On the dynamics of mental health*

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Abstract

This paper studies the dynamics of mental health over the life cycle and introduces a parsimonious statistical model suitable for structural economic applications. Using Panel Study of Income Dynamics (PSID) data, we document key patterns in depression symptoms: mental health generally improves with age, though it has worsened in more recent cohorts. Recovery rates are high and increase with age, while transitions between mental states depend on the duration in the current state. Mental health is strongly correlated with labor productivity, more productive individuals experiencing better outcomes, and inequality in mental health remains stable across age. We estimate the model using the Simulated Method of Moments and show it replicates key empirical patterns. We then embed it into a life-cycle model with labor supply, where mental health affects choices via reduced effective time endowment (interpreted as overthinking) and increased disutility from work. We calibrate the model to match labor force participation and hours profiles and find large monetary and welfare losses from depression symptoms, with significant heterogeneity by ex-ante conditions.

*The views expressed herein are those of the authors and not necessarily those of the Central Reserve Bank of Peru

1 Introduction

Recent studies have imrpoved the understanding of the dynamic properties of physical health and its role in economic outcomes, as shown by works such as De Nardi et al. (2010), De Nardi et al. (2016), Ameriks et al. (2020), Hosseini et al. (2024), Hosseini et al. (2022), Blundell et al. (2022), Blundell et al. (2023), and De Nardi et al. (2024). However, the dynamic properties of mental health have received far less attention in economic research. While mental health is acknowledged as a factor affecting productivity and decision-making, there are few studies that examine how it can be incorporated into economic models. Given the increasing prevalence of mental health issues and their economic implications, addressing this gap is important for both advancing theoretical models and informing policy design.

In this paper, we present a set of empirical facts about mental health over the life cycle and incorporate them into a statistical model to study the dynamics of mental health. In particular, we focus our attention on four crucial characteristics: modeling the transition dynamics from and to states with no mental health issues, the persistence of mental health shocks, the ex-ante heterogeneity in the form of health types and fixed-labor productivities, and health spillovers from physical health to mental health. We found that mental health dynamics are characterized by the improvement with age, the possibility of recovery from depression, and significant duration dependence in the transitions between good and bad mental health. Additionally, we observe that heterogeneity in mental health outcomes is influenced by labor productivity and health types. The model captures these features effectively, showing that recovery from depression and persistence of mental health shocks are critical factors in understanding mental health trajectories over the life cycle. Moreover, our counterfactual analysis reveals that excluding key components such as recovery and fixed labor productivity leads to biased estimates of depression incidence and its variance.

We start the analysis by documenting five stylized facts about mental health across the life cycle, using data from the Panel Study of Income Dynamics (PSID) for male individuals aged 25 to 89 with a high school diploma. Due to data availability, mental health is proxied by depression-related symptomatology, as measured by the Kessler Psychological Distress Scale (K6). Consistent with prior studies, we find that mental health tends to improve as people age and younger generations tend to report higher psychological distress.[1] Similarly, transition patterns into and out of the symptoms-free state are age-dependent, differing from those observed in physical health. The intertemporal dynamics of mental health and its transition probabilities exhibit characteristics of a long memory process. Specifically, we observe that staying in the free-symptoms state depends on duration. Furthermore, a significant fraction of the variability in mental-health outcomes is accounted for by initial conditions, particularly those related to mental health history and labor productivity. The former shows the long-run effect of mental health problems, while the latter highlights the strong link between income and psychological stress.

Finally, we find that the dispersion of mental health, remains flat over the life cycle, unlike the rising inequality observed in physical health and income with age. These results suggest that mental health inequality evolves differently, and factors beyond economic and physical health conditions potentially influence it.

Based on these empirical regularities, we propose a parsimonious statistical model to capture the dynamics of mental health that can be implemented in structural models. The model incorporates four essential components: (i) a high prevalence of individuals without depression symptoms, (ii) the possibility of recovery from depressive symptoms, (iii) duration dependence in the transition from good to bad mental health and vice versa, and (iv) heterogeneity in mental health outcomes based on ex-ante heterogeneity in terms of presence of depression during adolescence and fixed labor productivity. We also include mortality risk and feedback from physical health. The model is estimated using the Simulated Method of Moments (SMM), choosing the mean of the log of our depression measure and the variance-autocovariance profile as target moments. The results show that the model effectively captures key features of mental health dynamics over the life cycle. Specifically, it accurately estimates the probabilities of remaining without symptoms and recovering from depression symptoms, particularly when a fifth-degree polynomial is used. Moreover, the model replicates the average depression incidence, as well as its variance and first-order autocovariance.

To validate the model's structure, we perform counterfactual simulations that exclude key components one at a time: recovery, duration dependence, and fixed labor productivity. The results highlight the critical role of these elements in capturing men-

[1] Johnson (2021) and Luo et al. (2023), Blanchflower and Bryson (2024)

tal health dynamics. In particular, we find that excluding these components leads to significant biases in average depression incidence and the behavior of its stochastic part.

Finally, we apply our statistical model for mental health in a life-cycle model to evaluate the welfare and monetary losses associated with depression symptoms. Our analysis begins with the empirical observation of a substantial and persistent gap in labor supply—both at the extensive and intensive margins—between individuals experiencing moderate or severe depression symptoms and those who do not. This disparity not only exists but also widens over the life cycle. Motivated by this evidence, we develop a quantitative life-cycle model in which individuals are heterogeneous in terms of labor productivity, physical health, and mental health. Depression affects economic behavior through two distinct channels: (i) it reduces individuals' effective time endowment, interpreted as a consequence of cognitive overload or overthinking, thereby affecting the intensive margin of labor supply; and (ii) it increases the disutility associated with labor market participation, influencing the extensive margin. We calibrate the model to match the observed differences in labor supply across mental health statuses. Using our calibrated model, we find significant monetary and welfare losses attributable to depression symptoms, with these losses varying significantly across individuals depending on their initial conditions. Notably, we find that individuals who experience depression during adolescence—used here as a proxy for ex-ante conditions, incur monetary and welfare costs that are 77% and 46.4% higher, respectively, than those who do not experience depression at that stage.

2 Literature review

Our paper contributes to several strands of literature at the intersection of health dynamics, mental health, and labor market outcomes. The first relevant strand examines the evolution of mental health and well-being over the life cycle. A growing body of research has sought to document stylized facts in this area. Notably, recent evidence points to a marked decline in mental health among younger cohorts, a pattern observed consistently across countries (Blanchflower and Bryson, 2024; Blanchflower et al., 2024a,b). In parallel, a number of studies have explored the causal relationships between mental health and demographic as well as economic outcomes. Empirical analyses such as those by Bryan et al. (2022a,b); Germinario et al. (2022); Ringdal and Rootjes (2022); Pinna Pintor et al. (2024) provide robust evidence that individuals with better mental health generally achieve higher earnings and exhibit greater labor force participation. The consistency of these findings across different institutional and geographic settings underscores the broad economic relevance of mental health. Our contribution to this literature is twofold. First, we provide new empirical evidence on the dynamic properties of depression incidence over the life cycle. In particular, we highlight the presence of a substantial share of individuals who remain free of depression symptoms throughout life. This pattern arises from three key features of the mental health transition process: (i) high recovery rates among those experiencing symptoms, (ii) high persistence in remaining symptom-free, and (iii) a strong degree of history dependence in transition probabilities. These elements jointly account for the observed decline in depression prevalence with age and enrich the empirical foundation for modeling mental health dynamics in economic settings.

A second strand of literature relevant to our work concerns modeling health processes in structural economic settings. This line of research aims to accurately capture health dynamics to assess their economic implications more precisely. Traditionally, structural models have treated health as a composite measure, often without distinguishing between physical and mental health, or focusing primarily on physical health alone. Health status in such models is typically represented as a first-order Markov process based on self-reported health measures, as seen in studies such as De Nardi et al. (2010), De Nardi et al. (2016), and Ameriks et al. (2020). In recent years, however, researchers have devoted increased attention to the dynamic properties of health over the life cycle and how these should be incorporated into quantitative models. Notably, Hosseini et al. (2022) and De Nardi et al. (2024) provide two of the most relevant contributions in this regard. Both studies use data from the PSID to estimate stochastic processes governing health transitions. Hosseini et al. (2022) focus on a frailty index as a comprehensive measure of health—including cognitive deficits among other health dimensions—and highlight the importance of correcting for mortality selection. They employ the Simulated Method of Moments (SMM) to account for this source of attrition, an approach we also adopt in our analysis. De Nardi et al. (2024), on the other hand, propose a model of self-reported health that emphasizes history dependence and its strong correlation with fixed labor productivity—defined as the component of earnings unrelated to age or education. Other recent work, such as Blundell et al. (2022) and Blundell et al. (2023), has further enriched our understanding of how health should be modeled within structural frameworks. Our study contributes to this literature by focusing specifically on the dynamic properties of mental health and by proposing a statistical model tailored to its unique features. Drawing on insights from Hosseini et al. (2022), we model mental health as a continuous, normalized measure and incorporate mortality risk into the transition dynamics. In line with De Nardi et al. (2024), we allow for history dependence and explore the relationship between mental health and fixed labor productivity. Crucially, our model introduces the possibility of full recovery from depression symptoms—an empirically salient feature that distinguishes mental health from many physical health conditions. To the best of our knowledge, this is the first study to propose a statistical model for mental health that captures its empirical dynamics over the life cycle and aligns it with the requirements of structural economic analysis.

Finally, our work contributes to the structural literature examining the economic consequences of poor health. Much of this research relies on broad measures of health to analyze their implications for individual savings behavior, labor supply decisions, and the design of public policy (French, 2005; De Nardi et al., 2010, 2016; Ameriks et al., 2020; Hosseini et al., 2024, 2022; Blundell et al., 2022, 2023; De Nardi et al., 2024; Blanchflower and Bryson, 2024). While the majority of these studies treat health as an aggregate concept—typically encompassing both physical and mental health—there has been growing interest in isolating and quantifying the specific economic impact of mental health. Recent work has advanced this agenda by incorporating mental health into structural economic models. For example, Cronin et al. (2024) develops a dynamic choice framework to model the demand for treatment of depression and anxiety, demonstrating that improvements in mental health yield substantial gains in both utility and earnings. Similarly, Postel-Vinay and Jolivet (2024) investigates the interplay between mental health and labor market dynamics using British panel data. They estimate the effects of job-related stress and mental health shocks on occupational choices over the life cycle. More recently, Abramson et al. (2024) proposes a unified theoretical framework that integrates insights from psychiatry into macroeconomic modeling.

They explore how mental illness influences economic behavior through three key transmission channels: overthinking, pessimism, and reinforcement effects. Their findings show that mental health significantly affects consumption, savings, and labor supply. Our work builds on these insights by focusing specifically on labor supply decisions and by offering a detailed statistical characterization of mental health dynamics. In particular, we incorporate overthinking as in Abramson et al. (2024) and a direct effect of mental health on labor disutility to account for differences in labor supply decisions in the extensive and intensive margin by mental health status. We show that poor mental health triggers large welfare and monetary costs through labor supply decisions. In doing so, we provide additional structural evidence on the economic costs associated with poor mental health.

3 Facts about mental health over the life cycle

This section documents five facts about the evolution of mental health over the life cycle using depression symptoms incidence as a proxy for mental health. We rely on this measure due to data availability. Throughout the paper, we refer to both terms interchangeably.

Our main dataset is the Panel Study and Income Dynamics (PSID), a longitudinal survey representative of the U.S. population, with rich information at household and individual levels. Since 2001, the PSID has registered data on different depression symptoms and other mental disorders. In particular, data gathered by the PSID allows us to compute the Kessler Psychological Distress Scale (K6) index, a variable widely used by medical literature to assess psychological distress. This index combines information on psychological distress through six questions about a person's emotional state [2]. Similarly to the frailty index, these questions reveal deficits associated with depression. Each question is scored on a discrete scale from 0 ("none of the time") to 4 ("all of the time"). The indicator is calculated as the sum of these scores. A K6 score of 0–7 indicates low psychological distress, while a score between 8–12 suggests moderate distress, and scores higher than 13 describe significant distress.[3] The validity of the K6 has been supported by studies such as Khan et al. (2014), Ferro (2019), Umucu et al.

[2]These questions ask participants their feelings about sadness, nervousness, restlessness, hopelessness, effortlessness, and worthlessness.

[3]See (Yiengprugsawan et al., 2014; Frajerman et al., 2022).

(2022), among other. In this research, we normalized this indicator to have a maximum value of 1 to ease interpretation.

Our main sample consists of male household heads with 12 to 14 years of education (corresponding to a high school degree or, at most, 2 years of college education). We normalize all nominal variables to the base year (2021) using the Consumer Price Index (CPI). Because mental health has cohort effects, we either perform our empirical documentation for separate cohorts or extract cohort effects with a regression that includes cohort dummies.

