Model and the Data

Figure 5 shows the distribution of the risky investment share by mental health status in the model (left panel) and in the data (right panel). The height of the bars capture the fraction of individuals investing a particular share of savings in risky assets within each mental health status − healthy (blue), mild illness (orange), and serious illness (black).

Figure 5 reports the distribution of the risky investment share by mental health status. It shows that both in the model and in the data a significant mass of individuals do not hold risky investments. The model also captures that risky portfolio shares are concentrated at levels k_t of about 75 percent when individuals invest a positive amount of their savings in risky assets. In the model, this is due to the fixed cost of participation, which is only worth paying if a sufficiently large share of savings is invested in the risky asset. In both the model and the data, the fraction of individuals that does not participate in risky investments is higher for individuals with worse mental health, albeit somewhat stronger in the data than in the model. Healthy individuals invest larger shares of their savings in risky investments both in the model and the data.

Regression Evidence. We also validate the model by analyzing the extent to which consumption, labor supply, and portfolio choice vary with mental health conditional on other characteristics. Specifically, we estimate the following regressions in the model and in the data. Let Y_{it} be the dependent variable for individual i in year t, which are log consumption, log hours worked, and the risky investment share. Let D_{1it} be an indicator variable taking the value one when individual i experiences mild illness in year t. Let D_{2it} be an indicator taking the value one if individual i experiences serious mental illness in year t. The regressions also include a vector of additional individual controls X_{it}. We estimate the following

Table 8: Validation: Consumption, Labor Supply and Portfolio Choice Regressions

Variable	Log Consumption		Log Labor Supply		Risky Investment Share	
	Data	Model	Data	Model	Data	Model
Mild $\hat{\gamma}_1$	-2.6	-3.2	-12.8	-7.0	-4.3	-5.7
	(1.2)	(0.2)	(2.0)	(0.1)	(1.0)	(0.3)
Serious $\hat{\gamma}_2$	-7.0	-6.2	-23.3	-13.9	-6.0	-3.3
	(2.3)	(0.3)	(3.2)	(0.2)	(1.6)	(0.5)
Observations	30,095	128,194	32,136	128,194	36,987	128,194
R^2	0.54	0.89	0.06	0.28	0.30	0.58

Table 8 reports the regression coefficients estimated from (A.3) in the model and the data. For each dependent variable the first column shows the estimated coefficients from the data from Table A.2, while the second columns reports the model estimates.

regression:

$$Y_{it} = \gamma_t + \gamma_1 D_{1it} + \gamma_2 D_{2it} + \gamma_x X_{it} + \varepsilon_{it}. \tag{14}$$

All regressions include time fixed effects γ_t. The coefficients of interest γ_1 and γ_2 respectively measure how the dependent variable varies with mild and serious mental illness.

We estimate equation (14) on simulated data from the stationary distribution of the model, and compare the regression coefficients $\hat{\gamma} = (\hat{\gamma}_1, \hat{\gamma}_2)$ to their empirical counterparts that we estimate in Appendix B. We use $\hat{\gamma}_c$, $\hat{\gamma}_n$, and $\hat{\gamma}_k$ to denote the estimated regression coefficients with respectively log consumption, log labor hours, and the risky investment share as the dependent variable.

Table 8 reports the estimated regression coefficients in the model and in the data. For each dependent variable, the first column shows the estimated coefficients in the data, while the second columns reports the model estimates. The model generates matches conditional correlations between consumption, labor supply, portfolio choice, and mental health observed in the data. In the data, individuals experiencing mild illness consume on average 2.5 percent less than healthy individuals, and individuals experiencing serious illness consume on average 7.2 less. In the model, individuals with a mild illness consume 3.2 percent less and with a serious illness 6.2 percent less. In terms of labor supply, the model predicts that, conditional on the controls, individuals with mild illness work on average 7.0 percent less than healthy individuals, and individuals with a serious illness work on average 13.9 percent less, relative to 12.7

Table 9: Effects of Rumination

	Benchmark			No rumination $n_r = 0$		
	Healthy	Mild	Serious	Healthy	Mild	Serious
Treatment shares	0.000	0.414	0.658	0.000	0.379	0.562
Hours worked	0.405	0.376	0.349	0.405	0.401	0.402
Income (in thousands)	66	59	52	66	65	63
Wealth (in thousands)	296	289	276	293	291	283
Risky investment share	0.566	0.492	0.465	0.563	0.501	0.481
Risky participation rate	0.625	0.566	0.536	0.622	0.576	0.556
Consumption coefficient $\hat{\gamma}_c$	0.0	−3.2	−6.2	0.0	−4.4	−7.8
Labor supply coefficient $\hat{\gamma}_n$	0.0	−7.0	−13.9	0.0	−0.9	−0.9
Investment coefficient $\hat{\gamma}_k$	0.0	−3.8	−3.0	0.0	−4.5	−5.3

Table 9 reports moments from the benchmark economy with rumination and an economy without rumination.

and 23.4 percent in the data. The model is qualitatively in line with the data and captures 60 percent of the magnitude of the conditional correlation. In the data, individuals experiencing mild (serious) mental illness invest 4.1 (6.2) less of their savings in risky assets relative to healthy individuals. In the model, individuals experiencing mental illness also invest less of their savings in risky assets: individuals experiencing mild mental illness invest 5.7 percent less, and individuals experiencing severe mental illness invest 3.3 percent less, compared to healthy individuals.

5.4 Evaluating the Mechanisms of Mental Illness

We discuss the mechanisms through which mental illness affects economic outcomes. We examine how negative thinking and rumination affect consumption, labor supply, income, wealth, and portfolio allocations.

We first evaluate the impact of rumination. Table 9 compares the benchmark economy to an economy where mental illness is not associated with rumination, or $n_r(m) = 0$. Rumination decreases the total number of hours available to an individual and reduces work hours. Without rumination, individuals with

Table 10: Effects of Negative Thinking

	Benchmark			No negative thinking $\kappa = 0$		
	Healthy	Mild	Serious	Healthy	Mild	Serious
Treatment shares	0.000	0.414	0.658	0.000	0.294	0.354
Hours worked	0.405	0.376	0.349	0.406	0.379	0.353
Income (in thousands)	66	59	52	66	60	52
Wealth (in thousands)	296	289	276	258	242	230
Risky investment share	0.566	0.492	0.465	0.533	0.500	0.469
Risky participation rate	0.625	0.566	0.536	0.590	0.551	0.516
Consumption coefficient $\hat{\gamma}_c$	0.0	−3.2	−6.2	0.0	0.6	1.1
Labor supply coefficient $\hat{\gamma}_n$	0.0	−7.0	−13.9	0.0	−6.8	−13.9
Investment coefficient $\hat{\gamma}_k$	0.0	−3.8	−3.0	0.0	0.4	0.7

Table 10 reports moments from the benchmark economy with negative thinking and an economy without negative thinking.

mental illness do not lose a portion of available time and work similar hours as healthy individuals, as shown in the second row. Individuals with mental illness think negatively about their future productivity, and choose less demanding jobs even without rumination. As a result, their income and wealth are somewhat lower relative to healthy individuals. Individuals with mental illness are wealthier than in the benchmark economy as they have more time and work more. This increases risky investments on both intensive and extensive margins. Estimating equation (A.3) using the economy without rumination shows that the regression coefficients for consumption and investment remain constant, whereas the coefficient on labor supply drops almost to zero. Without rumination, individuals who experience mental illness seek less treatment, even though they have more time because the costs of experiencing mental illness are low.

We next evaluate the impact of negative thinking on economic outcomes. Table 10 compares the benchmark economy to an economy where mental health is not associated with negative thinking, or $\kappa(m) = 0$. Without negative thinking, individuals experiencing mental illness work slightly more, as shown in the second and third row. Due to rumination, they have less hours available to work and therefore work and earn less than healthy individuals. The absence of negative thinking reduces the precautionary savings motive, which lowers wealth and risky investments across all mental health groups. Since the cost of mental illness is lower without negative thinking, individuals seek less treatment relative to the benchmark economy.

The regression coefficients show that negative thinking strongly affects the conditional correlations between consumption, portfolio choice, and mental health. Absent negative thinking, there is no precautionary incentive for individuals with mental illness to consume less or invest less in risky investments after conditioning on age, income, and wealth. The bottom rows of Table 10 show that model regression coefficients on consumption and portfolio choice effectively revert to zero.

6 Quantitative Results

We evaluate the societal costs of mental illness and the consequences of a number of prominent policy proposals.

6.1 The Societal Costs of Mental Illness

In order to estimate the welfare costs of mental illness we first calculate the consumption equivalent welfare gain Δ_i^m of being mentally healthy for individual i. The consumption equivalent welfare gain is such that individual i is indifferent between a per period consumption increase Δ_i^m and being in the healthy state. This is the cost of mental illness for individual i.

Given logarithmic preferences for consumption, the individual consumption equivalent welfare gain of being healthy is:

$$\log \Delta_i^m = \beta_t \big(v_t(a_{it}, \nu_{it-1}, m_0, \omega_i) - v_t(a_{it}, \nu_{it-1}, m_{it}, \omega_i) \big), \tag{15}$$

where $\beta_t = 1/(1 + \beta + \cdots + \beta^{T-t})$. The aggregate welfare cost of mental illness Δ^m is the average of individual consumption equivalent gains.

We find an aggregate consumption equivalent cost of mental illness Δ^m of 1.7 percent of consumption, or 189 billion dollars annually.[27] The aggregate welfare cost of mental illness masks substantial heterogeneity in the cross-section. Figure 6 shows the distribution of the consumption equivalent welfare costs

[27] The welfare cost of mental illness can also be weighted, for example, by consumption. This lowers the cost of mental illness to 1.5 percent of aggregate consumption, indicating that the welfare gains are larger for individuals with low levels of consumption. An alternative measure of the cost of mental illness is foregone income. Using income by mental health status in Table 7, this calculation yields a loss of $0.04 \times \frac{52-66}{66} + 0.11 \times \frac{59-66}{66} = 2$ percent of income. Multiplying this figure by the sum of compensation of employees and proprietors' income in 2011 yields an estimate of 201 billion dollars.

