Depression, Risk Preferences and Risk-taking Behavior*

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Abstract: Depression affects the way that people process information and make decisions, including those involving risk and uncertainty. Our objective is to analyze the way that depressive episodes shape risk preferences and risk-taking behaviors. Using large, representative German household data we find no disparity in the behavioral risk preferences of the mentally well vs. depressed; yet depression is related to people's stated risk preferences and risk-taking behaviors in ways that are context-specific. We develop a conceptual model

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and show that differences in risk-taking behavior are largely explained by depression-related disparities in behavioral traits such as locus of control, optimism and trust.

Key Words: risk preferences; depression; mental health; risk-taking
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I. Introduction

Depression affects not only how people feel, but also the way they process information and make decisions. Psychologists note that people experiencing depressive symptoms often exhibit impairments in their decision making (Blanco et al. 2013; Chen et al. 2015). There is little to suggest, however, that depression is linked to deficits in general cognitive functioning or to biases in information processing across the board. Rather, the issue seems to be in the control of attention (especially in the face of hard-to-ignore, task-irrelevant information) and coping with negative automatic thoughts (see Matthews and Macleod 2005; Gotlib and Joormann 2010). During the acute phase of depression, people can have impaired executive function and memory for reasons which are not fully understood (Hammar and Årdal 2009). Overall, while “difficulty in making decisions is a core symptom of depressive illness, … the nature of these difficulties has not been well characterized” (Leykin et al. 2011 p. 333).

Our focus is on the way that risk preferences and risk-taking behaviors are shaped by depressive episodes. Choice almost inevitably involves an element of risk and uncertainty; this makes attitudes towards risk fundamental to understanding human behavior. Economists have shown that people’s willingness to take risks has consequences for their labor market and health outcomes, human capital investments, addictive behavior, financial decisions, and migration choices (e.g., Shaw 1996; see Schildberg-Hörisch 2018 for a review). The psychological evidence that people experiencing depression employ different decision-making strategies raises questions about whether this stems from their risk attitudes. Do risk attitudes differ by people's mental well-being? Are any depression-related disparities in risk preferences domain-specific or more pervasive? What mechanisms drive the divergence in the risk-taking behavior of those who do and do not experience depression? We are the first to address these questions using large-scale panel data that includes behavioral and stated risk preference measures as well as indicators of risk-taking behavior across multiple domains.[1]

Depression is both a pervasive and a costly public health issue. Common mental disorders, including depression, affect up to 20 percent of working-age adults across the OECD (OECD 2014), while worldwide more than 300 million people are thought to have suffered from depression in 2015 alone (WHO 2017). Common mental disorders add to society's overall disability burden more than severe mental disorders because their prevalence is so much higher (see ILO 2000; OECD 2012). We make an important contribution toward laying the foundation for a better understanding of the consequences of — and potential remedies for — poor mental health. There is the potential, for example, to improve both depression screening and treatment through the development of a fuller understanding of the breadth of behaviors and outcomes affected by this illness. We also need to know more about the usefulness of alternative policy levers in dealing with depression. Policymakers often rely on limiting direct health care expenditure, restricting access to disability support, and creating employment incentives as the primary means to contain the escalating fiscal costs of mental illness. Yet if the depressed do not respond to economic incentives in the usual way because their risk preferences differ, standard welfare-to-work and employment policies may be ineffective.

Our work also contributes to the rapidly growing economics literature on the measurement, drivers, and stability of risk preferences. Economists typically treat preferences as strictly stable; however, recent evidence shows that risk preferences respond to events such as financial shocks (Cohn et al. 2015; Paravisini et al. 2017; Guiso et al. 2018) and trauma (Callen et al. 2014; Cameron and Shah 2015; Hanaoka et al. 2018). Moreover, Decker and

Schmitz (2016) use the same dataset we do to show that physical health shocks increase stated risk aversion. Mental well-being is a potentially key source of heterogeneity in risk attitudes. The most closely related studies to ours are Chung et al. (2017) and Bayer et al. (2019) who explore how risk preferences differ for the depressed and the mentally-well in small clinical samples, and Li et al. (2019) who study how mental health shocks affect general willingness to take risks. In contrast, we utilize a large representative sample and consider not only a range of risk preferences, but also risk-taking behaviors and the mechanisms that link depression to those behaviors. Evidence of a relationship between depression and risk preferences lends support to neuroeconomic and behavioral economic models in which people's decision-making ability and opportunity sets are constrained by their cognitive, emotional, and physiological functioning. More importantly, knowing how attitudes towards risk and risk-taking behavior are shaped by episodes of depression would be extremely valuable in moving economists towards a deeper understanding of the way that human behavior is influenced not only by incentives and constraints, but also by the broader decision environment (see Schildberg-Hörisch 2018).