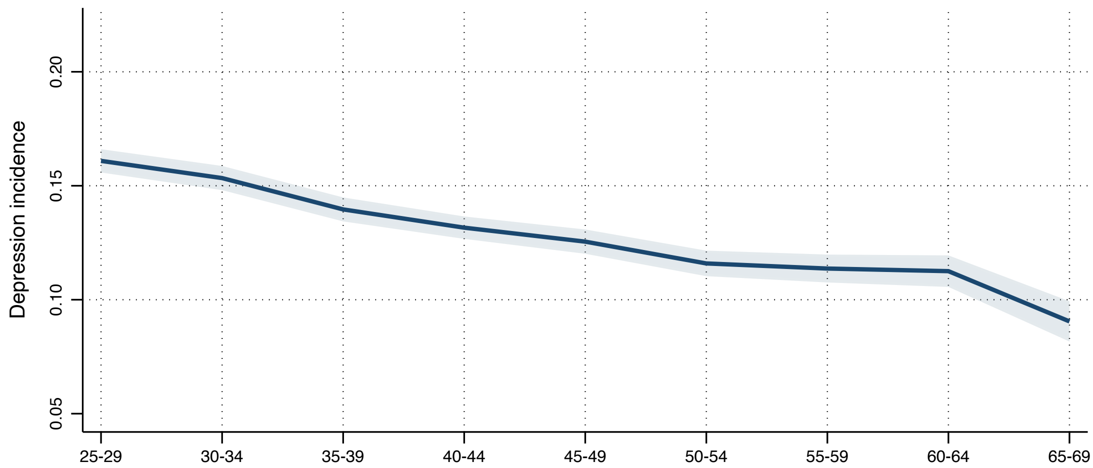
Fact 1: Mental health improves with age, but it is worse for younger cohorts

The dataset covers information for at least three different cohorts. Baby Boomers are composed of individuals born between 1946 and 1964, Generation X is the cohort born after 1964 and before 1981, and Millennials are those born after 1981 and before 1997. We compare the average depression incidence for 5-year age groups and separately in each of these cohorts. Here, we define depression incidence as the average value of the K6 index among individuals in the same age group. Figure 1 shows that depression symptoms exhibit a slightly downward path with age with different dynamics in age groups older than 60. This downward pattern is robust to using different ways to define depression. For example, literature commonly uses a cutoff of 8 out of 24 to classify people with moderate distress symptoms. In contrast, severe psychological distress, used in the diagnosis of depression, employs a cutoff of 13. Panels in Figure 2 show that although there are differences in the average depression levels computed in every case, the downward-sloping behavior of depression incidence is consistent.

Multiple studies have examined a potential upward trend in depression, though no clear consensus has been reached.[4] While this paper does not aim to resolve this controversy, accurate modeling must consider potential subgroup differences to prevent bias in the estimations. In that sense, in Figure 3, we explore the life-cycle patterns of our proxy of depression incidence by the different cohorts of our sample. Results show that there are signs that Millennials exhibit more depression symptoms than older cohorts. For example depression incidence is 2 percent higher among Millenials in comparison with Generation X for age groups in which both groups report data (between

[4]See Iranpour et al. (2022) for a detailed discussion on the topic.

Figure 1: Average depression incidence by 5-year age groups over the life cycle.



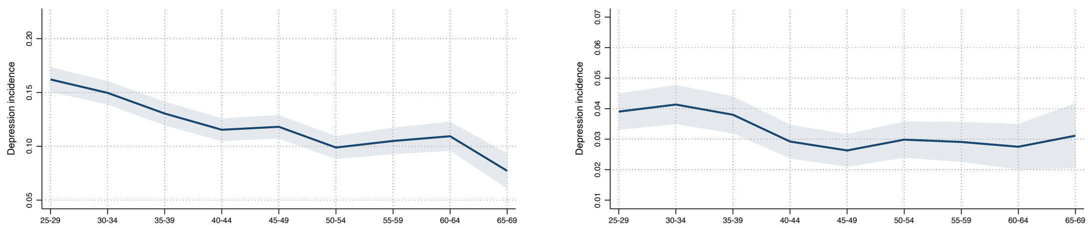
Note: The figure shows the incidence of depression across five-year age groups, with depression incidence estimated as the average K6 index. Dashed lines display one-standard deviation confidence intervals computed using bootstrap methods with 500 samples of 300 individuals in each age group.

25-44 years). Similarly, we observe that Generation X individuals report a 1.16 percent higher depression incidence than Baby boomers in the age range in which both overlap (35 to 59 years). This implies that it is important to control for cohort effects when modeling mental health.

Figure 2: Average depression incidence by 5-year age groups over the life cycle.

(a) Moderate psychological distress

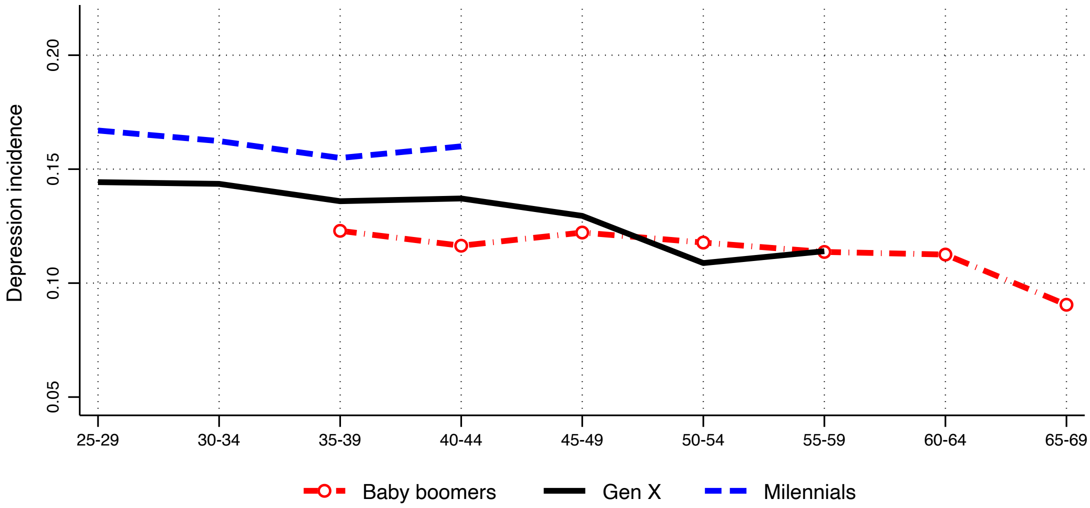
(b) Severe psychological distress



Note: Figure shows the incidence of depression across five-year age groups. Panel (a) shows moderate psychological distress (K6 index above 8 out of 24) and panel (b) shows severe psychological distress (k6i index above 13 out of 24). Dashed lines display one-standard deviation confidence intervals computed using bootstrap methods with 500 samples of 300 individuals in each age group.

A possible interpretation of the previous results is that life-cycle patterns can be driven only by differences across cohorts since younger generations experienced a higher average K6 index. To address this possibility, we conduct a regression analysis of observed K6 values against age and a set of control variables: sex-at-birth dummy, high-education dummy, time fixed-effects, first lag of k6, the first lag of frailty index, and cohort fixed-effects.[5]

Figure 3: Average depression incidence by 5-year age groups over the life cycle.



Note: The figure shows the incidence of depression across five-year age groups, with depression incidence estimated as the average K6 index. Patterns for three distinct cohorts are plotted: Baby Boomers, born between 1946 and 1964, are shown as a red dashed line with circular markers; Generation X, born from 1965 to 1980, is depicted as a solid black line; and Millennials, born between 1981 and 1996, are represented by blue dashed lines.

Table 1 reports the estimated coefficients associated to age, defined as group-age for 5 different specifications. Columns 1 to 3 show estimates of random coefficients models for the following dependent variable: (i) K6 index, (ii) dummy variable of moderate depression symptoms (K6>=0.3), and (iii) dummy variable of severe depression symptoms (k6>=0.54). Columns 4 and 5 present estimates from a probit model. In all cases, we observe that average depression incidence decays as people age.

Table 1: Life cycle trend of mental health

	Random Effect model			Probit model	
variable	(K6)	(K6>=0.3)	(K6>=0.54)	(K6>=0.3)	(K6>=0.54)
age	-0.0066^{***}	-0.013^{***}	-0.005^{***}	-0.072^{***}	-0.075^{***}

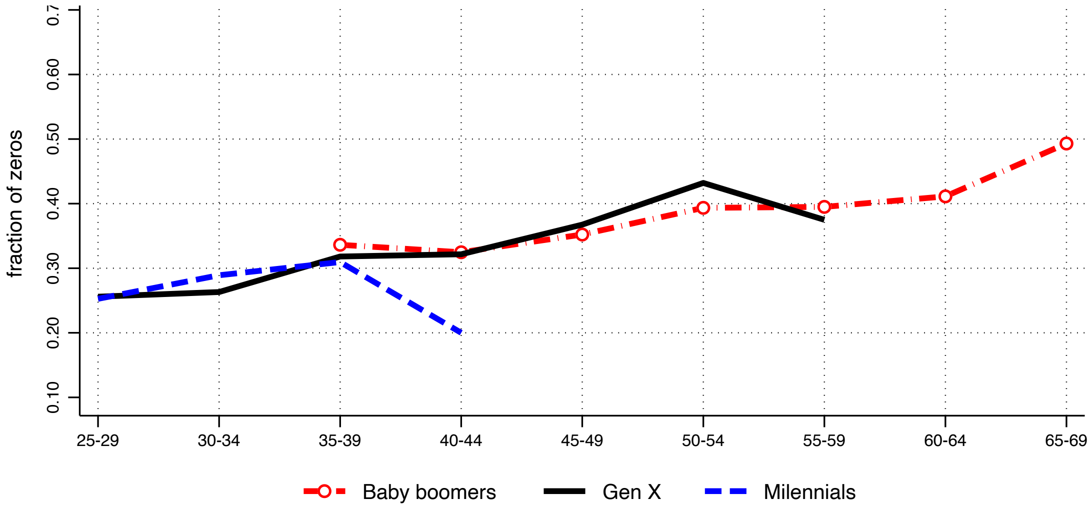
Note: Table reports the estimates of a regression of mental health (m_t) on age and a set of controls. All specifications include a sex-at-birth dummy, high-education dummy, time fixed-effects, first lag of k6, the first lag of frailty index, and cohort fixed-effects. Columns 1-3 were estimated by a random effect, while columns 4 and 5 were estimated using a probit model. Number of observations: 69 776, number of households: 14 718. Significance levels: * p-val< 0.1, ** p-val< 0.05, *** p-val< 0.01

Importantly, we find that one of the main reasons for this decreasing path in depres-

[5]The frailty index is a measure of the fraction of [physical-related] health deficits that an individual has accumulated over his lifespan (see Hosseini et al. (2022))

sion incidence is the higher fraction of individuals who do not report any depression symptoms in older age groups. As Figure 4 shows, among all cohorts, there is an increasing fraction of people without depression symptoms over the life cycle. This result is not affected by cohort effects since the fraction of individuals with a K6 index equal to zero in the same age group is similar across cohorts. The drop in fraction for the last observation in each cohort is related to the negative effect of the COVID-19 pandemic.

Figure 4: Population without any depression symptom over the life cycle (%)



Note: The figure shows the fraction of households who report no depression symptoms across five-year age groups, with depression. Patterns for three distinct cohorts are plotted: Baby Boomers, born between 1946 and 1964, are shown as a red dashed line with circular markers; Generation X, born from 1965 to 1980, is depicted as a solid black line; and Millennials, born between 1981 and 1996, are represented by blue dashed lines.

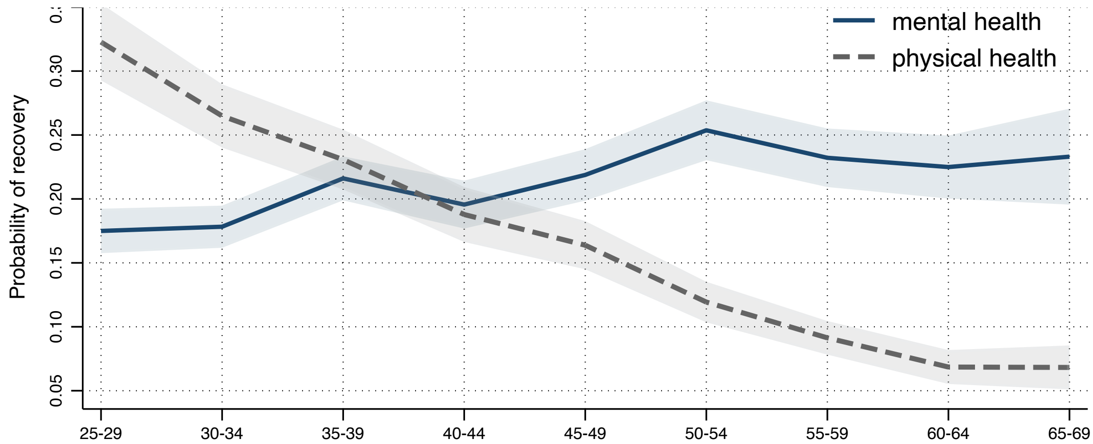
Fact 2: As people age, they stay more time in a symptoms-free mental health state

The large fraction of zeros in the sample suggests a need to model the dynamics of individuals who are in a symptom-free state. Modeling it involves tackling two transition dynamics: (i) passing from having symptoms to reporting a mental health index of zero and (ii) remaining in a symptom-free state. Regarding the former, we define mental recovery as a situation in which individuals report no current symptoms of depression (equivalent to a K6 index of zero) after having experienced symptoms in the previous period. Figure 5 plots the evolution of recovery probabilities over the life cycle. Panel (a) depicts the trend in average mental health recovery probabilities and their physical health counterparts. [6] Physical and mental recovery patterns dif-

[6]Similarly to mental recovery, physical recovery was defined as reporting a current frailty index equal to 0 having reported a non-zero frailty index in the previous period.

fer. While the probability of physical recovery declines exponentially, mental recovery probability increases during the early life cycle peaking in the 50-54 age group before starting to decline. In the early life cycle, physical recovery is more likely than mental recovery (30% compared to 20 %). However, this relationship reverses in age groups over 40.