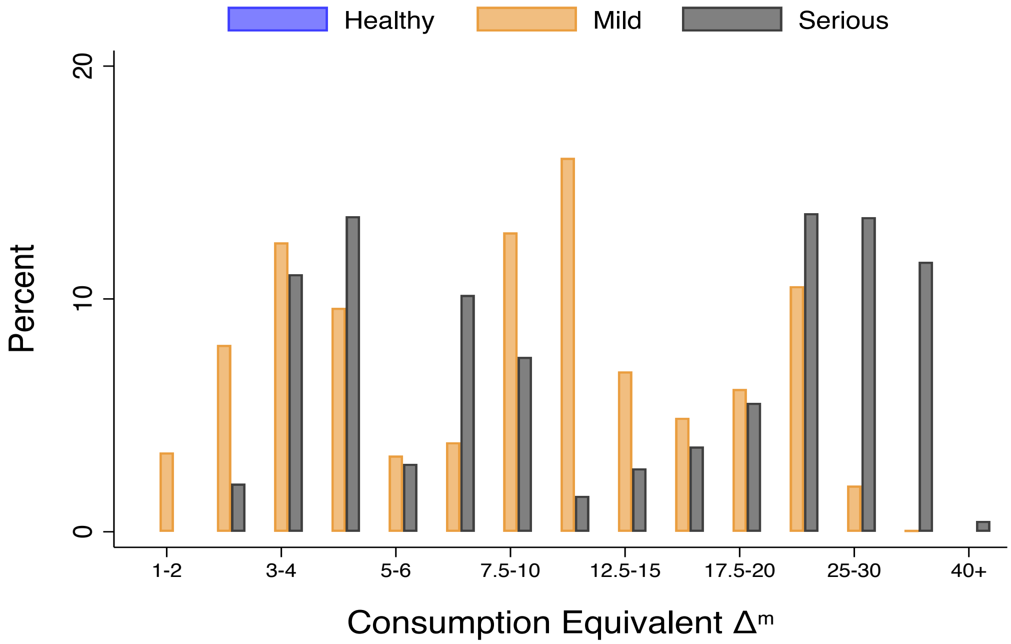

Figure 6: Welfare Cost of Mental Illness

Figure 6 shows the distribution of the consumption equivalent welfare costs of mental illness Δ_i^m by mental health status. The height of the bars captures the fraction of individuals with a particular welfare cost for each mental health status: healthy (blue), mild illness (orange), serious illness (black). Since individuals who are healthy do not experience a gain from becoming healthy, the blue bars record a value of zero.

by mental health status. The height of the bar is the fraction of individuals with a particular welfare cost within each mental health status: healthy (blue), mild illness (orange), serious illness (black). Since $\Delta_i^m = 0$ for individuals who are healthy, no blue bars appear in Figure 6. The welfare effects are driven by individuals who are not healthy, which is 15 percent of the population: 4 percent experience serious mental illness, and 11 percent experience mild illness. The average welfare cost of mental illness for individuals experiencing serious mental illness is equivalent to 15.6 percent of consumption, while the average consumption equivalent cost of mental illness for individuals experiencing mild mental illness is 10.3 percent. Taken together, this yields the aggregate consumption equivalent cost of $0.04 \times 15.6 + 0.11 \times 10.3 = 1.7$ percent.

We next evaluate cross-sectional heterogeneity in the welfare costs of mental illness by age and wealth groups. Figure 7 displays the average consumption equivalent welfare costs by age bracket (vertical axis) and by wealth bracket (horizontal axis). Different colors indicate different levels of the welfare costs of mental illness: dark shades indicate large welfare costs, and light shades indicate low welfare costs. Figure 7 shows that the welfare costs are larger for younger individuals than for older individuals. Younger

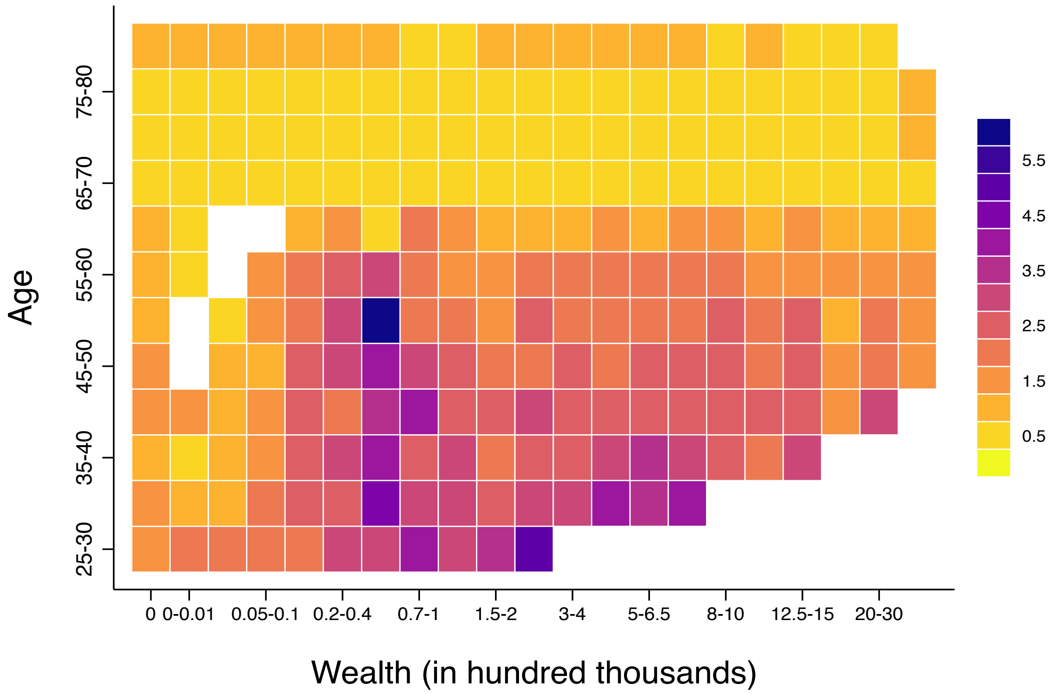

Figure 7: Welfare Cost of Mental Illness by Age and Wealth

This figure displays the average Δ_i^m by age bracket (vertical axis) and by wealth bracket (horizontal axis). The different colors indicate different levels of Δ_i^m: darker shades indicate a larger average Δ_i^m, and lighter shades indicate a lower average Δ_i^m.

individuals (below age 55) experience an average welfare cost of 2.4 percent, while older individuals (above age 55) experience a welfare cost of 1.0 percent. Among younger individuals the welfare costs are largest among the middle class, by which we mean individuals with wealth levels between 25 and 100 thousand dollars, for whom the average welfare cost is 3.4 percent.

Total Societal Burden of Mental Illness. We now quantify the total societal burden of mental illness. Our estimate is 282 billion dollars, which is 30 percent larger than established estimates from the epidemiological literature. The epidemiological literature focuses on three types of mental health costs: costs due to impaired functioning in the workplace, direct healthcare expenditures, and suicide-related costs.[28] Greenberg, Fournier, Sisitsky, Pike, and Kessler (2015) estimate a societal burden of mental

[28] Workplace costs are typically estimated by assessing the cost of missed days of work and the cost of hours where the individual is at work but not working. The estimates abstract from other work-related cost such as unemployment costs. The cost of selection into lower-earning jobs is also not accounted for since the cost of missed hours of work is typically computed assuming that the wage that the individual would have earned during these hours is equal to the average wage in the economy. Suicide-related costs are estimated as lifetime earnings lost due to mental health related suicides.

illness of 217 billion dollars per year.[29] This estimate consists of workplace costs (105 billion), direct expenditures on medical and pharmaceutical services (102 billion), and suicide-related costs (10 billion). The aggregate consumption equivalent welfare cost is our analog of the workplace costs together with the privately incurred healthcare costs. Holding constant all other healthcare expenses and suicide-related costs, our overall estimate of the societal burden of mental illness is $189 + 0.81 \times 102 + 10 = 282$ billion dollars per year, which is 30 percent larger than the estimate of 217 billion dollars from the epidemiological literature.[30]

We emphasize that our estimate of the societal cost of mental illness takes into account the stochastic life-cycle evolution of mental illness and optimal static and dynamic responses when experiencing mental illness. First, our welfare measure takes into consideration that being healthy today lowers the likelihood of experiencing mental illness later in life. Second, our welfare metric takes into account that mental health changes affect the contemporaneous labor supply decisions both in terms of the job choice and in terms of labor supply. Third, our estimate incorporates the effect of mental illness on dynamic savings decisions and portfolio choices. Improving mental health today improves future well-being through increased savings and increases returns on savings by changing the portfolio allocation towards higher expected-return investments. Finally, our welfare cost of mental illness takes into account the costs of the cognitive distortion of mental illness $-$ negative thinking. Relative to the epidemiological literature, our approach has the advantage of being able to account for optimal static and dynamic responses to mental illness regarding consumption, labor, savings, and asset allocation decisions. This structural approach is also necessary to evaluate policy alternatives.

6.2 Mental Health Policies

In this section, we evaluate the effects of three widely discussed policies: expanding availability of mental health services, lowering the out-of-pocket costs, and improving mental health of adolescents and young adults.

[29] We use the estimates of the economic cost of mental illness for 2010 in Greenberg, Fournier, Sisitsky, Pike, and Kessler (2015) and Greenberg, Fournier, Sisitsky, Simes, Berman, Koenigsberg, and Kessler (2021), which is the middle of our period of analysis. These papers also estimate that the societal cost of mental illness has increased from 179 billion to 299 billion dollars between 2005 and 2018.

[30] Our estimate of privately incurred welfare costs of 189 billion dollars is thus 52 percent larger than the estimate of Greenberg, Fournier, Sisitsky, Pike, and Kessler (2015) whose numbers imply a privately incurred direct costs of $105 + 0.19 \times 102 = 124$ billion. We assume that individuals pay 19 percent of the total mental healthcare costs out-of-pocket and 81 percent is covered by insurance (see Cronin, Forsstrom, and Papageorge (2023)). For 2018, we estimate a privately incurred welfare costs of 224 billion compared to $182 + 0.19 \times 105 = 202$ billion of Greenberg, Fournier, Sisitsky, Simes, Berman, Koenigsberg, and Kessler (2021).

6.2.1 Expanding Availability of Mental Health Services

We consider the consequences of increasing availability of treatment. Lack of availability of mental health services is one of the most commonly cited barriers to treatment.[31] According to the United States Department of Health and Human Services, in 2023, approximately 165 million Americans live in Health Professional Shortage Areas (HPSA), which are population groups in geographic areas that experience a shortage of mental health professionals.[32] In these areas, the number of mental health professionals is on average only 27.2 percent of the required capacity to meet the population's treatment needs. Relative to the U.S. population size of 341 million, the assessed shortage of availability is $(1 - 0.272) \times \frac{165}{341} = 0.35$. This estimate aligns with the limited availability of $1 - \omega_\tau = 0.33$ that we estimate in our structural model.[33]

Increasing availability of treatment services is the policy response to this shortage. One such policy is to increase the supply of mental health care professionals.[34] A second policy is to expand access to treatment through community health clinics.[35] A third set of policies aims to expand access to treatment through virtual mental health care.[36]

We evaluate a policy that makes treatment available to all. This corresponds to an economy where all

[31]See the White House Fact Sheets (www.whitehouse.gov/s1, www.whitehouse.gov/s2, www.whitehouse.gov/s3).

[32]For statistics on the number of Americans living in HPSA, see www.kff.org. The fraction of treatment needs met is calculated by the HPSA as the number of psychiatrists available to serve a population group divided by the number of psychiatrists that is needed to completely eliminate the shortage of mental health professionals to this population group, where the required number of psychiatrists is one for every 30,000 individuals. For more detail see www.kff.org.

[33]A shortage of mental health services is a challenge faced not only by the United States. Countries across the world are considering policies to close the accessibility gap. In the United Kingdom, the National Audit Office describes the shortage of mental health staff as the main constraint to improving mental treatment services and to reducing treatment gaps (see www.nao.org.uk). In Canada, access to services is a major constraint according to the Centre for Addiction and Mental Health (see www.camh.ca).

[34]In the U.S., in 2023, a total of 700 million dollars was invested into programs that provide training, access to scholarships and loan repayment to mental health clinicians. Further investments are made in addressing burnout and strengthening resiliency among health care workers and in programs that aim to train community health workers (see www.whitehouse.gov/s1). In the United Kingdom, the National Health Service Long Term Workforce Plan similarly sets out to increase training places for mental health nursing, as well as to increase the number of clinical psychologists and adolescent psychotherapists (see www.england.nhs.uk).

[35]The World Health Organization (see www.who.int) recommends decentralizing mental health services to the community settings. In the United States, Certified Community Behavioral Health Clinics (CCBHCs) are designed to ensure access to comprehensive behavioral health care. These health clinics are funded by the state and federal government and are required to serve anyone who requests care for mental health or substance use, regardless of ability to pay, residence, or age. In Belgium, a 2022 preventative care reform also aims to improve access to mental health services at the community level (see www.brusselstimes.com).