We proceed as follows. First, we provide new evidence that depression is associated with disparity in stated — but not (robustly) behavioral — risk attitudes and with risk-taking behavior in ways that are domain-specific. The depressive are more willing to, and do, take more health risks, for example, while the opposite is true for social risk-taking. In the absence of exogenous variation in depression, these effects cannot be interpreted causally; they are informative in characterizing those who are depressed. Second, we develop a conceptual framework informed by psychological research on depression and rooted in both neoclassical and behavioral economic theory to identify potential explanations for domain-specific differences in the willingness to take risks. Finally, we conduct empirical tests using detailed measures of both behavioral traits and risk-taking behavior. We find that gaps in risk-taking behavior are largely due to disparities in behavioral traits like locus of control, optimism and trust. Differences in financial risk-taking are largely due to locus of control, while disparities in trust are important in social risk-taking. Our mediators explain about half the depression-gap in health behaviors and there is no consistent pattern in the relative importance of mediators. We find that there is no overarching tendency for those who are depressive to engage in either more or less risk-taking. Rather, the decision-making context matters in ways that largely align with our theoretical expectations.

II. Data

Our analysis draws on data from the German Socio-Economic Panel (SOEP), a representative household panel survey (Goebel et al. 2019). First collected in 1984, SOEP contains data for around 30,000 people. A representative sample of more than 5,500 people — referred to as the SOEP Innovation Sample (SOEP-IS) — was added in 2012 to allow innovative, new survey elements to be trialed and tested (Richter and Schupp 2015). We use data from the 2002-2016 waves of SOEP and the 2014 SOEP-IS.[2]

Our measure of mental health is constructed using data from SOEP's SF-12 health questionnaire completed in even years starting in 2002 (see Table A1 in the Online Appendix). The SF-12 contains questions about both physical and psychological well-being, which are transformed into a continuous measure of mental health (the MCS score) by way of factor analysis (see Andersen et al. 2007). The MCS score is scaled such that in 2004 it has a mean of 50 and a standard deviation of 10. It is a psychometrically sound measure of mental health that is able to detect disorders (e.g., Gill et al. 2007; Salyers et al. 2000). Vilagut et al. (2013) conclude that an MCS score of less than 45.6 performs well at detecting 30-day depressive disorders, specifically major depressive episodes and dysthymia, in the general population. We use this threshold to classify respondents into two groups; those below the threshold who are vulnerable to experiencing a depressive episode we refer to as 'depressed', or simply 'depressive', and those above the threshold whom we refer to as 'mentally well'. This definition classifies 27 percent of our main sample as vulnerable to depression; for comparison, the lifetime incidence of *diagnosed* depression in the German population is estimated to be between 11.6 and 19 percent (Busch et al. 2013; Wittchen et al. 2010).[3] Moreover, individuals with an MCS score below the threshold at least once in our study period are 5.4 times more likely to also self-report having ever been medically diagnosed with depression (16.2 versus 3.0 percent).[4] Thus, our measure is correlated with, but not equivalent to, clinical definitions of depression. Using it has three key advantages: (i) it minimizes social desirability bias by eliciting depression vulnerability using indirect questions; (ii) it captures more marginal depressive episodes that may go clinically undiagnosed; and (iii) it is likely to be more robust to selective survey non-participation than are narrower definitions focused solely on those severely depressed.

The SOEP and SOEP-IS also include an extremely rich set of risk-preference measures and realized risk-taking behaviors, which form the basis of our analyses. Data on people's behavioral traits allow us to explore the mechanisms behind the depression-risk relationship. We introduce all measures in the relevant sections below. A description of each measure is provided in Table A2 and the underlying samples for different analyses are outlined in Table A3 in the Online Appendix. Summary statistics by depressive state are presented in Tables A4 and A5 in the Online Appendix.

III. Depression and Risk Preferences

A. Behavioral Risk Preferences

Parameterizing risk preferences is complicated by that fact that there are alternative views about their nature. In economics, the standard expected utility model characterizes risk preferences by the curvature of the utility function — often measured by the Arrow-Pratt coefficient of absolute or relative risk aversion. Utility is typically assumed to be increasing in consumption but at a decreasing rate implying that people are 'risk averse'; that is, they would prefer a certain payment over an uncertain payment with an equivalent expected value.