Figure 5: Recovery probabilities: mental vs physical health

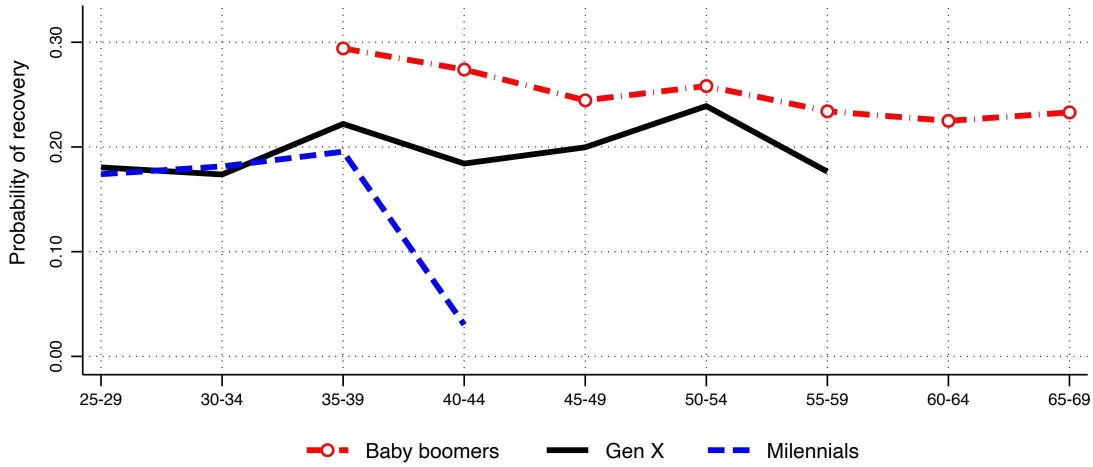


Note: Figure shows recovery probabilities for physical health (dashed gray line) and mental health (solid black line) across five-year age groups. Physical health is approximated by the frailty index as in Hosseini et al. (2022). Recovery is defined as the situation in which a household reports no current depression symptoms conditional to having reported depression symptoms in the previous wave.

The dynamic of mental recovery is complex when inspected across different cohorts. Panel (b) of Figure 5 shows the evolution of mental recovery probabilities for the different cohorts in our sample. Boomers exhibit a greater likelihood of recovering mental health over the life cycle compared to younger cohorts. This pattern could be attributed to older generations experiencing a different socio-economic environment with more job security and economic stability than today's younger adults. On the other hand, Millennials face unique stressors such as financial insecurity, student debt, and the impact of social media, all of which are linked to increased anxiety and depression. Moreover, when we compare patterns between Generation X and Baby Boomers, we see different trends. Recovery probability has a positive slope for the former group while it is negative for the latter.

Regarding the second transition dynamic, we define a "staying healthy" situation as the event in which an individual who reported no depression symptoms during the previous period remains with no depression symptoms in the current period. Figure 7

Figure 6: Recovery probabilities: cohort differences



Note: Figure displays recovery probabilities for mental health for different cohorts across five-year age groups. Baby Boomers, born between 1946 and 1964, are shown as a red dashed line with circular markers; Generation X, born from 1965 to 1980, is depicted as a solid black line; and Millennials, born between 1981 and 1996, are represented by blue dashed lines. Recovery is defined as the situation in which a household reports no current depression symptoms conditional of having reported depression symptoms in the previous wave.

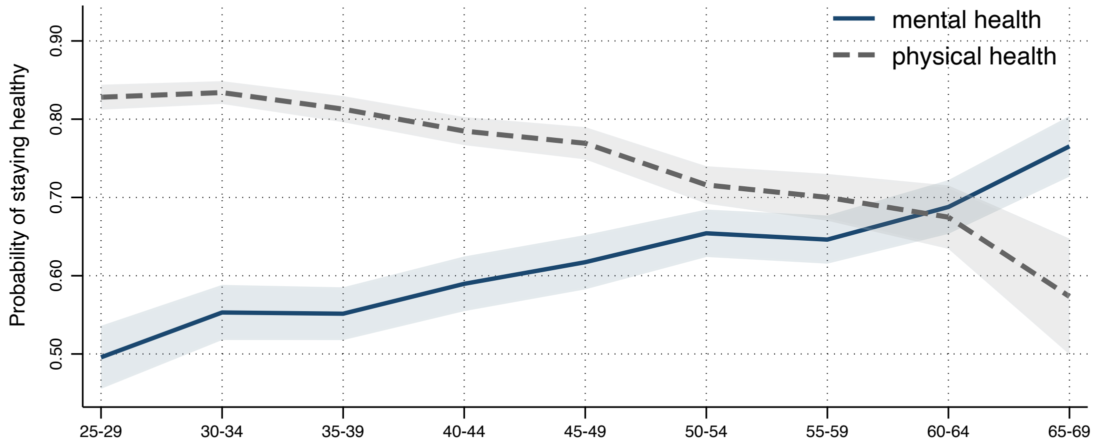
plots the evolution of staying-healthy probabilities along the life cycle and across different cohorts. As before, the data reveals different patterns for staying-healthy probabilities between physical and mental health. In the case of physical health, remaining healthy is harder as people age, decreasing from 80 percent for the 25-29 age group to less than 60 percent in age groups above 65. In contrast, mental health staying-healthy probability increases along the life cycle, from 50 percent for the 25-29 age group to more than 70 percent (see panel a). This upward slope pattern holds across generations with minimal differences among cohorts as shown by Figure 8.

Fact 3: Mental health and its transitions are long-memory processes

Given the previous results and since our objective is to provide a sensible model of mental health, it is important to know the level of persistence that drives mental health. Commonly, the literature has approximated both, physical and mental health, as first-order Markov processes (see Abramson et al. (2024) for an example). However, De Nardi et al. (2024) shows that physical health possesses properties of a long-memory process. In this sense, this section provides evidence that mental health dynamics is a long-memory process.

The PSID family dataset collects self-reported information on depression during

Figure 7: Staying healthy probabilities: mental vs physical health



Note: Figure plots staying-healthy probabilities for physical health (dashed gray line) and mental health (solid black line) across five-year age groups. Staying healthy is defined as the situation in which a household reports no current depression symptoms conditional to having no reported depression symptoms in the previous wave.

adolescence (before age 17). From this data, we create a dummy variable that is equal to 1 if the individual reported experiencing symptoms of depression before turning 17 (dep_{17}). In cases where an individual provides conflicting responses across different waves, we assume that the household experienced depression. Then, we regress the current levels of the K6 index on this dummy and other control variables.

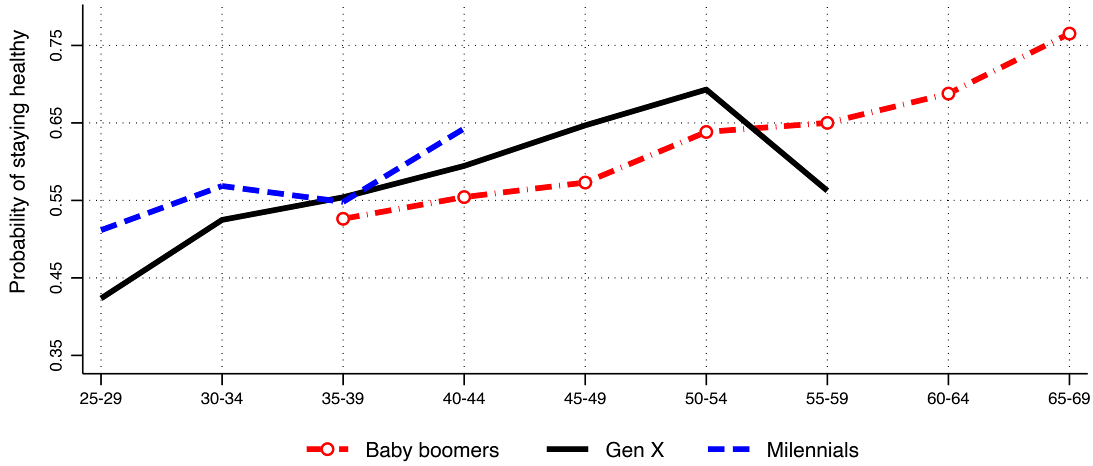
Table 2: Long-run effects of early life depression

variable	(1)	(2)	(3)	(4)	(5)
dep_{17}	0.080^{***}	0.074^{***}	0.067^{***}	0.051^{***}	0.040^{***}
m_{t-1}	0.440^{***}	0.422^{***}	0.397^{***}	0.335^{***}	0.293^{***}
m_{t-2}	–	–	–	0.210^{***}	0.179^{***}
m_{t-3}	–	–	–	–	0.151^{***}
f_{t-1}	–	0.165^{***}	0.158^{***}	0.115^{***}	0.096^{***}
w_t	–	–	-0.004^{***}	-0.003^{***}	-0.002^{***}
N. obs	66 590	66 590	49 002	33 175	24 468
N. households	13 377	13 377	11 770	9 765	8 427

Note: This table reports the estimates of a regression of mental health (m_t) on a dummy of depression in adolescence (dep_{17}). Column 1 includes the first lag of mental health, column 2 adds physical health, and column 3 also considers the log level of real wealth. Columns 4 and 5 add the second and third lag of mental health, respectively. All specifications include a linear trend on age, year of education, dummy of sex at birth, cohort fixed effect, and year fixed effect. Estimation by random effects model.
Significance levels: * p-val< 0.1, ** p-val< 0.05, *** p-val< 0.01

Results shown by Table 2 show that having experienced depression during adolescence triggers long-run negative effects on the levels of current mental health suggest-

Figure 8: Staying healthy probabilities: cohort differences



Note: Figure displays staying-healthy probabilities for mental health for different cohorts across five-year age groups. Baby Boomers, born between 1946 and 1964, are shown as a red dashed line with circular markers; Generation X, born from 1965 to 1980, is depicted as a solid black line; and Millennials, born between 1981 and 1996, are represented by blue dashed lines.

ing that mental health is a long-memory process. This table presents the estimated coefficients for five different specifications that explore the relationship between current mental health and depression in adolescence. The first specification adds the first lag of mental health while the second also adds the first lag of physical health (f_{t-1}). The third specification adds real wealth (w_t) approximated as the logarithm of wealth net of debt assets including equity in real terms and adjusted for the family size, and the last two specifications also include the second and third lag of mental health, respectively. Each model also controls for years of education, a linear trend in age, a dummy for sex at birth, and cohort and year-fixed effects. The estimated coefficients associated with the dummy of depression in adolescence are positive and significant for all specifications meaning that mental health conditions in childhood and adolescence would impact mental health during the whole life-span. These results are in line with Kim-Cohen et al. (2003), Schlack et al. (2021), and Otto et al. (2021). Moreover, results in column 5 show that, contrary to a first-order Markov process assumption, the second and third lags of mental health are also good predictors of the current state of mental health. These results imply that mental health levels have the properties of a long-memory process.

As mentioned before, an important component of mental health is the dynamics to and from the zero-K6 state. To make this assessment, we follow De Nardi et al. (2024)

and compute the probabilities of moving from bad (good) to good (bad) health over the next two years, conditional on being in bad (good) health for at least τ consecutive periods (with a period being two years). Consistent with the analysis in facts 2 and 3, we define the good health state as having a zero-K6 index in the baseline. However, we also provide an analysis when we level up on the medical literature that establishes a cutoff that is sensitive to dividing individuals with moderate-severe symptoms from everyone else. We show the results for two cutoffs: 0.3 (moderate symptoms) and 0.5 (severe symptoms).[7] We group observations in three age groups: 25-40, 40-60, and older than 60. Our results are shown in Figure 9. The first row plots the results for the cutoff of 0, while the second and third rows depict results for the 0.3 and 0.5 cutoff, respectively.