[36]In the United States, the government stated that it will ensure coverage of virtual mental health care across health plans (see www.whitehouse.gov/s1). In Scotland, the National Health Service provides free access to therapeutics apps to help individuals experiencing anxiety (see www.nhslothian.scot). German doctors can prescribe mental health apps to individuals through the 2019 Digital Healthcare Act with costs reimbursed through public health insurance (see www.bfarm.de).

Table 11: The Effects of Expanding Availability to Mental Health Services

	Benchmark $\omega_\tau = \frac{2}{3}$			Increased availability $\omega_\tau = 1$		
	Healthy	Mild	Serious	Healthy	Mild	Serious
Mental health shares	0.855	0.107	0.039	0.886	0.084	0.031
Treatment shares	0.000	0.414	0.658	0.000	0.789	0.621
Hours worked	0.405	0.376	0.349	0.406	0.368	0.350
Income (in thousands)	66	59	52	66	57	52
Wealth (in thousands)	296	289	276	288	269	257
Risky investment share	0.566	0.492	0.465	0.561	0.465	0.434
Risky participation rate	0.625	0.566	0.536	0.620	0.534	0.502

Table 11 reports the effects of expanding availability of mental health services. The first three columns report the averages by mental health status in the benchmark economy where a fraction $\omega_\tau = \frac{2}{3}$ of individuals has access to mental health services when mildly ill. The final three columns report the moments of a counterfactual economy where all individuals have access to mental health services when mildly ill, $\omega_\tau = 1$.

individuals can choose to get treated when they experience mild mental illness. That is, we consider an increase of ω_τ from $\frac{2}{3}$ to 1. Table 11 presents the results. Expanding availability of mental health services reduces the share of individuals who experience mental illness by 3.1 percentage points relative to the benchmark economy. The share of individuals with serious illness decreases by 0.8 percentage points, from 3.9 to 3.1 percent, while the share of individuals with mild illness decreases by 2.3 percentage points, from 10.7 to 8.4 percent. This reduction in mental illness is driven by a significant increase in the treatment share among individuals experiencing mild illness, which almost doubles from 41.4 to 78.9 percent.

The increase in the treatment share among individuals experiencing mild illness is driven by compositional and direct effects. When treatment is available, the distribution over mental health states is $(0.886, 0.084, 0.031)$ with corresponding treatment shares 0.789 and 0.621 for mild and serious. When treatment is not available, the stationary distribution over mental health states is $(0.794, 0.153, 0.054)$ with 0.696 of the individuals experiencing serious illness seeking treatment. The treatment share among individuals with mild illness in the benchmark economy is thus $\frac{2\times0.084}{2\times0.084+1\times0.153} \times 0.789 = 0.414$. When the remaining third of the population gains access to mental treatment services, the treatment share among individuals with mild illness increases for two reasons. First, the group that originally had access to treatment conditional on experiencing mild illness increases from $\frac{2\times0.084}{2\times0.084+1\times0.153}$ to $\frac{2}{3}$, which increases the treatment share from 0.414 to $\frac{2}{3}\times0.789=0.526$. Second, the direct effect increases the treatment share among individuals with mild illness from 0.526 by $\frac{1}{3}\times0.789$ to 0.789.

When treatment is available to all, average hours worked and average income slightly decrease among individuals experiencing mild illness. These decreases are driven by increased treatment. The treatment share increases by 37.5 percent. Since treatment is associated with a time cost of $n_\tau=0.02$, this reduces working hours by about 0.75 hours per week. Individuals save less as the precautionary motive for savings is lower when mental illness spells are shorter due to increased availability of treatment. While, all else equal, better mental health increases individuals' risky investment share, the fact that individuals are now less wealthy drives them to invest on average less in risky assets.

To evaluate the welfare benefits of expanding availability, we calculate the consumption equivalent welfare gain for the cross-section of individuals. Similar to the consumption equivalent measure of the welfare costs of mental health, we calculate the consumption equivalent measure of providing full availability to mental health services Δ_i^ω:

$$\log\Delta_i^\omega=\beta_t\big(v_t(a_{it},\nu_{it-1},m_{it},\omega_i=1)-v_t(a_{it},\nu_{it-1},m_{it},\omega_i)\big),\tag{16}$$

where $\omega_i\in\{0,1\}$ indicates whether individual i has access to treatment when experiencing mild illness. In the counterfactual economy, all individuals have access to treatment as indicated by $\omega_i=1$. The consumption equivalent welfare gain is such that individual i is indifferent between a per period consumption increase Δ_i^ω and between having full access to treatment.

The average welfare benefit of providing full availability of treatment services Δ^ω is 1.1 percent of aggregate consumption, or 118 billion dollars annually. This aggregate welfare benefit masks heterogeneity in the cross-section. For individuals who have access to treatment, this policy yields no welfare gain, or $\Delta_i^\omega=0$. Since two thirds of the population have access to mental health services with $\omega_\tau=\frac{2}{3}$, the welfare gains are driven by the remaining third of the population which gains access due to the policy.

Figure 8 illustrates the welfare gains from full accessibility to treatment by mental health status. The welfare gains of full availability increase with the expected use of treatment services among those who do not have access. The welfare gains are largest for individuals who are mildly ill, yet do not have access to treatment services (as indicated by the orange bars). The welfare gains for these individuals are concentrated between consumption equivalents of 5 and 20 percent. Welfare gains are also large for individuals who experience serious mental illness. Even though these individuals have access to treatment given their serious illness, they lose access if their mental illness becomes mild. When access to mental

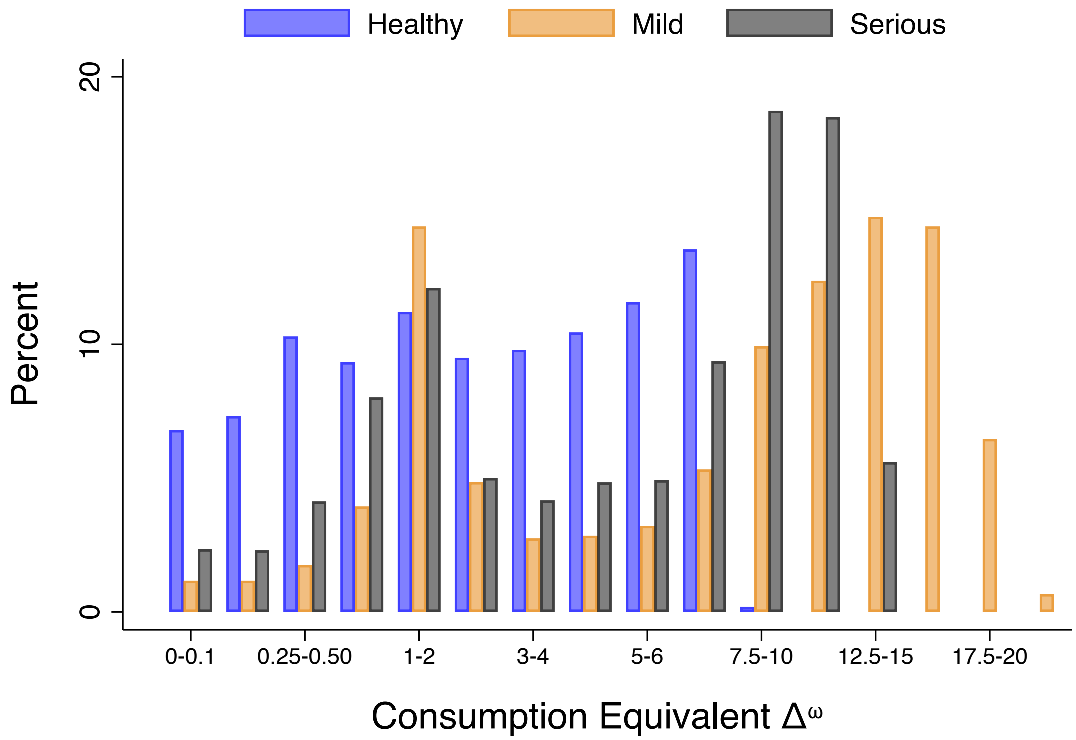

Figure 8: Welfare Gains from Increased Availability of Mental Health Services

Figure 8 displays the distribution of the consumption equivalent welfare gains of increased availability of treatment services by mental health status. The height of the bars captures the percentage of individuals with a particular welfare gain within each mental health status: healthy (blue), mild illness (orange), and serious illness (black).

health services is provided to all, they can continue receiving treatment when mildly ill. For the same reason, healthy individuals who do not have access to treatment if they become mildly ill also gain. These individuals are now less likely to experience serious mental illness and the length of the illness becomes shorter since they can get treatment if they become mildly ill.

Figure 9 shows the distribution of welfare gains by individuals' age and wealth in the baseline economy. Increased availability most strongly benefits individuals for whom the cost of mental illness is highest. These are individuals who are younger and middle class. The average welfare benefit of increased availability to younger individuals is 2.0 percent of consumption, relative to 0.2 percent for older individuals. Younger individuals with wealth levels between 25 and 100 thousand dollars see an average welfare gain of 2.7 percent of consumption.

In addition to calculating the consumption equivalent gains from expanding access to mental health services to all, we estimate the welfare gains of partial expansions. In particular, we vary ω_τ between its baseline value of 2/3 and 1. The results are shown in Figure 10. The average welfare gain from

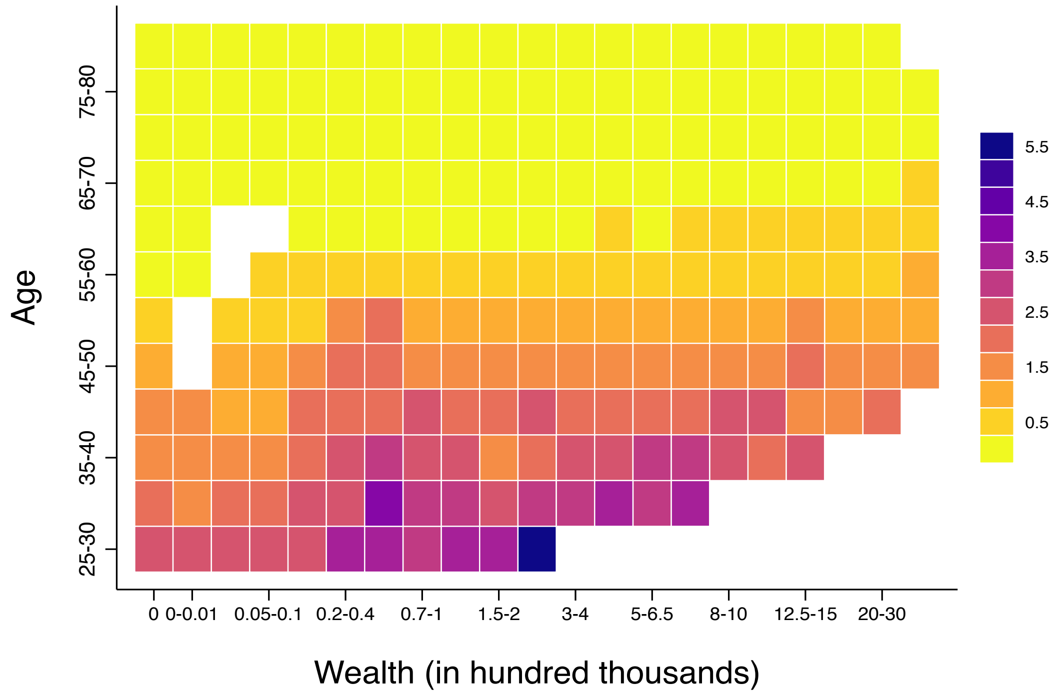

Figure 9: Welfare Gains from Increased Availability of Treatment Services by Age and Wealth

Figure 9 displays the average consumption equivalent welfare gain from increased availability of treatment by age (vertical axis) and by wealth (horizontal axis). Different colors indicate different levels of welfare gains: dark shades indicate larger welfare gains of increased availability, and light shades indicate lower welfare benefits.

providing access to treatment services accrue linearly. Every additional 10 percentage point increase in the availability of treatment translates into an average consumption equivalent welfare gain of $1.1 \times \frac{0.10}{0.33} = 0.33$ percent, or 36 billion dollars per year.