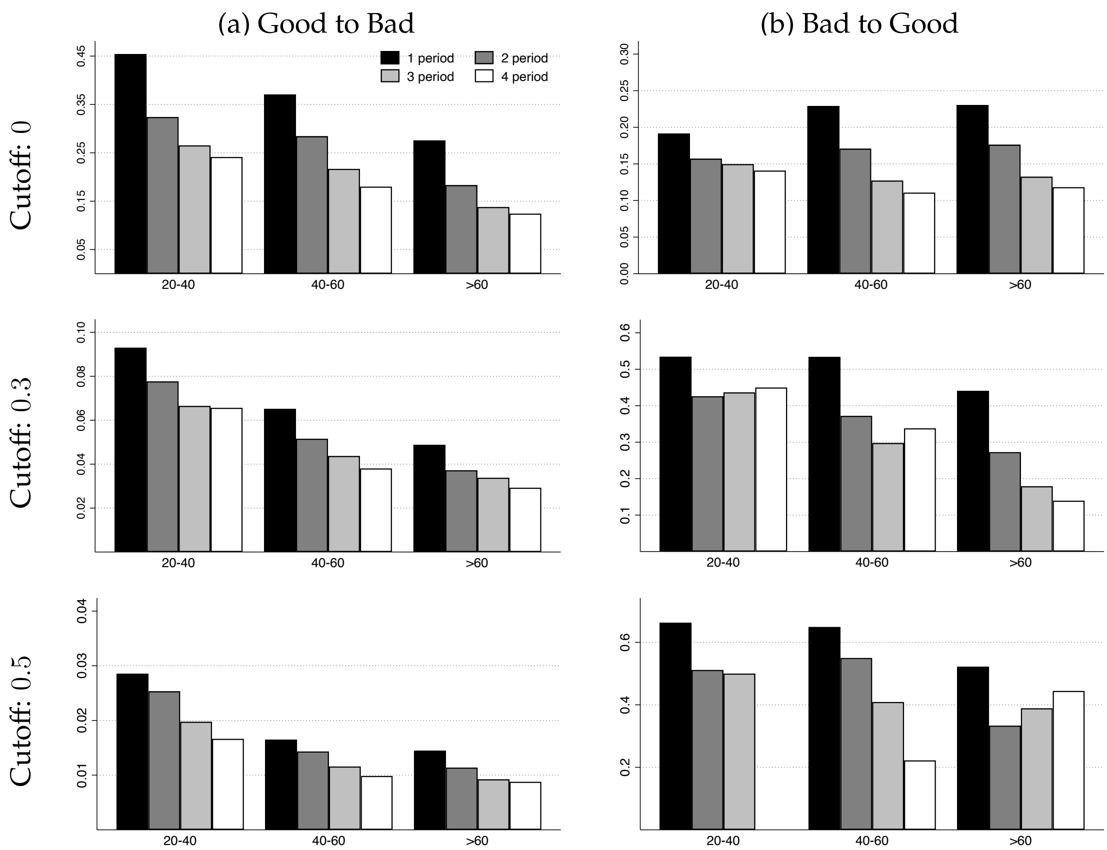
Our first observation is that the probability of transitioning from good to bad and transitioning from bad to good decreases as the duration of a good or bad state increases (first row of panels a and b). This would imply that a first-order Markov approximation does not fully capture the dynamics of depression, which leads us to model transitions allowing for duration dependence as in De Nardi et al. (2024). Second, there is a reduction in the probability of transitioning from a good to a bad mental health status. These results are robust to different cutoff levels. Third, there are differences in the transitioning patterns from bad to good mental health depending on the cutoff level. When we consider zero as the cutoff, there is an increasing pattern of people that pass from a bad to a good health status. In contrast, when a different cutoff is used the patterns become negative. It implies that although presenting non-depression symptoms is less likely as people get older, a big fraction of these households remain in the low/moderate level of psychological distress.

Fact 4: Fixed-labor productivity has a negative relationship with depression symptoms

The regression analysis discussed in the previous fact, consistent with the literature (see Thomson et al. (2022) for a meta-analysis), showed a positive and significant relationship between income and mental health. According to Guvenen et al. (2022), ex-ante heterogeneity plays a crucial role in income heterogeneity. Moreover, the re-

[7]These cutoffs have been used in the literature, for example, by Kessler et al. (1996), Yiengprugsawan et al. (2014), and Frajerman et al. (2022).

Figure 9: Transitioning from good to bad mental health and viceversa



Note: Figure plots transitioning probabilities between mental health status conditional different duration levels and over three different age groups: 20-40 years, 40-60, and >60. Panels in the left column show transition probabilities from being in a good health status at time $t-1$ to a bad health state at t. Panels in the right column show transition probabilities from being in a bad mental health status at time $t-1$ to a good health state at t. Good (bad) health status is defined as a k6 index above(below) a cutoff threshold $\overline{m}$. The first row shows results with $\overline{m} = 0$, the second row changes $\overline{m} = 0.3$, and the third row considers $\overline{m} = 0.5$. The black bar reports the transition probability conditional of being in the relevant state during the previous period), grey bars report this probability conditional on being in the same state during the two previous periods. Lighter grey and white bars show the transitioning probabilities conditional of having been in the relevant mental health state during the previous three and four periods, respectively.

cent findings of De Nardi et al. (2010) indicate that ex-ante heterogeneity is also relevant for physical health outcomes. Given our results that initial mental health conditions — reflecting ex-ante heterogeneity—are important to determining current mental health outcomes, we explore whether income ex-ante heterogeneity can help explain the differences in mental health across households.

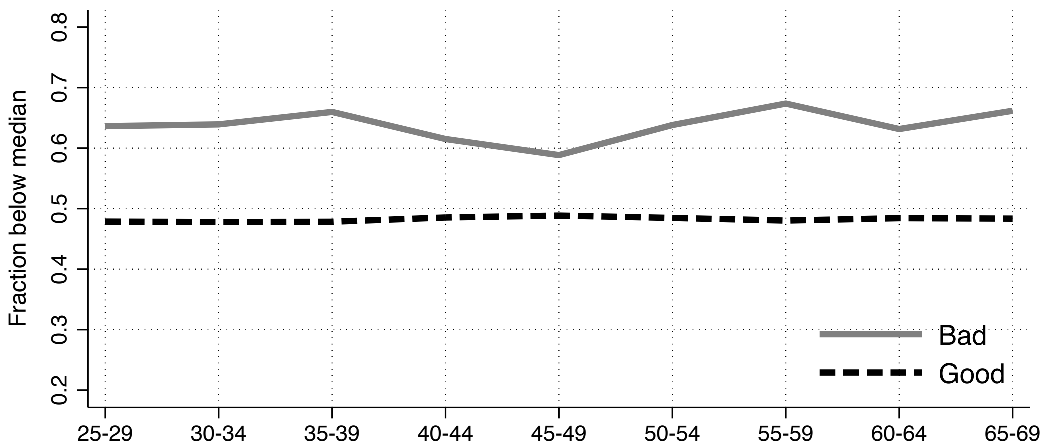
To tackle this task, we perform the following exercise. First, we estimate what the literature labels as ”fixed-labor productivity”, the part of income that is time-invariant and not related to age, physical health, or mental health. In particular, we estimate fixed-labor productivity as the individual fixed- effect from the following specification:

$$\ln(y_{it}) = \alpha_0 + \sum_t \sum_{j \in \{G,B\}} d_t^j \times D_{it}^{age} \times D_{m_{it}=j} + \alpha_1 f_{it} + \alpha_2 f_{it}^2 + \gamma_i + u_{it} \tag{1}$$

where y_{it} denotes persons' i labor income at age t, d_t^j is the coefficient corresponding to a dummy that captures the interaction between age and the j mental health status. To avoid identification problems, we restrict the number of mental health states to two: *good* and *bad* mental health. We prefer using a cutoff of 0.3 to reduce categorizing people with low stress levels as being in bad health. Finally, γ_i denotes a first approximation to the unobserved fixed labor productivity. Based on our previous results, we proceed to regress $\hat{\gamma}_i$ on dummies of cohort effects and the initial status of depression during adolescence. Therefore, our final measure of fixed-labor productivity $\tilde{\gamma}_i$ is

$$\gamma_i = \alpha_o + \sum_{j \in \{\text{cohorts}\}} k^j \times D_{i \in j} + \alpha_1\, dep_{17} + \tilde{\gamma}_i \tag{2}$$

Figure 10: Fraction of individuals with γ below the median by mental health status



Note: Figure shows the fraction of individuals below the median of fixed-labor productivity with good and bad health across five-year age groups. Fixed labor productivity is estimated using a fixed effect regression controlling by physical and mental health, cohort fixed effects, year fixed effects, and depression-in-adolescence dummy. The solid line depicts results for individuals with bad health, while the dashed lines do the same for people with good health.

Once we have a sensible estimate for fixed labor productivity, we can inspect if there is a relationship between fixed labor productivity and mental health. The first approach is plotting the fraction of people in each health status who are below the median labor productivity and observing if there are substantial differences between both groups.

These results are plotted in Figure 10. We observe that the number of people who are below the median productivity is higher in the bad mental health state (65%) than the corresponding fraction in the good mental health state (48%). This indicates that the composition of fixed labor productivity of the healthy and unhealthy is different. A second approach is by t-test to check whether the average productivity in both groups is significantly different. As shown by Table 3, a t-test suggests that given our sample data, there are statistically significant differences in productivity between healthy and unhealthy people.

Table 3: Fixed labor productivity by mental health status

	Whole sample	25-29	30-34	35-39	40-44	45-49	50-54	55=59	60-64	65-69
Good mental health	0.25	0.28	0.34	0.36	0.25	0.18	0.14	0.19	0.17	0.27
Bad mental health	-0.59	-0.28	-0.36	-0.55	-0.43	-0.47	-0.91	-1.33	-0.88	-1.20
$\mu_1 - \mu_2$	0.84	0.57	0.69	0.91	0.68	0.65	1.05	1.52	1.04	1.46
$\text{H0}: \mu_1 \neq \mu_2$ (p-value)	***	***	***	***	***	***	***	***	***	**

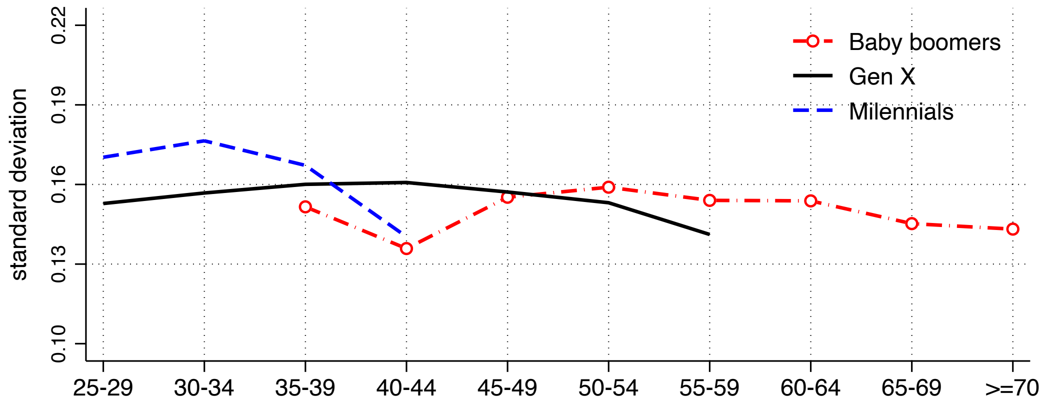
Note: Table reports average fixed labor productivity by age groups and health status. In addition, the table reports the p-values of the mean test. Null hypothesis: equal means. Significance levels: * p-val< 0.1, ** p-val< 0.05, *** p-val< 0.01.

Fact 5: The dispersion of depression incidence is flat over the life-cycle

We next turn to the question of how mental health inequality, measured as its standard deviation, evolves over the life cycle. We find that mental health inequality does not grow over the life cycle under this metric and it is also constant across different cohorts, as shown in Figure 11.

Because the mean is decreasing, and the standard deviation is flat, we would have that the coefficient of variation of mental health inequality is increasing over the life-cycle. To explore what is driving the flatness of the standard deviation, we compute separately the standard deviation of our depression measure conditional on presenting at least one depression symptom. Our results show that, for this group, the standard deviation is also flat. Therefore, fluctuations in mental health inequality are mostly accounted for by movements in the fraction of individuals without any depression symptoms. Overall, these facts result at least surprising considering that, previous literature, such as Deaton and Paxson (1998), De Nardi et al. (2024), Hosseini et al. (2022), document an increasing pattern of physical health and income inequality over the life-cycle. In particular, it is surprising to observe that more income and physical health inequal-

Figure 11: Standard deviation of depression symptoms over the life cycle

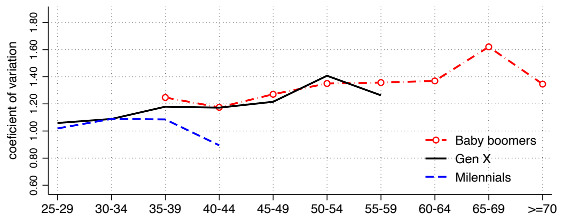


Note: Figure plots the evolution of mental health inequality over the life cycle. Inequality is proxied by the standard deviation of the K6 index. Patterns for three different cohorts are presented. Baby Boomers, born between 1946 and 1964, are shown as a red dashed line with circular markers; Generation X, born from 1965 to 1980, is depicted as a solid black line; and Millennials, born between 1981 and 1996, are represented by blue dashed lines.