6.2.2 Reducing Treatment Costs

The second policy we evaluate is reducing the private out-of-pocket costs of mental health treatment. In the United States, the out-of-pocket cost of mental health services was reduced through the expansion of Medicaid, and through mental health parity laws which require health insurers to cover mental health care in parity with physical health care. We consider a further reduction of the out-of-pocket costs of mental health services, specifically, a policy under which individuals do not pay out of pocket for their treatment, or $\varphi_\tau = 0$.[37]

[37] Across countries, governments use policy to reduce out-of-pocket expenses for mental health care. In the United States, the Biden administration proposed to expand mental health parity laws (see www.whitehouse.gov/s3). In France, the government launched an initiative that covers therapy costs (see www.weforum.org). In Germany, a patient can request reimbursement for outpatient psychotherapy "if the treatment cannot be carried out in a timely

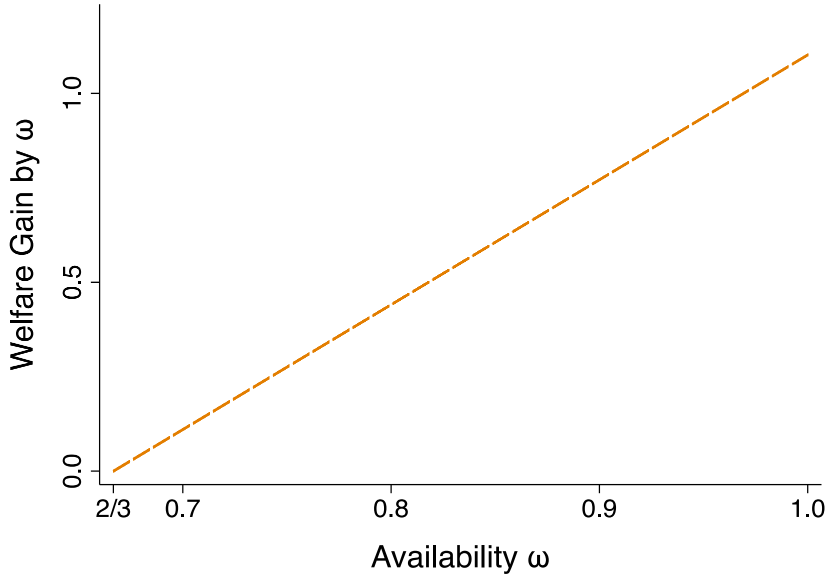

Figure 10: Welfare Gains from Increased Availability of Treatment Services

Figure 10 shows the average welfare gain from increasing the share of individuals that have access to treatment services when experiencing mild mental illness, from the baseline value of $\omega_\tau = \frac{2}{3}$ up to full availability $\omega_\tau = 1$.

Table 12: Eliminating Out-of-Pocket Treatment Costs

	Benchmark			Treatment costs $\varphi_\tau = 0$		
	Healthy	Mild	Serious	Healthy	Mild	Serious
Mental health shares	0.855	0.107	0.039	0.860	0.105	0.036
Treatment shares	0.000	0.414	0.658	0.000	0.439	0.745
Hours worked	0.405	0.376	0.349	0.405	0.375	0.348
Income (in thousands)	66	59	52	66	59	52
Wealth (in thousands)	296	289	276	295	289	277
Risky investment share	0.566	0.492	0.465	0.565	0.492	0.466
Risky participation rate	0.625	0.566	0.536	0.624	0.566	0.538

Table 12 displays the effects of eliminating out-of-pocket costs for mental health services. The first three columns display the averages by mental health group in the benchmark economy where the cost of treatment is equal to 1,250 dollars. The final three columns report the moments of the counterfactual economy where the out-of-pocket costs are equal to zero.

manner or at an acceptable distance for the patient" (see www.pksh.de).

We construct the welfare gain by measuring the consumption equivalent welfare gain Δ_i^{φ}:

$$\log \Delta_i^{\varphi} = \beta_t\big(v_t(a_{it}, \nu_{it-1}, m_{it}, \omega_i; \varphi_\tau = 0) - v_t(a_{it}, \nu_{it-1}, m_{it}, \omega_i; \varphi_\tau)\big), \tag{17}$$

where φ_τ indicates the explicit dependence of welfare on the out-of-pocket cost of treatment. We find that the average welfare benefit of eliminating the out-of-pocket cost of treatment Δ^{φ} is effectively zero, with $\Delta^{\varphi} = 0.014$ percent of consumption. Since the monetary cost of treatment in the benchmark economy is relatively low at 1,250 dollars, a further reduction does not lead to to a significant uptake in treatment and to substantial welfare improvements. We summarize the findings in Table 12. The second row shows that treatment shares increase slightly for individuals experiencing mild and serious mental illness, which translates to a slightly lower rate of mental illness in the population (first row). The small response to lower treatment costs is similar to Cronin, Forsstrom, and Papageorge (2023). By comparing these results with the large welfare benefits of increasing treatment availability, we conclude that lack of availability is the critical barrier for mental health treatment.

6.2.3 Improving Mental Health of Young Adults

The third policy we consider is improving the mental health of adolescents and young adults (16 to 25 year olds). Examples of such policy measures are increasing the number of mental health professionals in schools and providing better mental health education.[38]

To evaluate the implications of increased treatment of young adults, we change the initial distribution over mental health states. Mental health treatment in late adolescence and young adulthood under the proposed policy takes place before age 25, when individuals enter our model, and hence alters the initial distribution over mental health states. Specifically, we consider a counterfactual economy with the initial distribution of mental health that would emerge at age 25 if: (1) the distribution of mental illness at age 16 is identical to our baseline distribution of mental illness at age 25, and (2) all individuals who are ill between the age of 16 and the age of 25 receive treatment. To assess the welfare implications of treatment for individuals in young adulthood, we consider the welfare gains for 25 year olds in the model. The consumption equivalent $\Delta_i^{\tau_0}$ is such that a 25-year old individual i is indifferent between a per period

[38] In the United States, the Biden administration proposed investing one billion dollars to double the number of school-based mental health professionals such as counselors, social workers, and school psychologists (see www.whitehouse.gov/s1). In the United Kingdom, the government announced it would allocate funds to community hubs to deliver mental support for children and young adults (see www.gov.uk). In Japan, education about mental illness has been included in the high school curriculum (Ojio, Mori, Matsumoto, Nemoto, Sumiyoshi, Fujita, Morimoto, Nishizono-Maher, Fuji, and Mizuno, 2021).

Table 13: Transition Matrix with Improved Mental Health Treatment

Treatment	Healthy	Mild	Serious	*Improved Tech*	Healthy	Mild	Serious
Healthy	0.949	0.045	0.006	Healthy	0.949	0.045	0.006
Mild	0.574	0.356	0.070	Mild	0.614	0.316	0.070
Serious	0.154	0.343	0.502	Serious	0.165	0.367	0.468

Table 13 presents the mental health transition matrix for individuals receiving treatment in the benchmark economy, which is displayed on the left, and for individuals receiving treatment in the economy with a treatment technology that is 10 percent more effective, which is displayed on the right. The entries in the strictly lower triangular part of the transition matrix increase by a factor $\delta_+ = 1.07$ under the improved treatment technology.

consumption increase $\Delta_i^{\tau_0}$ and the counterfactual economy:

$$\log \Delta_i^{\tau_0} = \beta_1 \left(v_1(0, \nu_{i0}, \tilde{m}_{i1}, \omega_i) - v_1(0, \nu_{i0}, m_{i1}, \omega_i) \right), \tag{18}$$

where $\tilde{m}_{i1}$ corresponds to the mental health of individual i under the counterfactual policy and m_{i1} corresponds to the mental health of individual i in the baseline.

The average consumption equivalent gain of treatment in young adulthood Δ^{τ_0} is equal to 1.7 percent. In order to decompose the gain of 1.7 percent, we note that the consumption equivalent gain of being healthy is 14.4 percent for 25 year olds with mild mental illness and 27.2 percent for individuals with serious illness. Treatment of young adults improves the mental health distribution of 25 year olds. The share of healthy individual increases by 9.3 percentage points to 90.4 percent, with a corresponding reduction in individuals with mild illness from 13.7 percent to 7.5 percent (a decrease of 6.2 percentage points) and a reduction in individuals with serious illness from 5.3 percent to 2.2 percent (a decrease of 3.1 percentage points). As a result, the consumption equivalent welfare benefit is $0.062 \times 14.4 + 0.031 \times 27.2 =$ 1.7 percent.

6.3 Improving Mental Health Treatment

We quantify the welfare consequences of improving the efficacy of mental health treatment. More efficient treatment corresponds to technological or medical advances in therapy and anti-depressant medication. We consider a counterfactual economy where treatment is 10 percent more effective.

In order to evaluate the impact of improved treatment efficacy, we re-estimate the transition matrix between mental health states, conditional on treatment, to match an SMD of -0.77, relative to an SMD of -0.7 in the baseline economy discussed in Section 5. We assume improved treatment implies that the likelihood that mental health improves following treatment is a factor δ_+ higher than in the baseline, and that the likelihood that mental health deteriorates following treatment is a factor δ_- lower. We estimate the parameters δ_+ and δ_- such that the model implied SMD given mild illness and the model implied SMD given serious illness both equal -0.77. We obtain $\delta_+ = 1.07$ and $\delta_- = 1$. The right panel of Table 13 illustrates the mental health transition matrix under this improved treatment technology. Relative to the baseline in the left panel, the entries in the strictly lower triangular part of the transition matrix increase by a factor $\delta_+ = 1.07$ under the improved treatment technology. For example, the transition probability from serious to mild illness is 0.343 in the baseline economy and $0.343 \times 1.07 = 0.367$ under the improved technology.

In order to quantify the implications of improved mental health treatment, we evaluate the welfare gain for 25 year olds for the economy with improved treatment. The average consumption equivalent gain of a 10 percent increase in treatment efficacy is 0.7 percent, or 78 billion dollars annually. The results are locally linear in the extent of the improvement of mental healthcare. For example, a 5 percent increase in treatment efficacy translates into a consumption equivalent gain of 0.4 percent, while a 20 percent increase in treatment efficacy translates into a consumption equivalent gain of 1.3 percent. These estimates can be used to evaluate the expected value of improved treatment technologies and research programs on improved treatment.

7 Conclusion

This paper develops an economic theory of mental health. Based on classic and modern psychiatric theories, we model mental illness as a state of negative thinking and rumination which are reinforced through behavior. In the model, agents who experience mental illness have pessimistic expectations of future productivity, risky returns, evolution of mental health, and lose time due to rumination. As a result, they work less, consume less, invest less in risky assets, and forego treatment. Foregoing treatment, in turn, reinforces their mental illness.

We quantify our model using micro data on mental health. We identify the extent of negative thinking among individuals with mental illness from subjective worst-case probabilities, which are elicited using survey data. We estimate parameters that govern rumination, the efficacy and availability of treatment, and its costs so that the model matches the prevalence of mental illness, transition dynamics of mental health, observed treatment shares, and labor choices among individuals with mental illness. We validate our model by showing that it also matches non-targeted moments that describe the relation between mental illness, consumption, income, wealth and portfolio choice.

We use our model to evaluate the welfare costs of mental illness and the effects of mental health policies. We find the societal cost of mental illness to be 1.7 percent of aggregate consumption every year. Our policy analysis shows that expanding the availability of mental health services substantially improves mental health and welfare. In contrast, reducing the out-of-pocket cost of mental health services has minimal impact. Finally, we find that policies that promote treatment of mental illness among adolescents and young adults can substantially improve welfare.

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Macroeconomics of Mental Health

Online Appendix

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A Eliciting Negative Thinking

The Ellsberg module of the ALP elicits an individual's indifference point between a gamble with an unknown urn $\mathcal{U}$, and a gamble with a known urn $\mathcal{K}$ as follows. Each urn contains balls that are purple or yellow. For the known urn, the individual knows the exact proportion q of yellow balls. The unknown urn contains purple and yellow balls in unknown proportion. Individuals are asked to choose between the known urn $\mathcal{K}$ and the unknown urn $\mathcal{U}$. One ball is drawn from the selected urn, and the individual wins a prize of 15 dollars if a purple ball is drawn. If the urns are perceived as equally attractive, the individual responds "indifferent". The individual is asked to respond multiple rounds, that differ as follows. If the individual reports to prefer the known urn $\mathcal{K}$, then this urn is subsequently made less attractive by increasing the proportion of yellow balls. If the respondent again prefers the known urn, it is made less attractive again. When the unknown urn is chosen, the known urn is made more attractive. The process continues until a point of indifference is attained.[39] The measure of risk aversion in the Ellsberg module builds on Tanaka, Camerer, and Nguyen (2010).[40]

Risk Aversion. We next show that risk aversion does not vary systematically with mental illness. In order to see how risk aversion varies with the severity of mental illness, we estimate the following

[39]The updating scheme follows a bisection algorithm. In the first round, the known urn has a proportion $q = 0.5$ of yellow balls. If the individual prefers the known urn $\mathcal{K}$ in the first round, the subjective probability p is above 0.5 and the proportion of yellow balls increases to $q = 0.75 = \frac{1}{2} \times (0.5 + 1)$. If the individual prefers the unknown urn $\mathcal{U}$ in the next round, the subjective probability p is below 0.75 and the proportion of yellow balls in the known urn decreases to $q = 0.625 = \frac{1}{2} \times (0.5 + 0.75)$. The difference between the upper and lower bound in the subjective probability is cut in two in each round. The maximum number of rounds without reaching the point of indifference is four. In this case, the average of the remaining upper and lower bound is the subjective probability.

[40]To measure risk aversion, the indifference point between a certain payoff, and a gamble with a known probability of losing q, is elicited. When the individual prefers the certain outcome, the probability of losing is decreased in the next round. When the gamble is preferred, the probability of losing is increased in the next round. The updating scheme follows a bisection algorithm, and stops when the respondent is indifferent.

Table A.1: Risk Aversion and Mental Illness Severity

Mild κ_1	0.4	2.1	2.1	2.7	1.5
	(2.7)	(2.7)	(2.7)	(2.7)	(2.7)
Serious κ_2	-1.1	-1.5	-1.6	-1.2	-3.6
	(4.6)	(4.6)	(4.6)	(4.6)	(4.5)
Observations	2,974	2,974	2,974	2,974	2,974
Controls	None	+ Income, Age	+ Education	+ Race, Gender	All
R^2	0.01	0.03	0.03	0.03	0.06

Table A.1 displays the regression coefficients κ_1 (first row) and κ_2 (third row) estimated from equation (A.1) and their corresponding standard errors (in rows 2 and 4). The control variables include income, age, education, race, gender, employment, and the subjective loss probability. Table A.1 shows how risk aversion varies with mental health. From the first to the final column, we incorporate additional control variables. All numbers are statistically insignificant as implied by the standard errors, which are reported in parentheses below the regression coefficients.

regression:

$$\text{Risk Aversion}_i = \kappa_1 D_{1i} + \kappa_2 D_{2i} + \kappa_x X_i + \varepsilon_i, \tag{A.1}$$

where Risk Aversion$_i$ is the measure of risk aversion in the Ellsberg module for individual i, D_{1i} is a dummy variable taking the value one when individual i is classified as experiencing mild illness, and D_{2i} is a dummy variable taking the value one when individual i is classified as experiencing serious illness.

Table A.1 shows how risk aversion varies with mental health, where each column corresponds to a regression that differs in the controls that are included. The main result of the table is that the differences in risk aversion between healthy individuals and those experiencing mental illness are not statistically significant. Similarly, the difference in risk aversion between individuals experiencing mild and serious mental is not statistically significant. The finding is robust across all columns. In sum, risk aversion does not vary systematically with mental illness.

B Empirical Evidence

In this section, we present empirical results on the relationship between mental health and consumption, hours worked, and portfolio choice.

B.1 Consumption, Hours Worked, Portfolio Choice

We quantify the relationship between mental health and consumption, hours worked, and portfolio choice. Data on consumption, income, hours worked, and wealth is from the Panel Study of Income Dynamics (PSID). We incorporate data from all waves from 2000 to 2020. Earlier waves lack information on respondents' mental health. Our analysis focuses on heads of households between 25 and 65 years of age. All dollar values are reported in 2015 values. Our measure of income is the individual's labor income over the past calendar year. Hours worked are measured as total hours worked including overtime. Hourly wage rates are computed as individual income divided by hours worked. Our measure of consumption is annual nondurable expenditures which include expenditures on food, utilities, child care, clothing, home insurance, telecommunications, home maintenance, and variable transportation costs.[41] For all analyses, we use the sample weights provided by the surveys.[42]

The PSID reports the mental health status of respondents using the Kessler Psychological Distress Scale. The Kessler Psychological Distress Scale (K6 scale) is widely used by the epidemiological literature to measure the mental health of survey respondents.[43] We classify individuals into three groups based on their K6 scale following Kessler, Galea, Gruber, Sampson, Ursano, and Wessely (2008). Individuals with a K6 score between 13 and 24 are classified as experiencing serious mental illness, individuals with a K6 score between 8 and 12 are classified as experiencing mild mental illness, and individuals with K6 scores between 0 and 7 are classified as healthy. The K6 scale is included in all PSID waves conducted between 2000 and 2020 expect for 2004.

We next describe the wealth variables. We categorize equity holdings, business assets and liabilities, and real estate assets and liabilities as risky investments, which we denote as the set $\mathtt{R}$. We classify

[41] Our measure of consumption is closest to the measures used by Aguiar and Hurst (2013) and Boerma and Karabarbounis (2021). We conduct robustness exercises using broader measures of consumption in Appendix B.2. We show robustness of our results to additionally incorporating education and vacation and recreation expenditures into expenditures (Krueger and Perri, 2006), and to considering total spending. Since detailed consumption expenditures are available in the PSID starting from 2004, we restrict the analysis with respect to consumption to this period.

[42] We drop observations where the head of the household is a student; where reported consumption expenditure is in the top and bottom 1 percent of the consumption distribution; and where reported wealth is in the top 0.1 percent and bottom 1 percent of the wealth distribution. For the labor market analysis, we drop observations where the hourly wage is below 3 dollars or above 300 dollars in 2010 dollars, and observations where respondents reported working less than 20 hours per week or more than 92 hours per week.

[43] The K6 scale is calculated based on respondents' answers to six questions (Kessler, Andrews, Colpe, Hiripi, Mroczek, Normand, Walters, and Zaslavsky, 2002; Kessler, Barker, Colpe, Epstein, Gfroerer, Hiripi, Howes, Normand, Manderscheid, Walters, and Zaslavsky, 2003). In particular, respondents are asked the following: "In the past 30 days, about how often did you feel (1) sadness, (2) nervous, (3) restless or fidgety, (4) hopeless, (5) that everything was an effort, and (6) worthless". For each question, the individual responds (0) none of the time, (1) a little of the time, (2) some of the time, (3) most of the time, or (4) all of the time. The K6 scale is computed as the sum of respondents' answers to the six questions.

Table A.2: Consumption, Labor Supply, and Mental Health

Variable	Log Consumption	Log Labor Hours	Risky Investment Share
Mild γ_1	-2.6	-12.8	-4.3
	(1.2)	(2.0)	(1.0)
Serious γ_2	-7.0	-23.3	-6.0
	(2.3)	(3.2)	(1.6)
Observations	30,095	32,136	36,987
R^2	0.54	0.06	0.30
Mean	24,300	2,085	55.1

Table A.2 reports the regression coefficients estimated from equation (A.3). The set of control variables include dummies for education, age, sex of the household head, time, race, household composition, and wealth. In the regressions for consumption and portfolio choice, we also control for household income. Standard errors are in parenthesis. The risky investment share is measured in percentage points.

checking accounts, vehicles, certificates of deposit, government bonds and debt balances (except for business loans and real estate debt) as safe investments, which we denote by the set $\mathtt{S}$. Individual retirement accounts and other assets are labeled mixed investments which we denote by the set $\mathtt{M}$. Total assets, or wealth, are the net sum of risky, safe, and mixed investments. The total set of assets is the union of sets $\mathtt{R}$, $\mathtt{S}$, and $\mathtt{M}$. The risky investment share measures the proportion of risky assets in a portfolio. It is the sum of absolute values of risky investments and a half of mixed investments relative to the sum of absolute values over all investments:

$$\text{Risky Investment Share}_i = \left(\sum_{h\in\mathtt{R}} |a_{hi}| + \frac{1}{2} \sum_{h\in\mathtt{M}} |a_{hi}| \right) \Big/ \sum_{h\in\mathtt{A}} |a_{hi}|, \tag{A.2}$$

where a_{hi} denotes asset holdings in category h for an individual i. When the risky investment share is strictly positive, the individual participates in risky investments.

In order to assess the extent to which consumption, labor supply, and portfolio choices vary with mental health, we estimate the following regressions. Let Y_{it} be the dependent variable of interest for individual i in year t. The variables of interest are log consumption, log hours worked, and the risky investment share. Let D_{1it} be an indicator variable taking the value one when individual i experiences mild illness in year t. Let D_{2it} be an indicator variable taking the value one if individual i experiences serious mental illness in year t. The regressions further include a vector of additional individual controls

X_{it}, such as the individual's age, sex, education, race, and household composition, income, and wealth.[44] We estimate the following regression:

$$Y_{it} = \gamma_t + \gamma_1 D_{1it} + \gamma_2 D_{2it} + \gamma_x X_{it} + \varepsilon_{it}. \tag{A.3}$$

All regressions include time fixed effects γ_t. The coefficients γ_1 and γ_2 measure how the dependent variable varies with mild and serious mental illness.

Table A.2 reports our findings. The first column presents the results from estimating equation (A.3) where the dependent variable is logarithmic consumption. The coefficient on γ_1 indicates that individuals experiencing mild mental illness consume 2.6 percent less relative to healthy individuals. The coefficient on γ_2 indicates that individuals experiencing serious mental illness consume 7.0 percent less relative to healthy individuals, or 1,700 dollars.

The second column of Table A.2 shows how labor supply measured by log hours worked varies by mental health status. On average, an individual who experiences mild mental illness works 13 percent less relative to a healthy individual, while an individual who experiences serious mental illness works 23 percent less.[45] Finally, the third column of Table A.2 reports how portfolio choices vary by mental health. We find that, relative to healthy individuals, individuals experiencing mild mental illness invest 4.3 percentage points less of their portfolio in risky assets, while individuals experiencing serious illness invest 6.0 percentage points less in risky assets.

B.2 Robustness

We next provide evidence for the robustness of our empirical results.

Consumption. We first show the robustness of regressions results on the relation between consumption and mental health. Specifically, we estimate (A.3) using broader measures of consumption.