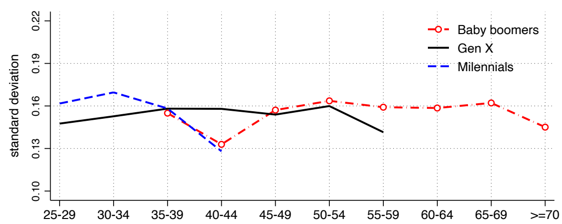
ity does not translate into more mental health inequality. There is at least one reason why this could be the case. First, it would be possible that there are other determinants of mental health beyond health and economic conditions. Second, it could also be the case that the presence of depression symptoms is associated mostly with whether very basic needs are satisfied or not. In particular, in a high-income country like the United States, these needs are mostly satisfied. We can not provide more light on why this is the case, as this would require either observing data on a poorer country or having other informative covariates for mental health inequality.

Figure 12: Alternative measures of dispersion of depression symptoms

(a) Coefficient of variation



(b) SD conditional on $K6 \neq 0$



Note: Figure plots the evolution of alternative measures of mental health inequality over the life cycle. Panel (a) plots the coefficient of variations, and panel (b) shows the standard deviation conditional on having depression symptoms. Patterns for three different cohorts are presented. Baby Boomers, born between 1946 and 1964, are shown as a red dashed line with circular markers; Generation X, born from 1965 to 1980, is depicted as a solid black line; and Millennials, born between 1981 and 1996, are represented by blue dashed lines.

4 A statistical model for mental health

In this section, we propose and estimate a statistical model to characterize the dynamics of mental health. The model is parsimonious enough to be incorporated into a structural life-cycle model and captures the main empirical facts documented in this paper: (i) a large mass point of individuals without depression symptoms, (ii) recovery probabilities, (iii) duration dependence in the likelihood of transitioning from different states of mental health, and (iv) compositional heterogeneity by fixed labor productivity and initial presence of depression.

4.1 Elements and dynamics of the model

Figure 13 illustrates the timeline between two consecutive periods and the elements of the model. An individual i ends her age t with a mental health history of the last three periods $\mathfrak{m}_t = \{m_{i,t-2}, m_{i,t-1}, m_{i,t}\}$. This history is summarized by the realization of $m_{i,t}$, and the multinomial variables $d_{i,t}^{health}$ and $d_{i,t}^{sick}$. The former captures the number of consecutive periods in which an individual has reported no depression symptoms, while the latter describes how many consecutive periods the same individual has been with any depression symptoms:

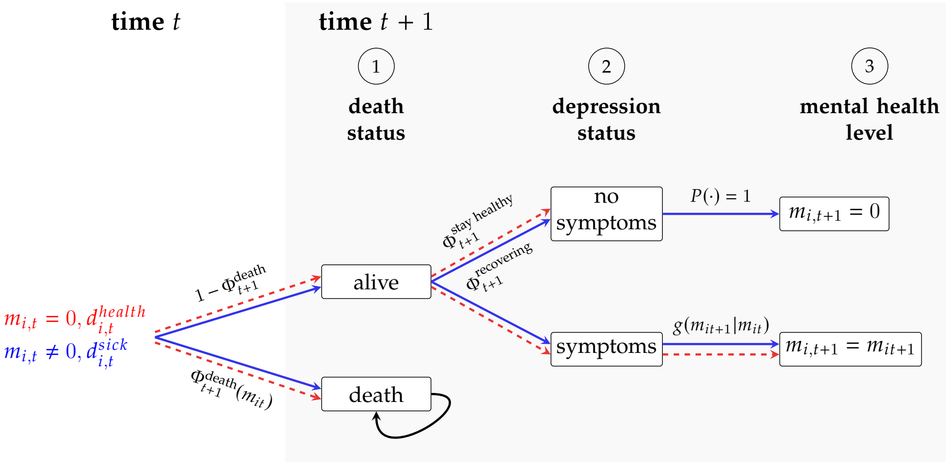
$$d_{i,t}^{healthy} = \begin{cases} 2 & \text{if } m_{i,t} = 0, m_{i,t-1} = 0, m_{i,t-2} = 0 \\ 1 & \text{if } m_{i,t} = 0, m_{i,t-1} = 0, m_{i,t-2} \neq 0 \\ 0 & \text{if } m_{i,t} = 0, m_{i,t-1} \neq 0, \exists\, m_{i,t-2} \end{cases} \qquad d_{i,t}^{sick} = \begin{cases} 2 & \text{if } m_{i,t} \neq 0, m_{i,t-1} \neq 0, m_{i,t-2} \neq 0 \\ 1 & \text{if } m_{i,t} \neq 0, m_{i,t-1} \neq 0, m_{i,t-2} = 0 \\ 0 & \text{if } m_{i,t} \neq 0, m_{i,t-1} = 0, \exists\, m_{i,t-2} \end{cases}$$

Mortality risk: To control for attrition coming from mortality we include mortality risk in our model. Individuals alive in period t die in the next period with probability $\Phi_{t+1}^{\text{death}}$ which depends on observable characteristics. Following standard literature, we model death probability as a probit that has a quadratic polynomial in age and frailty as covariates:

$$\Phi_{t+1}^{\text{death}}(\cdot) = \Phi(h_t, h_t^2, f_t, f_t^2), \tag{3}$$

where Φ denotes the cumulative distribution function of the standard normal distribution, h_t is age, and f_t is physical health. It is important to mention that we estimate mortality using data from the Health and Retirement Study (HRS) as it has more observations for the elderly where most of the mass of deaths happen.

Figure 13: Mental health dynamics



Note: Timeline of mental health symptomatology.

At the begining of period $t+1$ and conditional on surviving, a realization for the stochastic variable that characterizes physical health ($f_{i,t+1}$) is drawn. In the next period, mental health dynamics is then determined conditional on the realization of f_{it+1}

Transitions from no-depression symptoms state: An individual who does not experience any depression symptoms at t and survives to $t+1$ stays without any in the same state ($m_{it+1}=0$) with probability $\Phi^{\text{stay healthy}}_{t+1}$ ruled by the following specification:

$$\Phi^{\text{stay healthy}}_{t+1}(\cdot)=\Phi(h_{t+1},h^2_{t+1},f^2_{t+1},f^2_{t+1},dep_{17},d_\gamma,d^{health}_t) \tag{4}$$

In line with the stylized facts, we include duration dependence as an explanatory variable due to emboid the model with a long-memory. Fixed labor productivity (γ) is added to the model due to its impact on the composition of mental health. We include fixed-labor productivity with the variable d_γ that indicates whether an individual belongs to the middle or top tercile of the fixed-labor productivity distribution. In other words, that captures possible effects on transitions that arise from fixed-labor productivity, relative to the ones at the bottom tercile. We also include the variable dep_{17}, which denotes a dummy variable that indicates whether an individual had depression as a teenager or not. This last variable captures ex-ante possible propensities to get depression symptoms. On the contrary, if the same individual gets depression symptoms at $t+1$, a strictly positive level of $m_{i,t+1}$ is drawn. We give more details about how this value is drawn below.

Transitions from depression symptoms states: If an individual reports a strictly positive level of m_{it} and survives to the next period, there are two possibilities: she can either fully recover in period $t+1$ or remain with depression symptoms. Recovering occurs with probability $\Phi_{t+1}^{\text{recovery}}$, which among other covariates, depends on the number of consecutive periods the individual has experienced depression symptoms (d_{it}^{sick}) and the level of depression symptoms currently experienced (m_{it}). As before, we model this probability as a probit model with the specification:

$$\Phi_{t+1}^{\text{recovery}}(\cdot) = \Phi(h_{t+1}, h_{t+1}^2, f_{t+1}, f_{t+1}^2, dep_{17}, d_\gamma, d_t^{sick}), \tag{5}$$

If she does not recover, she draws a different strictly positive level of mental health deficits from the following process:

$$\ln(m_{t+1}) = dep_{17} + d_\gamma + X_{t+1}'\beta + s_{t+1}, \tag{6}$$

In this specification, we allow for mental health to have a deterministic and a stochastic component. The deterministic component includes the two forms of ex-ante heterogeneity descrtibed above: presence of depression symptoms as a teenager (dep_{17}) and innate differences in labor productivity (d_γ). In addition, we include a set of covariates $X_{t+1} = [h_t, h_t^2, h_t^3, h_t^4, f_t, f_t^2]$, which captures the life-cycle dynamics and also the variability by physical health.

The stochastic component is composed of a persistent component η and a fully-transitory shock ν:

$$s_{t+1} = \eta_{t+1} + \nu_{t+1} \tag{7}$$

$$\eta_{t+1} = \rho_\eta \eta_t + \epsilon_{t+1} \tag{8}$$

where η_{it} follows an AR(1) process with a persistence coefficient of ρ_ν, ϵ_{ij} is a zero-mean normally distributed variable with variance σ_ϵ^2. Finally, ν_t captures transitory fluctuations in mental health. We assume that $\nu_{ij} \sim N(0, \sigma_\nu^2)$.

Physical Health: As seen before, physical health is an important covariate in all transitions of our mental health model. As such, and because we estimate our model through simulations, it is important to have a proper model and measure for physical health. To do this, we follow Hosseini et al. (2022). First, we use the previously computed frailty index to measure physical health. The frailty index represents the cumulative total of all negative health events that an individual has experienced. Generally, the frailty index combines deficits from the following categories:[8]

- Restrictions or difficulty in activities of daily living (ADL) and instrumental ADL (IADL), such as difficulty eating, dressing, or managing money. I refer to these as ADL/IADL variables.

- Medical diagnosis or measurement such as has, or had, high blood pressure, diabetes, heart disease, cancer, or high BMI and is a current or former smoker.

- Mental or cognitive impairment such as loss of memory or mental ability or diagnosis of psychological problems. I refer to these as mental health variables.

There is also an important mass of individuals without physical health deficits which reduces as people age. The probability of staying with zero frailty in the next period follows:

$$P(f_{it+1} = 0 | f_{it} = 0) = \Phi(h_{it}, h_{it}^2, h_{it}^3, h_{it}^4),$$

As in Hosseini et al. (2022), with rule out for the possibility of recovery in physical health as it is significantly lower than in the case of mental health and quickly decreases with age. The nonzero dynamics of frailty is governed by the following process:

$$\ln(f_{it+1}) = \beta_1 h_{it+1}^1 + \beta_2 h_{it+1}^2 + \beta_3 h_{it+1}^3 + \beta_4 h_{it+1}^4 + s_{it+1}^f, \tag{9}$$

where s_{it+1}^f denotes the stochastic component of physical health. We allow for physical health to exhibit ex-ante heterogeneity and be subject to both persistenet and transitory shocks:

$$s_{it+1}^f = \alpha_i^f + \eta_{it+1}^f + \nu_{it+1}^f \tag{10}$$

$$\eta_{it+1}^f = \rho_\eta^f \eta_{it}^f + \epsilon_{it+1}^f \tag{11}$$

with α^f describing the individual-specific ex-ante heterogeneity in initial frailty levels.

[8] The full set of deficits we consider to measure physical health can be found in the Appendix **??**

We assume that α^f follows a normal distribution across individuals with mean zero and variance $\sigma^2_{\alpha,f}$. This could be interpreted as being attributed to genetic factors. The second component characterizes the random nature of individuals' health events over their life cycles. The shocks ϵ^f, and ν^f are assumed to be independent of each other and independent of α^f. Both, are normally distributed with mean 0 and variance $\sigma^2_{\epsilon,f}$ and $\sigma^2_{\nu,f}$, respectively.

4.2 Estimation

We estimate using a sequential approach. In the first step, we estimate those parameters that govern mortality, recovery, the likelihood of staying with zero frailty, and the likelihood of staying without symptoms of depression. In other words, we estimate those parameters that can be estimated directly from the data. In a second step, we estimate the parameters related to the nonzero dynamics of physical health using the simulated methods of moments (SMM). It is important to remember that in our model, physical health affects mental health but not vice-versa, that is what allows us to perform this step. Finally, using the estimates from the first two steps, we estimate the parameters of the nonzero dynamics of mental health using also SMM.

For both frailty and mental health, we compute two types of target moments. The first set of moments consists of means of the log of our measures of health by a two-year-age group from 25 to 75 years old for males with a high school diploma. These moments are informative about the deterministic component. Importantly, we separately target the average level of depression symptoms by tercile of fixed-labor productivity and also by whether an individual had depression as a teenager or not. The second set of parameters consists of the autocovariance age profiles of the stochastic part conditional on survival. These moments are informative about the parameters governing the stochastic component of depression[9]. On the other hand, conditional on the set of parameters θ, we simulate the history of 50 thousand individuals. Our simulations are done such that they are consistent with the initial mass of individuals without depression symptoms for the case of mental health and without physical health deficits for the case of frailty. Let $m_k^{sim}(\theta)$ and m_k^{data} denote the vector of model-generated moments given a vector of parameters θ and the data-based moments, respectively.

[9]We target a total of 201 moments for mental health and 152 moments for physical health

The subscript k indexes physical and mental health, $k = \{\text{physical}, \text{mental}\}$. Then, the parameters are chosen to solve:

$$\hat{\theta} = \underset{\theta \in \Theta}{\text{argmin}} \left[m_k^{data} - m_k^{sim}(\theta)\right]' W[m_k^{data} - m_k^{sim}(\theta)].$$

where W is the optimal weighting matrix that minimizes the asymptotic variance of our estimates.

4.3 Results

Table 4 shows our estimated coefficients for $\Phi^{mortality}$. Consistent with former estimates, mortality risk increases with age and frailty with certain nonlinearities. Table 5 reports the estimated coefficient for $\Phi^{\text{no symptoms}}$ and $\Phi^{\text{recovering}}$ over 5-year age groups. Consistent with the graphical analysis, the probability of reporting no symptoms increases as people age. People with worse contemporaneous physical health outcomes report lower probabilities of remaining without depression symptoms. Estimates for ex-ante heterogeneity show that people who experienced depression during adolescence have a significantly lower probability of staying without depression symptoms. Moreover, our results also confirm that the coefficients of duration dummies are statistically significant and positive, suggesting that the longer an individual has remained without depression symptoms, the more likely is that she will remain in that stage. Regarding the probability of recovery, the estimates suggest a non-linear effect of the physical health deficits and previous periods of mental health. In particular, the worse is physical and mental health, the lower the chances of recovery. As before, there are significant effects of ex-ante heterogeneity and duration. Meanwhile, figure 14 depicts the model fit for the first step. The dots represent the empirical probabilities while the dashed red line represents our estimates. Both panels show the good fit of the estimated model for the first step.

Table 6 shows second-step estimation results. Our results show that there is a non-linear relationship between depression symptoms and age. It also shows that physical health increases the severity of depression symptoms[10]. Furthermore, the picture shows that consistent with our empirical analysis, the presence of depression as a

[10]Our estimates for the parameters governing physical health can be found in the Tables 11 and 12.

Table 4: Estimated parameters, mortality

	constant	h_t	h_t^2	f_t	f_t^2
$\Phi^{\text{mortality}}$	-3.33^{***}	-0.84^{*}	4.18^{***}	2.57^{***}	-0.35^{**}

Note: Table reports estimated coefficients for $\Phi^{\text{mortality}}$. The model was estimated using the whole sample including dummies for sex-at-birth and education level. Reported constant was constrained for our sample of interest. We normalize age $h_t = \left(\frac{age-25}{100}\right)$. Significance levels: * p-val<0.1, ** p-val<0.05, *** p-val<0.01.

Table 5: Estimated parameters, zero transition dynamics

	constant	h_t	f_t	f_t^2	dep_{17}	γ $\gamma=2$	 $\gamma=3$	duration $d_t=1$	 $d_t=2$	mental health m_{t-1}	 m_{t-1}^2
$\Phi^{\text{no symptoms}}$	-0.14^{***}	0.50^{***}	-1.99^{***}	-	-0.29^{***}	0.04	0.04	0.29^{***}	0.79^{***}	-	-
$\Phi^{\text{recovering}}$	0.01^{*}	0.43^{***}	-2.57^{***}	2.81^{***}	-0.21^{***}	-0.07^{***}	-0.11^{***}	-0.23^{***}	-0.74^{***}	-3.61^{***}	3.16^{***}

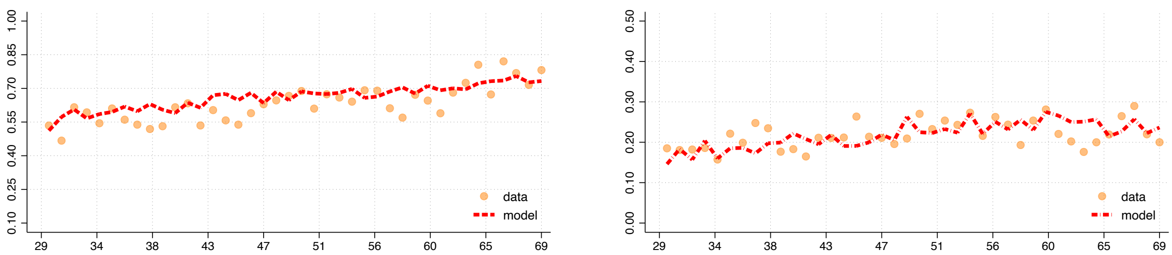
Note: Table reports estimated coefficients for $\Phi^{\text{no symptons}}$ and $\Phi^{\text{recovering}}$. Models were estimated using the whole sample including dummies for sex-at-birth and education level. Reported constant was constrained for our sample of interest. We normalize age $h_t = \left(\frac{age-25}{100}\right)$Adding quadractic frailty in $\Phi^{\text{no symptons}}$ gives not significant results. Significance levels: * p-val<0.1, ** p-val<0.05, *** p-val<0.01.

teenager is associated with higher depression symptoms during adulthood. Finally, we find that there is a non-monotonic relationship between fixed labor productivity and depression symptoms. In particular, it can be observed a negative effect on depression symptoms from being in the second tercile of fixed labor productivity relative to the bottom tercile, while this effect is positive if one belongs to the top tercile.

Relative to the stochastic component, we find that the persistence coefficient for η is 0.77 which is lower than the typical estimate (usually above 0.9). Based on the small variance of the transitory component, we argue that persistent shocks account for the most part the volatility within the nonzero dynamics. Figure 15 shows that

Figure 14: Model Fit: Zero dynamics

(a) $\Phi^{\text{no symptoms}}$ (b) Φ^{recovery}



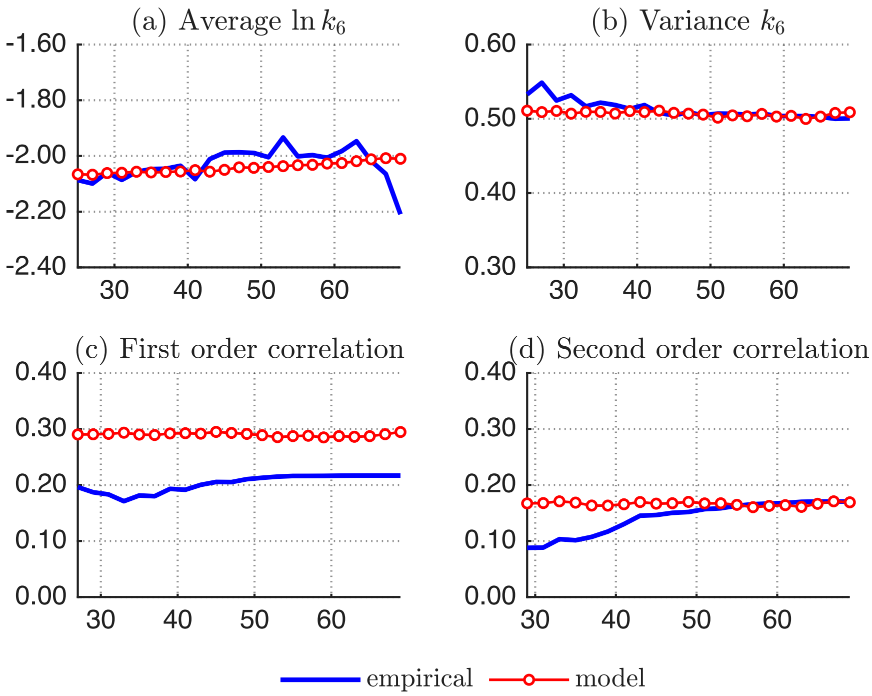
the model does a good job fitting average depression incidence, variance, and the first-autocovariance.

Table 6: Estimated parameters, non-zero dynamics

	constant	h_{it}	h_{it}^2	h_{it}^3	h_{it}^4	f_{it}	f_{it}^2	dep_{17}	$\gamma == 2$	$\gamma == 3$
$\ln(m_{it})$	-2.10	0.07	0.13	0.001	-0.01	0.09	0.1	0.1	-0.08	0.38
$\rho_\eta = 0.72$		$\sigma_\nu^2 = 0.19$		$\sigma_\epsilon^2 = 0.0002$						

Note: Age has been normalized to lie between 0 and 1. Significance levels: * p-val< 0.1, ** p-val< 0.05, *** p-val< 0.01.

Figure 15: Model fit - Nonzero dynamics

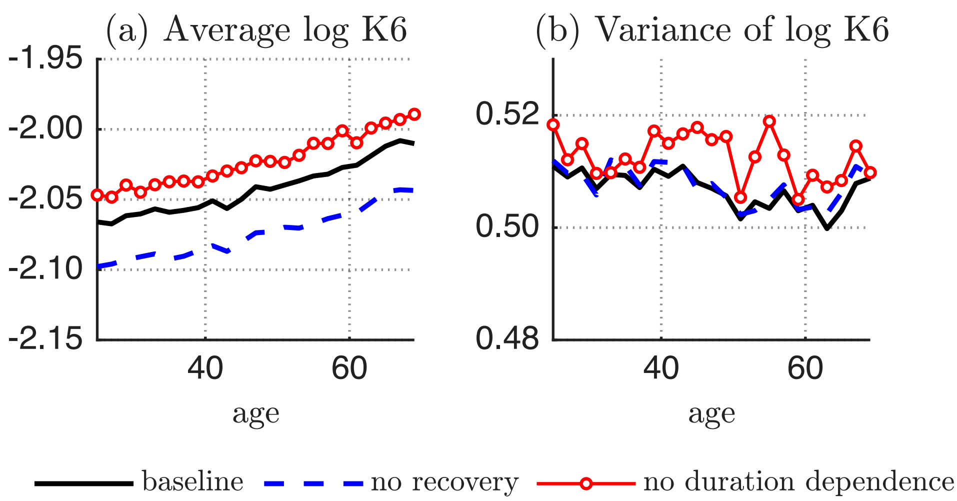


Note: Figure shows the fit of the estimated statistical model. Solid blue line represents empirical moments while red line with markers are those computed from the model.

To assess which elements of our model matter for accounting the empirical properties observed in the data, we shut down one-by-one different components of the model and assess how much the produced moments change relative to our baseline model.

No recovery: We begin our analysis by considering a counterfactual scenario in which recovery from depression is not possible. The results, presented in Figure 16, indicate that disabling the recovery mechanism leads the model to generate strictly positive values for depression symptoms. These values can either increase or decrease the conditional mean values of depression symptoms. Notably, individuals with a higher likelihood of recovery in the baseline model tend to be those with favorable physical health and no history of teenage depression. When recovery is removed, these individuals disproportionately remain in the population with persistent symptoms, thereby skewing the distribution. As a result, the model systematically underestimates the mean level of depression symptoms due to the lower-than-average symptom values drawn for this subgroup. In contrast, the impact of excluding recovery on the variance of the residuals that come from the part of depression symptoms that is not explained by observable variables depression symptoms appears to be minimal.

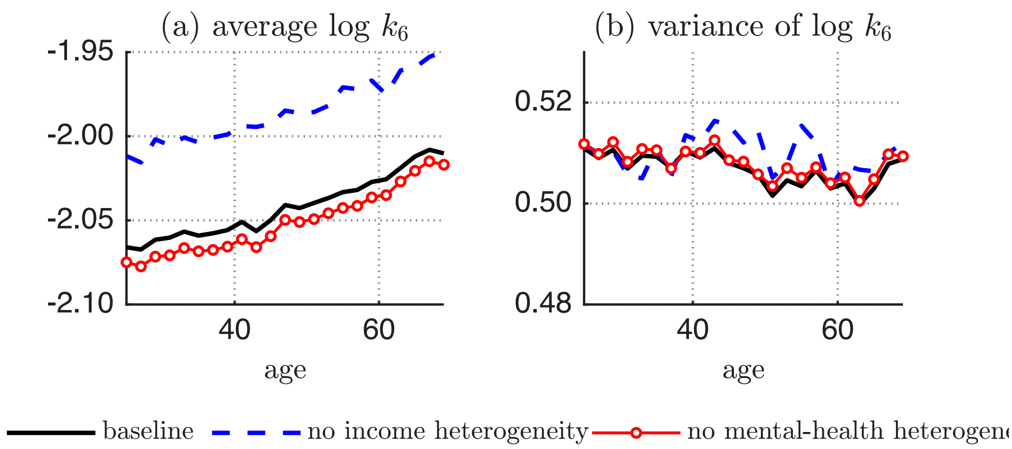
Figure 16: Counterfactual 1: No Recovery and No Duration Dependency



Note: The black line represents the baseline simulation of the mean of log k6 and the variance of its residuals (see equation (11)). Dashed blue line shows the counterfactual excluding recovery in the model and red line with market simulate the model assuming no effects of duration.

No Duration Dependence: We next assess the quantitative importance of incorporating duration dependence in the model. In our framework, duration dependence influences both the likelihood of recovery from depression and the probability of remaining without symptoms. To evaluate its role, we conduct a counterfactual exercise by setting the coefficients on the duration dummies to zero in both the recovery and zero-to-zero transition equations. The results, presented in Figure 16, reveal that omitting duration dependence leads the model to overestimate the prevalence of depression symptoms. As previously discussed, the probability of remaining symptom-free increases with the number of consecutive periods without symptoms. Removing this mechanism reduces the likelihood of sustained remission, thereby increasing the mass of individuals experiencing symptoms. At the same time, excluding duration effects in the recovery process results in individuals with longer histories of symptoms being more likely to recover than under the baseline, which introduces additional zeros into the distribution. Although the overall effect on the mean level of depression symptoms is not analytically straightforward, our quantitative findings indicate that the absence of duration dependence results in an upward bias in both the mean and the variance of depression symptoms. Notably, the variance of the residuals increases, suggesting a greater portion of individual heterogeneity is left unexplained by observable characteristics when duration dependence is excluded.