Table A.3 reports the estimation results of equation (A.3) using broader measures of consumption. The first column repeats the results from Table A.2 with nondurable consumption, which include expenditures on food, utilities, child care, clothing, home insurance, telecommunications, home maintenance, and variable transportation costs. In the second column, we add education expenditures into the consumption

[44] We control for education by including dummies for whether the individual is a high-school dropout, a high-school graduate or a college graduate. We control for race by including dummy variables for white, Black, and others. We control for household composition by including dummy variables for the number of adults as well as the number of children in the household, each up to a maximum of five. We control for household wealth in all regressions and for logarithmic household income in the consumption and investment regressions.

[45] In Appendix B.2, we also report regression results with other labor market outcomes such as earnings, wage rates, and unemployment rates.

Table A.3: Consumption and Mental Health

Variable (in logs)	Non-durables	+ Education	+ Recreation	+ Durables
Mild γ_1	-2.6	-3.2	-3.9	-3.9
	(1.2)	(1.3)	(1.3)	(1.3)
Serious γ_2	-7.0	-8.0	-9.3	-8.8
	(2.3)	(2.4)	(2.5)	(2.4)
Observations	30,095	30,095	30,095	30,095
R^2	0.54	0.54	0.55	0.54
Mean (in levels)	24,300	25,800	28,600	29,900

Table A.3 displays the regression results using individual data from the PSID. The set of control variables include dummies for education, age, sex of the household head, time, race, household composition as well as household wealth and income.

measure. The regression coefficient γ_1 indicates that individuals with mild mental illness consume 3.2 percent less, while γ_2 indicates that individuals with serious illness consume 8.0 percent less. The third column further adds vacation and recreation expenditures into the measure of consumption, similar to Krueger and Perri (2006). With this measure, individuals with mild mental illness consume 3.9 percent less while individuals with serious illness consume 9.3 percent less. In the final column, we add expenditures on durables by including payments on car loans, car down payments, car leases, and furniture. Individuals with a mild mental illness consume 3.9 percent less and individuals with a serious illness consume 8.8 percent less.

Labor Supply. Table A.4 shows regression results on the relationship between mental health and labor market outcomes. The first column repeats the regression estimates for labor supply, measured by the log of hours worked, of Table A.2. Workers who experience mild mental illness work 13 percent less, while workers who experience serious illness work 23 percent less. The second column presents the results of estimating equation (A.3) with the dependent variable being logarithmic earnings. Individuals with mild mental illness earn 0.27 log points less (or 24 percent), while individuals with serious mental illness earn 53 log points less (or 41 percent). Finally, the third column displays regression results when the dependent variable is the fraction of the year that an individual is unemployed. The results show a clear

Table A.4: Labor Supply and Mental Health

Variable	Labor Hours (in logs)	Earnings (in logs)	Unemployment
Mild	−12.8	−27.4	1.9
	(2.0)	(3.3)	(0.3)
Serious	−23.3	−53.1	2.8
	(3.1)	(4.7)	(0.7)
Observations	32,136	32,136	32,136
R^2	0.06	0.20	0.02
Mean	2,085	63,542	2.2

Table A.4 reports regression coefficients estimated from equation (A.3). The set of control variables include dummies for education, age, sex of the household head, time, race, household composition and wealth.

positive conditional correlation between mental illness and unemployment. Individuals with mild mental illness are unemployed 1.9 percent more in the year, compared to 2.8 percent for individuals with serious mental illness.

Portfolio Allocation. Table A.5 displays the conditional variation between mental health and portfolio decisions. The first column repeats the estimation results of Table A.2. Individuals experiencing mild mental illness invest 4.3 percentage points less of their savings in risky investments, while individuals experiencing serious illness invest 6.0 percentage points less of their savings in risky investments. The second column presents the results of estimating equation (A.3) with the dependent variable being the extensive margin of risky investments. As discussed in Section 5, an individual is said to participate in risky investments if the share of their portfolio invested in risky instruments exceeds 0.5. This regression shows that individuals with serious and mental illness are less likely to invest in risky assets. Individuals with mild illness are 5.3 percent less likely to invest in risky investments, whereas individuals with serious illness are 7.1 percent less likely to invest in risky investments.

Table A.5: Portfolio Allocation and Mental Health

Variable	Intensive Margin	Extensive Margin
Mild	−4.3	−5.3
	(1.0)	(1.2)
Serious	−6.0	−7.1
	(1.6)	(1.9)
Observations	36,987	36,987
R^2	0.30	0.31
Mean	63,542	2,085

Table A.5 reports regression coefficients estimated from equation (A.3). The set of control variables include dummies for education, age, sex of the household head, time, race, household composition, household income and wealth.

C Mental Health Transition Matrix

We estimate the transition rates between mental states as a function of undergoing treatment. Specifically, we calculate transition probabilities between states m and m' for treatment decisions $\tau = 0$ and $\tau = 1$. We denote the transition probability from state m to m' by $\Gamma_m(\tau, m, m')$, and we drop the subscript m on Γ_m to simplify notation in this appendix.

Data. We first describe the data moments used for the estimation. First, we use biannual unconditional transition rates by mental health status from the PSID. For every mental health state m and m' in the set $\mathcal{M} = \{m_0, m_1, m_2\}$ we construct $\Gamma^d(m_{t+2}|m_t)$, where d labels data. The empirical transition probabilities are not conditional on treatment as treatment is not observed in the PSID.

We use population shares in each mental health state from the 2021 PSID wave. In the 2021 PSID wave, 5.3 percent of individuals are classified as experiencing serious illness, and 13.7 percent are classified as mildly ill. The remaining 81 percent are classified as healthy. These empirical shares are denoted $\pi_d(m)$ for $m \in \mathcal{M}$.

Treatment shares by mental health status are obtained from the 2021 National Survey on Drug Use and Health of the Substance Abuse discussed in Footnote 25. The report shows that 47.2 percent of all adults with a mild mental illness receives treatment, while 65.4 percent of individuals experiencing serious mental illness receive treatment. We denote the empirical share of individuals with mental health status m by treatment status τ by $\pi_d^\tau(m)$. We assume that healthy adults do not receive treatment, or $\pi_d^1(m_1) = 0$.

Finally, the impact of treatment is taken from the medical literature, where a vast literature estimates the effects of different treatments on mental health using randomized trials. The effect sizes are typically standardized to facilitate comparison across different studies. Specifically, they are reported in terms of the standardized mean difference (SMD), the mean effect divided by the combined standard deviation of the outcome, that is, $SMD = \frac{\mu_T - \mu_C}{\sqrt{\frac{1}{2}(\sigma_T^2+\sigma_C^2)}}$, where μ_T is the average outcome in the treatment group, μ_C is the average outcome in the control group, σ_T^2 is the variance of the outcome in the treatment group, and σ_C^2 is the variance of the outcome in the control group. As discussed in the main text, we pick an intermediate value of -0.70.[46]

Estimation. To estimate the treatment-dependent transition probabilities $\Gamma(\tau_t, m_t)$, we solve a system of 18 unknowns and 18 equations. The 18 unknowns are the annual transition probabilities between state $m \in \mathcal{M}$ and $m' \in \mathcal{M}$ when the individual does not receive treatment, $\tau = 0$, and when the individual does receive treatment, $\tau = 1$.

We next describe the 18 equations we use in our estimation. First, all the rows of the transition matrix Γ sum to one. With three mental health states, and a transition matrix for treatment and for no treatment, this gives six equations. Second, we assume that treatment does not yield any benefits for healthy individuals. This is consistent with our assumption that healthy adults do not receive treatment $\pi_d^\tau(m_0) = 0$, and provides two additional equations: $\Gamma(1, m_0, m') = \Gamma(0, m_0, m')$ for $m' = \{m_1, m_2\}$.

For each mental health classification $m = \{m_0, m_1, m_2\}$ and $m' = \{m_1, m_2\}$, we compute the biannual transition rates between mental states implied by the treatment-dependent annual transition rates in the model together with the empirical treatments shares of seriously and mildly ill. These additional six equations ensure consistency between to the observed biannual unconditional transition probabilities in the data and the model:

$$\begin{aligned}\Gamma^d(m' \mid m) = &\sum_{\hat{m}\in\mathcal{M}} \pi_d^1(m)\Gamma(m,\hat{m},1)\big(\pi_d^1(\hat{m})\Gamma(\hat{m},m',1) + \pi_d^0(\hat{m})\Gamma(\hat{m},m',0)\big) \\ &+ \sum_{\hat{m}\in\mathcal{M}} \pi_d^0(m)\Gamma(m,\hat{m},0)\big(\pi_d^1(\hat{m})\Gamma(\hat{m},m',1) + \pi_d^0(\hat{m})\Gamma(\hat{m},m',0)\big)\end{aligned} \tag{A.4}$$

In addition, we assume that observed shares of individuals across mental health states correspond to

[46] With respect to antidepressants, a meta-analysis by Turner, Matthews, Linardatos, Tell, and Rosenthal (2008) reports a standardized mean difference of -0.37.

steady state shares. This provides an additional two equations for $m = \{m_1, m_2\}$:

$$\pi_d(m) = \pi_d(m_0)\pi_d^0(m_0)\Gamma(m_0, m, 0) + \pi_d(m_0)\pi_d^1(m_0)\Gamma(m_0, m, 1) + \pi_d(m_1)\pi_d^0(m_1)\Gamma(m_1, m, 0)$$
$$+ \pi_d(m_1)\pi_d^1(m_1)\Gamma(m_1, m, 1) + \pi_d(m_2)\pi_d^0(m_2)\Gamma(m_2, m, 0) + \pi_d(m_2)\pi_d^1(m_2)\Gamma(m_2, m, 1). \tag{A.5}$$

Finally, we express the SMD as a function of the transition probabilities and ensure its consistency with the pooled effect size in the medical literature. To be consistent with the outcomes measured in the medical literature, we measure the SMD implied by our transition probabilities in terms of a depression severity rating. In particular, we use the K6 scale discussed in Section 3. Individuals with mental health status m are assigned $\overline{\text{K6}}(m)$, the median K6 scale for individuals in state m in the PSID. For each state $m = \{m_1, m_2\}$, we align the model-implied SMD to its empirical counterpart from the medical literature SMD_d, giving the remaining two equations:

$$\text{SMD}_d(m) = \frac{\mathbb{E}\left[\overline{\text{K6}}(m') \mid m, \tau = 1\right] - \mathbb{E}\left[\overline{\text{K6}}(m') \mid m, \tau = 0\right]}{\sqrt{\frac{1}{2}\left(V\left[\overline{\text{K6}}(m') \mid m, \tau = 1\right] + V\left[\overline{\text{K6}}(m') \mid m, \tau = 0\right]\right)}}, \tag{A.6}$$

with the conditional mean and the conditional variance respectively given by:

$$\mathbb{E}[\overline{K6}(m') \mid m, \tau] = \sum_{m'} \Gamma(m, m', \tau)\overline{\text{K6}}(m') \tag{A.7}$$

$$V\left[\overline{K6}(m') \mid m, \tau\right] = \sum_{m'} \Gamma(m, m', \tau)\overline{\text{K6}}(m')^2 - \left(\mathbb{E}\left[\overline{\text{K6}}(m') \mid m, \tau\right]\right)^2 \tag{A.8}$$

D Sensitivity to Model Parameters

We show how the targeted data moments are affected by changes in the model's endogenous parameters. The spirit of this exercise is to show which moments identify what parameter. Since we calibrate seven structural parameters to seven data moments, we show how each of the data moments vary with a change of parameters.

Discount Factor. We first analyze the sensitivity of model moments to variation in the discount factor. The results is shown in Figure A.1. All sensitivity figures adopt an identical structure. The top left panel shows the sensitivity of average savings; the top right panel shows the sensitivity of the average risky investment share; the bottom left panel shows the sensitivity of treatment share by mental health state; while the bottom right panel shows the sensitivity of labor supply by mental health. The sensitivity of the model moment is measured relative to a factor of one, which represents the value of the data moment under the baseline model calibration of Table 6. On the horizontal axis, we display the different values

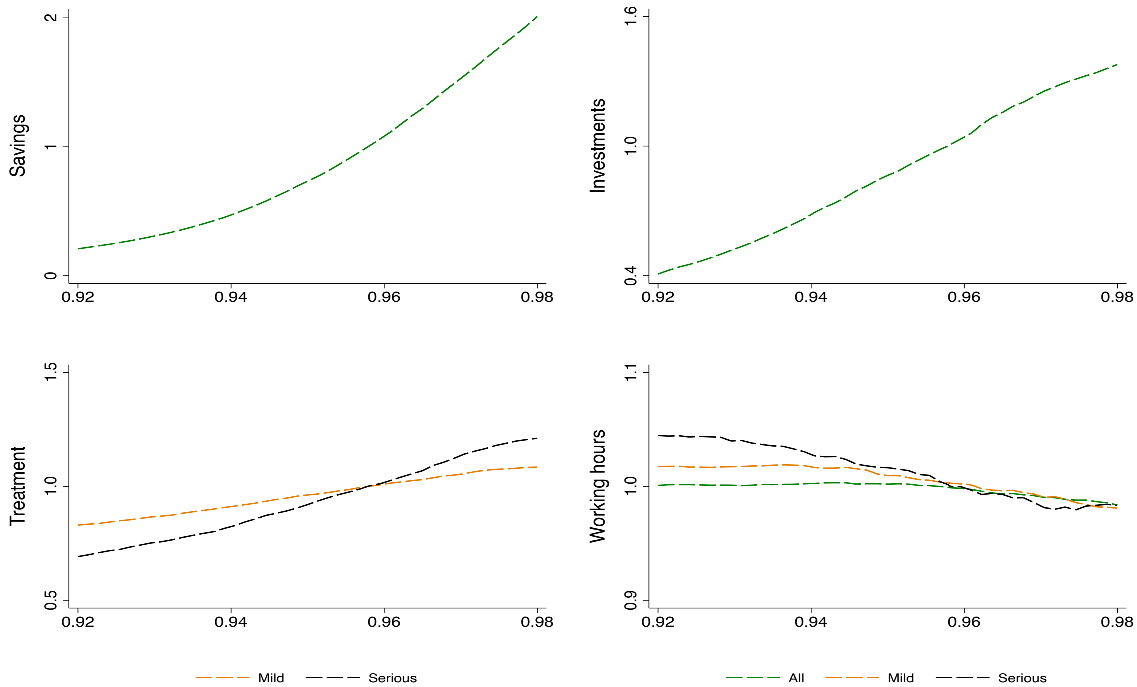

Figure A.1: Sensitivity of Moments to Discount Factor β

Figure A.1 illustrates the sensitivity of model moments with respect to changes in the discount factor β between 0.92 and 0.98. The baseline parameter value for the discount factor is equal to 0.958

for the parameter of interest, where the interval we consider is centered around the baseline parameter value.

Figure A.1 shows that the discount factor has a pronounced impact on savings, investments, and the treatment share. As individuals become increasingly patient, they save more. Holding fixed the costs of investing in risky assets, the share of savings invested in risky assets increases as shown in the top right panel. As individuals become increasingly patient with respect to their future, the cost of negative thinking about this future rise. The benefit from receiving treatment thus increases, which leads to an uptake in treatment shown in the bottom left panel. The bottom right panel shows that the response in labor supply is small relative to the other moments.

Figure A.2 shows the sensitivity of the model to changes in the participation costs between about 400 and 1000 dollars, corresponding to the values 0.006 and 0.011 on the horizontal axis. The figure shows that the participation costs for risky assets governs the extent to which individuals invest in risky assets, while having negligible impact on the other moments. Reducing the participation costs to 400 dollars per period increases the share of savings in risky assets by 10 percentage points.

Figure A.3 shows the sensitivity of the model to changes in the disutility cost of work, which is governed by the parameter φ. We vary the disutility cost between 0.20 and 0.35 as displayed on the

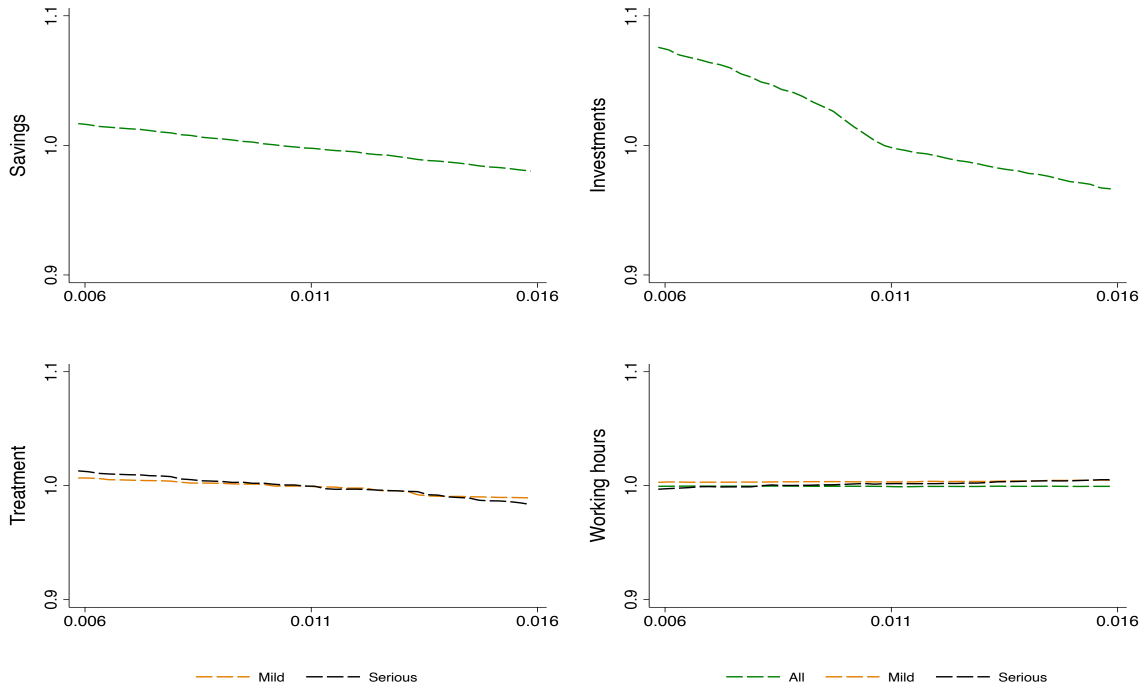

Figure A.2: Sensitivity of Moments to Participation Cost φ_k

Figure A.2 display the sensitivity of model moments to changes in the participation costs for risky investments φ_k between about 400 dollars (corresponding to 0.006) and 1000 dollars (corresponding to 0.011).

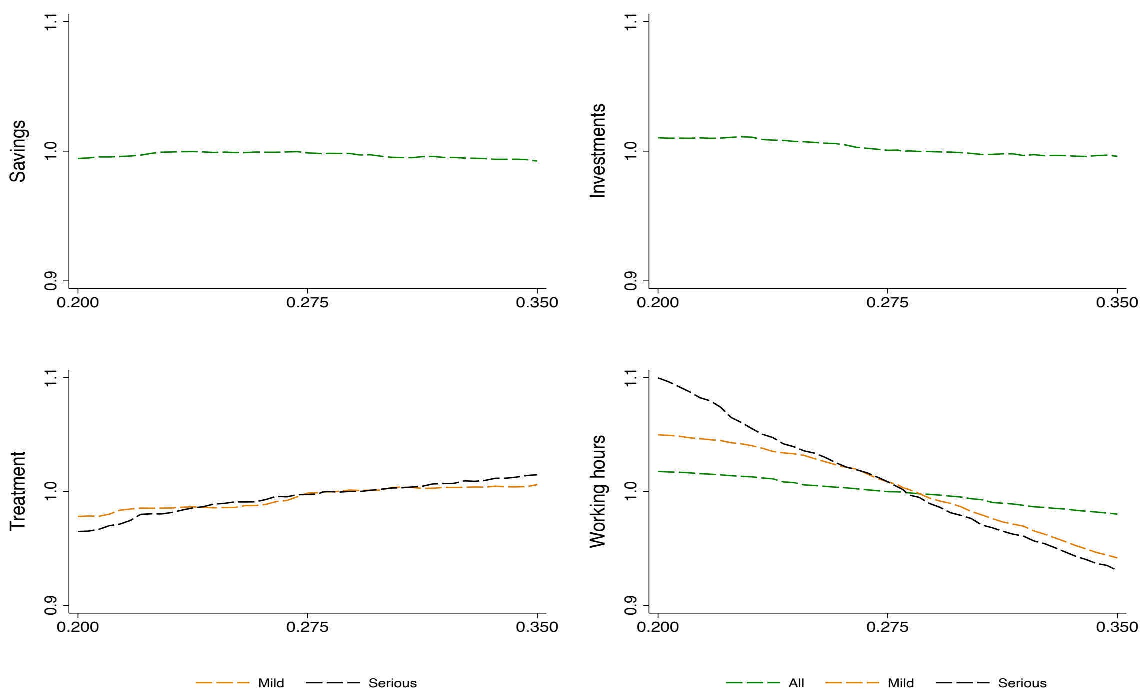

Figure A.3: Sensitivity of Moments to the Disutility of Work φ

Figure A.3 shows the sensitivity of the model to changes in the disutility cost of work, which is governed by the parameter φ. We vary the disutility cost between 0.20 and 0.35 as displayed on the horizontal axis.

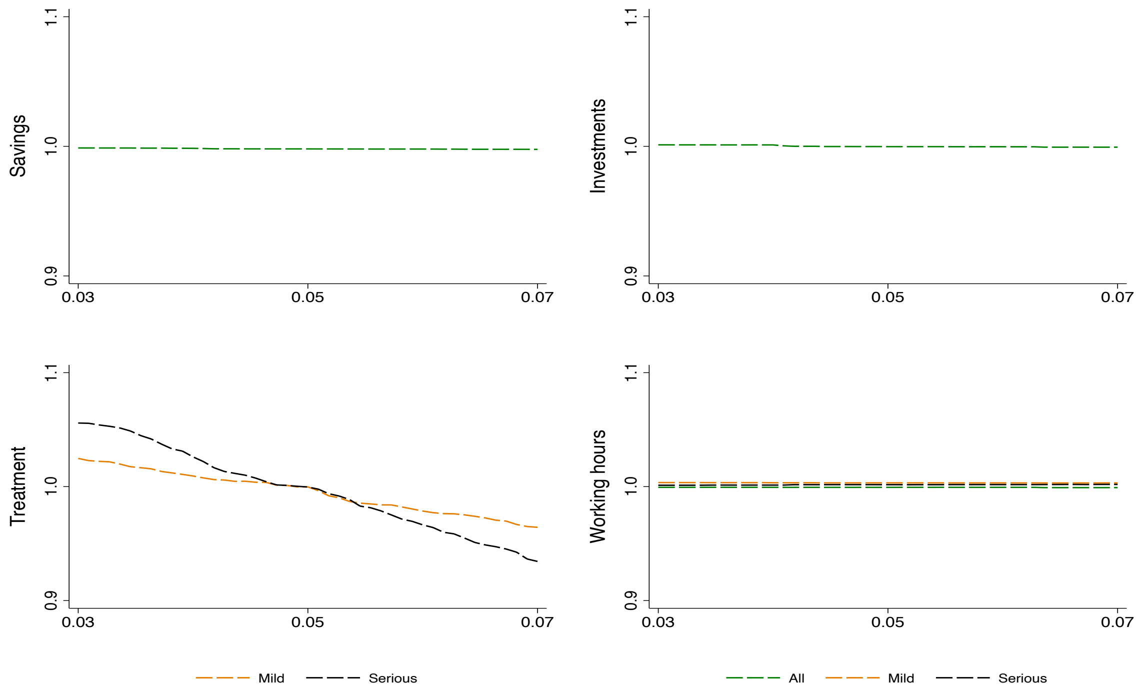

Figure A.4: Sensitivity of Moments to the Utility Cost of Treatment ξ_τ

Figure A.4 reports the sensitivity of the model to changes in the utility cost of treatment ξ_τ. We vary the disutility cost ξ_τ between 0.03 and 0.07 as displayed on the horizontal axis, around the model parameter value of 0.05. The utility costs of treatment has no implications for aggregate savings, portfolio choice, and labor supply, while impacting the rate at which individuals undergo treatment.

horizontal axis. Increasing the disutility from working decreases hours worked across all mental health groups, with labor supply of individuals with serious illness being most strongly affected. Since a decrease in the utility cost from work increases labor supply, the marginal cost of undergoing treatment increases. As a result, the decrease in the utility cost from working decreases the propensity of seeking treatment for individuals with mental illness as is illustrated in the bottom left panel.