Figure 17: Counterfactual: Duration Dependence



Note: The black line represents the baseline simulation of the mean of log k6 and the variance of its residuals (see equation (11)). Dashed blue line shows the counterfactual excluding income heterogeneity in the model and red line with market simulate the model assuming no initial depression as a teenager.

No Fixed-Labor Productivity Heterogeneity: To evaluate the quantitative importance of incorporating fixed-labor productivity heterogeneity, we conduct a counterfactual exercise in which the parameters associated with the terciles of fixed labor productivity are set to zero. This adjustment affects the nonzero dynamics, as well as the recovery and healthy state transition processes. Figure 17 presents the results of this exercise. Removing fixed-labor productivity heterogeneity leads to a substantial overestimation of depression symptoms. This outcome is largely driven by the fact that the estimated coefficients for the top tercile of labor productivity are sizable and negative in the nonzero dynamics equation. Without this mitigating effect, the model predicts higher levels of depressive symptoms across the population. In addition, excluding fixed labor productivity increases the likelihood of recovery. These combined effects contribute to the observed upward bias in depression prevalence. Finally, the counterfactual also results in a notable increase in the variance of the residuals, indicating that a greater portion of the variation in depression symptoms remains unexplained when this source of heterogeneity is omitted.

No Depression as a Teenager: We conclude our counterfactual analysis by examining the role of ex-ante heterogeneity in mental health, captured through a dummy variable indicating whether an individual experienced depression during adolescence. To assess its importance, we set to zero the coefficients associated with this indicator in the recovery, healthy-state, and nonzero dynamics equations. According to our baseline estimates, early-onset depression is associated with lower recovery rates, reduced likelihood of remaining symptom-free, and higher severity of symptoms when present. Removing this source of heterogeneity results in a notable underestimation of depression symptoms over the life cycle. This occurs because individuals with a history of teenage depression, who typically face worse outcomes, are treated identically to those without such a history in the counterfactual. Despite the substantial impact on the mean level of symptoms, the omission of this ex-ante heterogeneity has only minimal effects on the variance of the residuals. This suggests that while early mental health status plays a key role in shaping the average trajectory of symptoms, it contributes relatively little to the unexplained variation once other observables are accounted for.

Taken together, the counterfactual exercises underscore the importance of incorporating key behavioral mechanisms and sources of heterogeneity in modeling the dynamics of depression symptoms. Excluding recovery results in a systematic underestimation of mean symptom levels, as individuals who would otherwise recover remain persistently symptomatic. Omitting duration dependence biases the model toward higher symptom prevalence and greater unexplained variability, by disrupting the realistic timing of recovery and sustained health. Removing fixed-labor productivity heterogeneity leads to a marked overestimation of both the level and dispersion of symptoms, reflecting the loss of a strong mitigating factor among higher-productivity individuals. Finally, ignoring early-life mental health status significantly understates the burden of depression across the life cycle, although its effect on residual variance is limited. Overall, these results highlight that both dynamic features and ex-ante heterogeneity are critical to accurately capturing the empirical patterns in mental health outcomes.

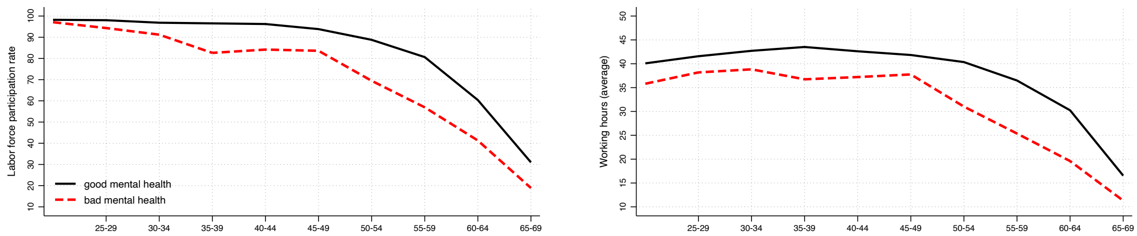
5 Application: a life-cycle model with labor supply decisions

In this section, we develop a quantitative model for working-age individuals that incorporates the dynamics of mental health. The primary objective is to demonstrate an application of our statistical framework and to evaluate the importance of modeling mental health as a stochastic process with rich dynamics. The model focuses on the channels through which mental health influences labor supply decisions. This is motivated by the significant disparities in labor supply—both at the extensive and intensive margins—observed across mental health statuses over the life cycle, as illustrated in Figure 18. Panel (a) of the figure highlights differences in the extensive margin, showing that labor force participation varies substantially by mental health status and that this gap widens with age. To do this exercise, we classify individuals with bad mental health as those with a normalized $K6$ index greater than 0.3. Notably, during middle age, individuals with poor mental health exhibit labor force participation rates more than 10 percentage points lower than those of their counterparts with good mental health. Panel (b) presents differences in the intensive margin, displaying average weekly hours worked, conditional on employment. Similar to the extensive margin, individuals with poor mental health consistently work fewer hours than those with good mental health, with the disparity increasing over the life cycle. The following sections describe our model in detail.

Environment: We consider a decision problem in a life-cycle model populated by a continuum of individuals of measure one. Individuals are born with an initial financial wealth a_1, initial physical health f_1, and initial mental health m_1. Individuals in this model make two decisions: saving/consumption and labor supply decisions. The model contemplates uncertainty regarding labor productivity, physical health, and

Figure 18: Labor force participation and hours of work by mental health status.

(a) Labor force participation (b) Hours of work per week



Note: Figure illustrates differences in labor supply by mental health status along both the extensive and intensive margins. Individuals are classified as having poor mental health ("bad") if their K6 mental health index exceeds 0.3. Panel (a) presents labor force participation rates by mental health status, while panel (b) displays average weekly hours worked, conditional on employment. All values are calculated using five-year age group averages.

mental health. Because we are interested in labor supply decisions, we only model the working stage of individuals. In particular, life in this model starts at 25 and ends at 70.

Preferences: Households have separable preferences over consumption and leisure. The following utility function represents these preferences:

$$u(c,\ell) = \frac{c^{1-\psi}}{1-\psi} - \phi_{\mathrm{w}}(m)\mathbb{I}_{\{\ell>0\}}$$

We assume that labor supply is indivisible; therefore, in each period, people must choose whether to work or not. In that sense, $\mathbb{I}$ is an indicator function that takes the value of 1 when an individual chooses to work and zero otherwise. Conditional on working, the disutility from work is amplified with depression symptoms. This is captured by the function $\phi_w(m)$, which we assume takes the form of $\phi_{\mathrm{w}}(m) = \phi_m(1+m^{1+\alpha})$ with $\phi_m > 0$ and $\alpha > 0$. Then, the utility function can be written as:

$$u(c,\ell) = \frac{c^{1-\psi}}{1-\psi} - \phi_m\left(1+m^{1+\alpha}\right)\mathbb{I}_{\{\ell>0\}}$$

Notice that an individual receives disutility from labor even when she does not experience depression symptoms ($m = 0$). In that sense, ϕ_m captures the disutility from labor regardless of mental health status.

Time Endowment: individuals are endowed with one unit of time in each period. However, in the presence of depression symptoms, this endowment of time is reduced as a consequence of rumination or overthinking. The following expression represents the time endowment for work as a function of depression symptoms:

$$\bar{\ell} = e^{-\theta m}$$

The parameter θ captures the effect of mental health on time endowment. Through this channel, depression generates two effects: 1) it reduces the likelihood that an individual decides to work as it makes working less appealing (lower income), and 2) it reduces the number of hours an individual works, conditional on choosing to work.

Labor productivity and physical health: Labor productivity has a deterministic and a stochastic component. The deterministic component captures the effects of age and physical health on how productive individuals are at work. The stochastic component, which we denote by s^{ω}, comprises a fixed component (γ^{ω}), which captures ex-ante heterogeneity, which is related to what we called previously fixed-labor productivity. The stochastic component has a persistent component (ν_t^{w}). In this way, labor productivity is given by:

$$\begin{aligned} ln(\omega_{it}) &= \beta_0^{\omega} + \beta_1^{\omega} h_{it}^1 + \beta_2^{\omega} h_{it}^2 + \beta_3^{\omega} f_{it} + \beta_4^{\omega} f_{it}^2 + s_{it}^{\omega} \\ s_{i,t}^{w} &= \gamma_i^{\omega} + \eta_{i,t}^{\omega} \qquad , \epsilon^{\omega} \sim N(0, \sigma_{\epsilon,\omega}^2), \\ \eta_{i,t}^{\omega} &= \rho_{\eta}^{\omega} \eta_{i,t-1}^{\omega} + \epsilon_{i,t}^{\omega} \quad , \end{aligned}$$

Where h represents age and f represents physical health (frailty). Physical health is modeled as in our statistical model, except that for computational purposes, we shut down transitory shocks of this variable.

Markets: markets are incomplete as individuals only have access to a risk-free asset that yields a gross return R, which they can purchase every period. Individuals are subject to a borrowing limit given by $\overline{b}$. We assume that individuals start their lives with zero assets. The cash-on-hand of any individual at period t is then:

$$coh_t = [\omega_{it}\exp(-\theta m_t)]\,\mathbb{I}_{\{\ell>0\}} + Ra_t.$$

Timeline: At the beginning of each period, individuals learn about their frailty, mental health history, and productivity. Based on this information, they make consumption/savings decisions and labor supply decisions.

Individual Decision Problems To ease notation, we denoted a subset of our state variables at age t as:

$$X_t \equiv (t, a_t, f_t, \{m_{t-i}\}_{i=0}^{2}, \omega_t). \tag{12}$$

The set of state variables X_t is composed of age (t), the level of assets a_t, physical health (f_t), the levels of mental health for the last three periods ($\{m_{t-i}\}_{i=0}^{2}$), and labor productivity (ω_t). We restrict our history tracking of mental health to three periods for computational feasibility. Individuals who are in their working stage need to make two decisions: 1) consumption and savings, and 2) labor supply decisions. We denote consumption by c, and savings for the next period as a'. Let $V(x)$ denote the value function of an individual with state variables x. In each period, the individual needs to decide whether to work or not $\ell_t \in \{\text{work}, \text{no work}\}$:

$$V(x_t) = \max_{\ell_t}\{V_t^{\ell_t=\text{work}}(a_t, x_t), V_t^{\ell_t=\text{no work}}(x_t)\}$$

If the household chooses to work, the value function is

$$\begin{aligned} V_t^{\ell_t=\text{work}}(x_t) &= \max_{c_t, a_{t+1}} \frac{c_t^{1-\psi}}{1-\psi} - \phi_m(1+m_t^{1+\alpha}) + \beta\delta(x_t)\mathbb{E}[V(x_{t+1})|x_t] \\ s.t \quad & c_t + a_{t+1} \leq e^{z_t}e^{-\theta m_t} + Ra_t \\ & a_t \geq -b \end{aligned}$$

In contrast, if the household chooses not to work, the value function is

$$V_t^{\ell_t=\text{no work}}(x_t) = \max_{c_t, a_{t+1}} \frac{c_t^{1-\psi}}{1-\psi} + \beta\delta(x_t)\mathbb{E}[V(x_{t+1})|x_t]$$

$$s.t \quad c_t + a_{t+1} \leq Ra_t$$

$$a_t \geq -b$$

Our model generates dispersion in labor force participation essentially through mental health and physical health. Individuals with poor mental health spend more time ruminating and have fewer space to generate labor income (lower returns of working), and also experience higher disutility from working. In the case of physical health, this variable is affects labor force participation through its effect on mental health, and also through its direct effect on labor productivity. As people engage in poor physical health, they experience a decline in their labor productivity and also experience higher depression symptoms, which further increases the chances of participating in the labor market.

5.1 Calibration

Our model has three sets of parameters. The first set is based on values commonly used in the existing literature and includes the discount factor (β), set to 0.98; the gross interest rate (R), set to 1.02; and the risk aversion parameter (ψ), which is set to 2 in line with standard assumptions. The second set consists of parameters related to mortality, physical health, labor productivity, and mental health. These parameters are calibrated directly from the data and are informed by our empirical analysis.

Finally, the third set of parameters is composed by the one governing the disutility from labor (ϕ_m), the nonlinear effect of mental health on labor disutility (α), and the effect of mental health one's time endowment (θ). To calibrate these parameters, we use the SMM method and discipline the model to ensure consistency with the labor force participation profile across the life cycle of individuals with and without depression symptoms. The labor force participation of individuals without depression symptoms is informative for calibrating ϕ_m, as it provides the disutility for someone with $m = 0$. The labor force participation of individuals with depression is informative for α , as we document differences in labor force participation by mental health status. Finally, we also discipline the model to be consistent with the intensive margin of labor supply for individuals with and without depression symptoms, which captures the effect that mental health has on time endowment.

5.1.1 Calibration Results

Table 7 shows our calibration results. Our estimated parameter for α suggests that the effect of depression symptoms on labor disutility is not linear. ϕ_m is negative as expected. Notice that because we want to focus only on the role of mental health, we do not make this parameter vary by physical health. Finally, our calibrated value for θ suggests that an increase of depression symptoms by a standard deviation reduces the effective time endowment by 2.6%.

Table 7: Calibrated parameters

Parameter	α	ϕ_m	θ
Value	-0.68	0.62	0.17

5.1.2 Model Fit

Figure 19 illustrates the model's fit to the targeted moments. The model closely replicates labor force participation across the life cycle up to age 70, beyond which the data reveal a more pronounced decline. This pattern largely reflects the fact that a considerable proportion of individuals retire around age 65. Given that the model does not explicitly incorporate a retirement decision, it is less capable of accurately capturing labor market behavior at this later stage. Importantly, the model successfully reproduces the observed gap in labor force participation by mental health status. It also provides a good fit for the number of hours worked per week across the life cycle, differentiated by mental health condition. Having established that the model reliably captures these key features of labor market behavior, we now proceed to analyze the monetary and welfare consequences associated with poor mental health.

5.2 Measuring the monetary and welfare losses from depression symptoms

Within our model, monetary losses associated with the presence of depressive symptoms arise either by from individuals exiting the labor market or from a reduced time

Figure 19: Model fit

Note: the figure presents the model fit by comparing the calibrated model's predictions with their empirical counterparts. The model specifically targets two key labor market outcomes: the labor force participation rate and the average hours worked, distinguishing between individuals with and without depressive symptoms. Panel (a) displays the results for individuals without depressive symptoms ("good" mental health), while panel (b) shows the results for those with depressive symptoms ("bad" mental health). All values are computed as averages within two-year age intervals. In each panel, red lines represent the model-generated moments, and blue lines represent the corresponding empirical data.

endowment conditional on continued participation. The objective of this exercise is to quantify the lifetime income losses attributable to experiencing depressive symptoms during the working phase of life. To conduct this analysis, we follow the approach of De Nardi et al. (2024), computing income trajectories for individuals who, in the baseline simulation, exhibit poor mental health but are counterfactually assumed to have no depressive symptoms keeping decisions fixed. Formally, let y^{BS} and y^{NS} denote the lifetime income sequences for an individual in the baseline simulation and in the no-symptom counterfactual, respectively. Following De Nardi et al. (2024), we define the lifetime cost of depressive symptoms as the average discounted difference between the two income paths, computed as $\frac{1}{\hat{T}} \sum_{t=1}^{\hat{T}} \frac{y_{it}^{NS} - y_{it}^{BS}}{R^t}$.

The results of this exercise are presented in Table 8. All of our variables are expressed in 2024 US dollars. Our results indicate that, in the absence of depressive symptoms—while holding all individual histories equal to those in the baseline scenario—the average monetary loss per individual amounts to $568.70. To contextualize this figure, cite{denardipaschenko2023} estimate that average earnings losses associated with poor overall health are approximately $1,031 for working individuals, suggesting that the economic impact of depression symptoms alone is considerable. Furthermore, we find significant heterogeneity in monetary losses based on individuals' mental health status during adolescence, highlighting the relevance of ex-ante conditions in shaping the economic burden of poor mental health. Specifically, individuals without depressive symptoms as teenagers experience average losses of $555.20, while those who exhibited depressive symptoms during adolescence face considerably higher losses, averaging $986.60.

Table 8: Monetary losses from depression symptoms

	All	$dep_{17} = 1$	$dep_{17} = 0$
Monetary losses	568.7	986.6	555.2

Note: Monetary losses from depression symptoms over the life-cycle (working stage).

It is essential to note that we make the strong assumption that physical health influences mental health, but not vice versa. In reality, one might expect that poor mental health, particularly persistent episodes, could adversely impact physical health, potentially amplifying the economic losses associated with mental health conditions. Furthermore, we are omitting possible monetary costs that arise due to bad mental health such as medical appointments, medication, etc.

5.3 The welfare costs of depression symptoms

We next turn to measure the welfare losses that arise from depression symptoms. While the monetary losses are informative about how much labor income an individual loses on average from depression, it does not capture that depression also affects through other channels not directly related to the budget constraint. To meassure welfare effects, we follow De Nardi et al. (2024) and compute by how much consumption needs to be reduced for an individual to be indifferent with a scenario in which mental health is absent. In particular, we compute:

$$\tilde{V}^{BS} = \sum_{t=0}^{\hat{T}} U(c_t^{BS}, \ell_t^{BS}),$$

where $\tilde{V}^{BS}$ denotes the lifetime utility that is obtained under the baseline scenario. c_t^{BS} and ℓ_t^{BS} denote the optimal consumption and labor decisions in such a scenario. $\hat{T}$ denote the age at which an individual die or T. We compare this lifetime utility with the one corresponding to having unexpected good mental health over the life-cycle:

$$\tilde{V}^{NS} = \sum_{t=0}^{\hat{T}} U((1-\lambda)c_t^{NS}, (1-\lambda)\ell_t^{NS}),$$

c_t^{NS}, ℓ_t^{NS} are the optimal decisions under the counterfactual. Because mental health does not affect mortality in our model, individuals live the same in the baseline and the counterfactual scenario. Our variable of interest is λ, which denotes the amount of consumption that needs to be reduced on average over the life cycle to be indifferent to our baseline scenario.The results of this analysis are presented in Table 9. We find that depression symptoms generate substantial welfare costs, with significant heterogeneity based on individuals' mental health status during adolescence. On average, the welfare loss due to depression symptoms—measured as a compensating variation in consumption—is 13.8% across the population. This figure rises to 19.3% for individuals who experienced depression during their teenage years, compared to 13.6% for those who did not. To express these welfare costs in monetary terms, we compute $\lambda\bar{c}$ where $\bar{c}$ represents average lifetime consumption. The average monetary equivalent of the welfare loss is \$6,132.80 for the overall population. For individuals with a history of teenage depression, the loss amounts to \$8,861.20, whereas for those without such a history, the loss is \$ 6,048.60. These findings underscore the importance of ex-ante conditions in shaping the lifetime welfare costs associated with poor mental health.

Notably, this pattern aligns with the findings of De Nardi et al. (2024), who report substantial variation in the lifetime economic costs of poor health driven by initial health conditions.

Table 9: Welfare losses from depression symptoms

	All	$dep_{17} = 1$	$dep_{17} = 0$
Consumption equivalent compensation	\$6,132.8	\$8,861.2	\$6,048.6
(% consumption equivalence)	13.8%	%19.32	%13.6

Note: Welfare losses from depression symptoms over the life-cycle (working stage).

6 Conclusions

This paper explores the dynamics of depression symptoms over the life cycle, using data from the PSID for a sample of male individuals with a high school diploma. Our analysis identifies five key stylized facts, including the improvement of mental health with age, as people age, they experience more time without depression symptoms, mental health and its transitions are long-memory processes, a narrow connection with fixed labor productivity, and constant dispersion over the life cycle.

Building on these empirical regularities, we proposed a statistical model to capture the dynamics of mental health over the life cycle. Our model successfully captures the patterns observed in the data. Our results highlight the importance of incorporating recovery, duration dependence, fixed labor productivity, and ex-ante heterogeneity in modeling mental health, as excluding any of these introduces significant biases in estimating depression incidence. By capturing these elements, the proposed model provides a foundation for integrating mental health dynamics into structural life-cycle models.

We embed our statistical model within a quantitative life-cycle framework that incorporates heterogeneity in physical health, mental health, and labor productivity. The model is calibrated to capture observed differences in labor supply along both the extensive and intensive margins. Our results reveal substantial monetary and welfare losses associated with depressive symptoms, with significant heterogeneity depending on ex-ante conditions, proxied by the presence of depressive symptoms during adolescence.

Future research should aim to incorporate mental health into structural models to better evaluate policies designed to mitigate the costs and disparities associated with poor mental health. Additionally, this paper assumes a unidirectional relationship in which physical health influences mental health. A valuable direction for future work is to explore the joint dynamics of physical and mental health, accounting for their potential bidirectional interactions. In particular, it is crucial to disentangle the respective contributions of physical and mental health to overall welfare and monetary losses.

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A Frailty Index

Table 10: List of health deficits employed to construct frailty index (PSID)

Variable	Value
Some difficulty with ADL/IADLs	
Eating	Yes= 1, No= 0
Dressing	Yes= 1, No= 0
Getting in/out of bed	Yes= 1, No= 0
Getting outside	Yes= 1, No= 0
Using the toilet	Yes= 1, No= 0
Bathing/shower	Yes= 1, No= 0
Walking	Yes= 1, No= 0
Using the telephone	Yes= 1, No= 0
Managing money	Yes= 1, No= 0
Shopping for toilet items or medicines	Yes= 1, No= 0
Preparing meals	Yes= 1, No= 0
Doing heavy housework	Yes= 1, No= 0
Doing light housework	Yes= 1, No= 0
Ever had one of the following conditions	
High Blood Pressure	Yes= 1, No= 0
Diabetes	Yes= 1, No= 0
Cancer	Yes= 1, No= 0
Lung disease	Yes= 1, No= 0
Heart disease	Yes= 1, No= 0
Stroke	Yes= 1, No= 0
Arthritis	Yes= 1, No= 0
Asthma	Yes= 1, No= 0
Other chronic condition	Yes= 1, No= 0
BMI ≥ 30	Yes= 1, No= 0
Has ever smoked ≥ 30	Yes= 1, No= 0
Smokes now ≥ 30	Yes= 1, No= 0

B Frailty Dynamics over the Life Cycle

B.1 Zero frailty dynamics

The frailty dynamics over the life cycle statistical model follows Hosseini et al. (2022). Where a mass of people in good physical health conditions (zero frailty) at age 25, then each period, these people have either a probability of staying at zero frailty or 1 minus that probability of going to a bad physical health condtion (positive frailty value). Once a person's frailty becomes positive, it never goes back to zero (Hosseini et al., 2022).

Let f_{it} denote the frailty of individual i at time t t. Each period, the probability that the individual's frailty is zero follows a probit model, that is,

$$P(f_{it} = 0|Z_{it} = 0) = \Phi(Z_{it}^{'}\gamma),$$

where Φ is the cdf of the standard normal distribution and Z_{it} is a set of covariates: age, age2, high school graduate and college graduate education dummies, and a male gender dummy. The probability of having zero frailty conditional on having zero frailty in the previous period is given by

$$P(f_{it} = 0|f_{it-1} = 0) = P(f_{it} = 0|Z_{it})/P(f_{it-1} = 0|Z_{it} - 1).$$

B.2 Nonzero frailty dynamics

The log of the frailty index, $\ln f_{it}$, for individual i at period t is the sum of a deterministic component whose effect is common to all individuals and a residual that is individual-specific:

$$\ln f_{it} = X_{it}^{'}\beta + R_{it},$$

where β is a vector of coefficients and X_{iT} is a set of covariates that includes a fourth order age polynomial, high school graduate and college graduate education dummies, and a male gender dummy.The residual consists of two components and is given by

$$R_{it} = \alpha_i + z_{it} + u_{it},$$

where α_i is individual speciffic and allows to capture ex ante heterogeneity in individuals' initial frailty levels, and is assume normally distributed across individuals with mean zero and variance σ_α^2. The second component captures the dynamics in frailty as individuals go through various random health events over their life cycles. This component is the sum of an AR(1) process and a white noise shock ϵ_{it}.

$$z_{it} = \rho z_{it-1} + \epsilon_{it},$$

The shocks ϵ_{it} and u_{it} are assumed to be independent of each other and over time, and independent of α_i

C Additional calibration results

Table 11: Estimated parameters, zero transition dynamics (frailty)

	constant	h_{it}	h_{it}^2
$\Phi_f^{stayhealthy}$	1.05^{***}	-0.25^{***}	-0.55^{***}

Note: We normalize age $h_t = \left(\frac{age-25}{100}\right)$. The regression includes controls for sex and education dummies. Significance levels: * p-val<0.1, ** p-val<0.05, *** p-val<0.01.

Table 12: Estimated parameters, non-zero dynamics (frailty)

	constant	h_{it}	h_{it}^2	h_{it}^3	h_{it}^4
$\ln(f_{it})$	-1.87	0.62	2.88	-1.03	3.56
$\rho_\eta^f = 0.94$	$\sigma_{\nu,f}^2 = 0.01$	$\sigma_{\epsilon,f}^2 = 0.03$	$\sigma_{\alpha,f}^2 = 0.74$		

Note: We normalize age $h_t = \left(\frac{age-25}{100}\right)$.

Table 13: Estimated parameters, labor productivity

	constant	h_{it}	h_{it}^2	f_{it}	f_{it}^2
$\ln(\omega_{it})$	0.027^{***}	5.08^{***}	-11.17^{***}	-2.60^{**}	-1.30^{*}
$\rho_\eta^\omega = 0.72$		$\sigma_{\epsilon,\omega}^2 = 0.44$			

Note: We normalize age $h_t = \left(\frac{age-25}{100}\right)$. Significance levels: * p-val<0.1, ** p-val<0.05, *** p-val<0.01.