Figure A.4 reports the sensitivity of the model to changes in the utility cost of treatment ξ_τ. We vary the disutility cost ξ_τ between 0.03 and 0.07 as displayed on the horizontal axis, around the model parameter value of 0.05. The utility costs of treatment has no implications for aggregate savings, portfolio choice, and labor supply, while impacting the rate at which individuals undergo treatment. Lowering the utility costs of treatment increases the propensity of undergoing treatment for individuals with mental illness as is illustrated in the bottom left panel. The sensitivity of the propensity of undergoing treatment increases with the severity of illness.

We next analyze the sensitivity of the model moments to changes in the rumination parameters. First, we analyze the sensitivity to rumination among individuals with mild mental illness. Figure A.5 shows

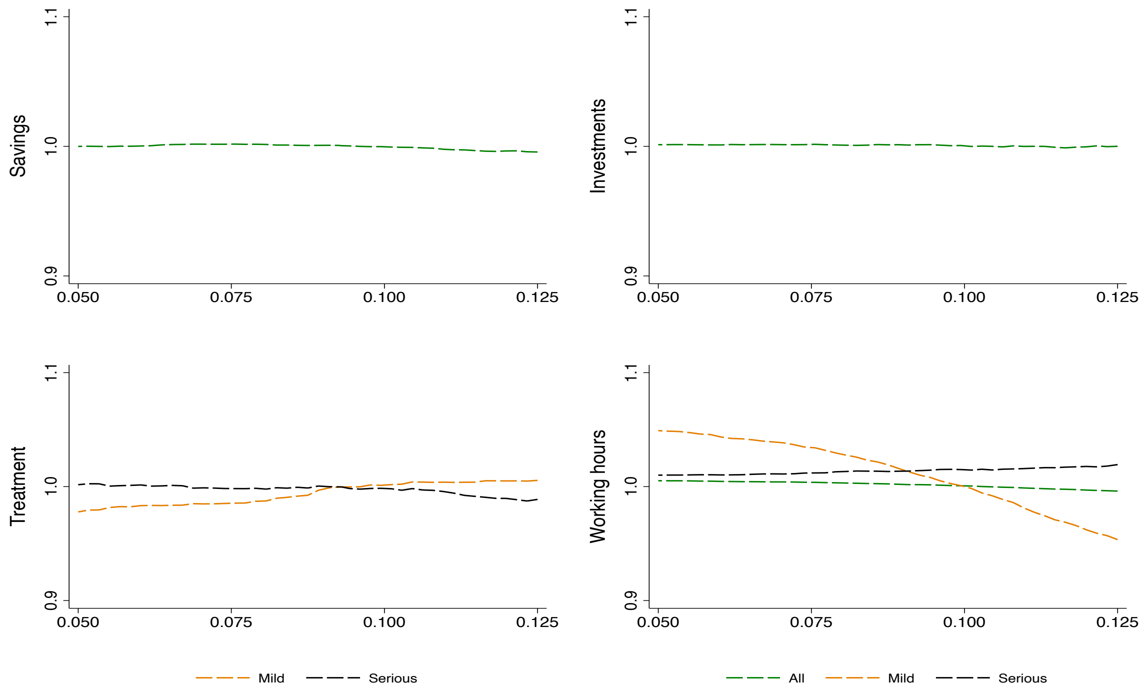

Figure A.5: Sensitivity of Moments to Rumination of Mild $n_r(m_1)$

Figure A.5 analyzes the sensitivity of the model moments to changes in rumination when individuals experience mild mental illness. Labor supply of individuals with mild mental illness decreases by 10 percentage points as rumination increases from 5 hours per week to 12.5 hours per week.

that rumination when mildly ill, $n_r(m_1)$, predominantly affects the labor supply of individuals with mild mental illness, illustrated by the decreasing orange dashed line in the bottom right panel in Figure A.5. Labor supply of individuals with mild mental illness decreases by 10 percentage points when rumination increases from 5 hours per week to 12.5 hours per week.

Second, we evaluate the sensitivity of model moments to rumination among individuals with serious mental illness. Figure A.6 shows that rumination for those experiencing serious illness, $n_r(m_2)$, mostly affects labor supply of individuals with serious mental illness, illustrated by the decreasing black dashed line in the bottom right panel in Figure A.6. Labor supply of individuals with serious mental illness decreases by 15 percentage points when rumination increases from 9 hours to 16 hours per week. With serious mental illness becoming more costly as rumination increases, the propensity to get treatment also increases despite the reduction in available time, as shown in the bottom left panel.

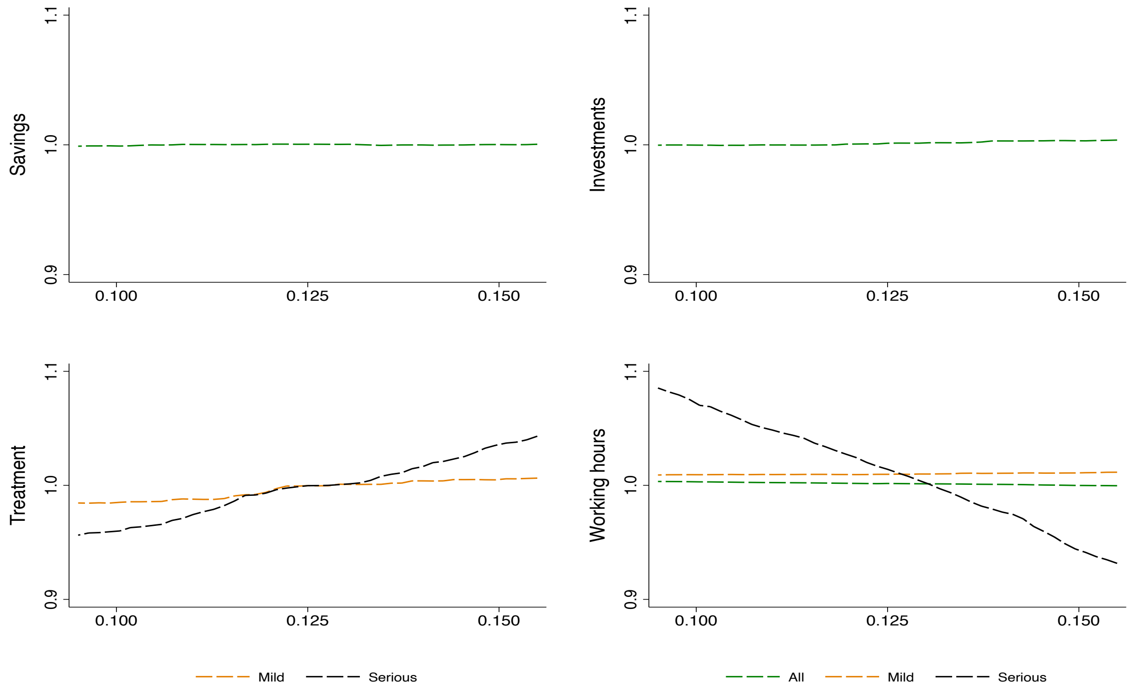

Figure A.6: Sensitivity of Moments to Rumination of Serious $n_r(m_2)$

Figure A.6 analyzes the sensitivity of the model moments to changes in rumination when individuals experience serious mental illness.

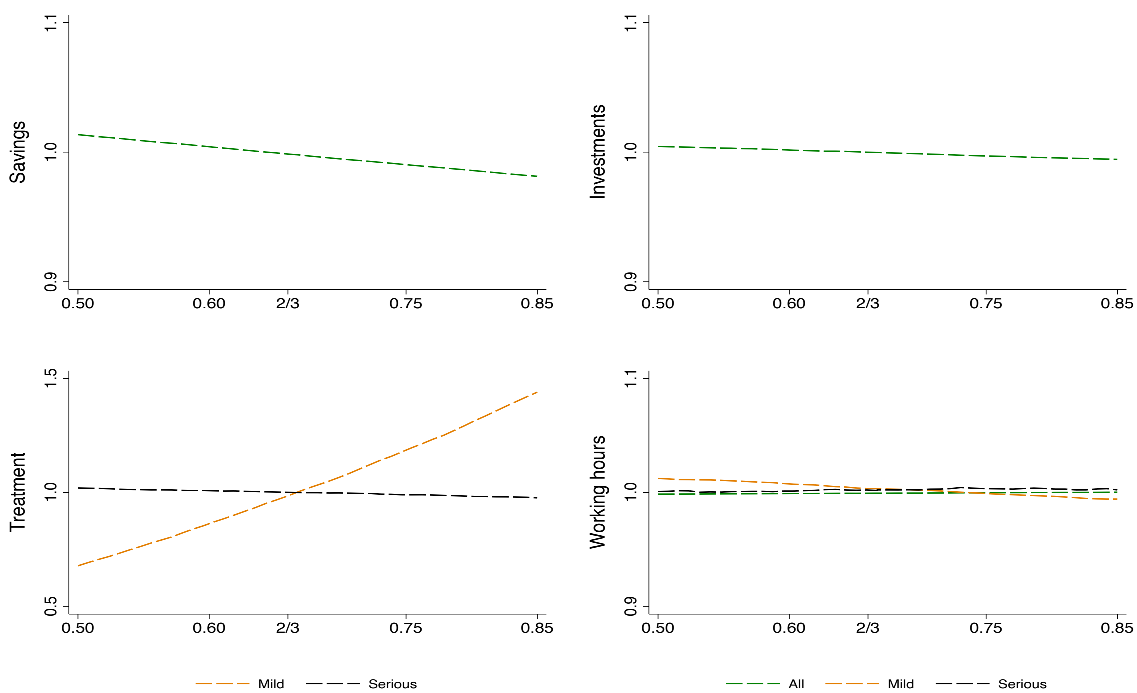

Figure A.7: Sensitivity of Moments to the Availability of Treatment ω_τ

Figure A.7 shows the sensitivity of the model moments to the availability of treatment ω_τ. We vary the availability of treatment when individuals experience mild illness from 0.50 to 0.85, around the calibrated parameter value $\omega_\tau = \frac{2}{3}$.