The usual approach for studying risk preferences in economics is to ask people to make repeated selections from a set of monetary lotteries. Responses can then be used in non-parametric estimation or in structural estimation of the parameters of the utility function to recover risk preferences (Harrison and Rutström 2008). A key advantage of this approach is that participants are induced to reveal their true preferences because they earn real monetary rewards based on the choices they make. We study whether behavioral risk preferences differ by depressive state using such choice data for SOEP-IS respondents who participated in a risky choice experiment in 2014 (DIW Berlin / SOEP 2018). We classify 21 percent of these respondents as depressive.

The behavioral risk preference task involved participants selecting a preferred lottery from choice sets of varying size. There were four scenarios in total — two scenarios involved two lottery options and two involved four lottery options.[5] The display order for the scenarios was randomized. For each lottery option that involved risk, there were two possible payoffs and participants were told the values and probabilities of these payoffs. In every scenario there was also a safe option (3€ with certainty). The payoffs and probabilities for each scenario are set out in Table 1.

Insert Table 1 Here

Note that in scenario 4, option B stochastically dominates option C; therefore, option C should never be chosen unless by random error. We will come back to this issue, but for now proceed as if all choices are equally valid. We compare the choices of the depressive and the mentally well in the lottery task using three approaches. First, we compare the unconditional choice distributions in each scenario; this provides little support for differences in risk preferences (see Figure A1 in the Online Appendix). Second, we estimate the probability of choosing an option involving risk (i.e., not option A) with and without conditioning on controls. Third, we structurally estimate the coefficient of relative risk aversion. The theoretical limitations of the standard expected utility theory model in the face of small-stakes lotteries (Rabin 2000) lead us to examine both parametric and non-parametric evidence.

Logistic regression results for the likelihood of choosing a risky option are reported in Table 2, panel A. Column 1 does not include controls, Column 2 includes our standard controls, and Column 3 excludes those who chose the dominated option in scenario 4 (coefficients on controls are reported in Table A6 in the Online Appendix). In columns 1 and 2, the odds ratios are close to one and statistically insignificant, indicating that those who are depressive are not more likely to choose an option involving risk than those who are mentally well. The odds ratio increases slightly (1.22) and is marginally significant ($p = 0.093$) when we drop people choosing the dominated option.

Insert Table 2 Here

We also find no consistent evidence that depression is related to risk preferences in our structural estimation. We estimate the coefficient of relative risk aversion, r, assuming people maximize utility subject to a constant relative risk aversion utility function (see Appendix B in the Online Appendix for details). Our estimation allows for subjective probability distortion using the weighting function of Tversky and Kahneman (1992); γ is a shape parameter which weights the probability of events. If $\gamma < 1$, then the weighting follows an inverse S-shape, which gives higher (lower) weight to low (high) probability events. We allow the shape parameter to vary by depressive state. The baseline estimates for r and γ are 0.18 and 0.83 respectively. The negative coefficients on our depression indicator in the relative risk aversion equation suggest lower risk aversion among the depressive. However, the estimates are statistically insignificant across specifications (with the exception again that excluding people choosing the dominated option results in estimates that are marginally significant). Finally, in a sensitivity analysis, we re-estimate our models using a stricter threshold (i.e. MCS < 36.54) which classifies 6.7 percent of the SOEP-IS sample as depressed in line with more conservative estimates of the rate of depression in Germany (e.g., Busch et al. 2013). Our conclusions are unaffected.[6]

Overall, we find no evidence that depression is in general associated with people's behavioral risk preferences.

B. Stated Risk Preferences

In psychology, risk preferences are commonly defined as the preference for actions that are rewarding but involve some chance of an adverse outcome (Mata et al. 2018). Behavioral risk preference measures are unlikely to fully capture this more general notion of risk preference. For example, eliciting risk preferences through monetary decision tasks may tell us very little about the variation in people's preferences for risky consumption goods (e.g., smoking). Behavioral risk preference measures are also silent about whether people are more willing to take risks in one context (e.g., driving) than another (e.g., health). If the ultimate goal of eliciting risk preferences is to predict risk-taking behavior, measures based on simple monetary gambles are unlikely to be first-best.[7]

Stated risk preferences are available in SOEP for selected years. Respondents were asked "How willing are you to take risks, in general?"; each responded on an ordinal scale from 0 (not willing) to 10 (very willing). The favorable predictive properties of this question are well-established (Dohmen et al. 2011; Vieider et al. 2015; Falk et al. 2016) and it is widely used as an overall measure of risk preferences.[8] Domain-specific versions of this question with respect to financial, health, occupational, sports/leisure, driving, and social (trust) decisions were also asked in some years. Domain-specific, rather than general, risk preferences have been shown to be better predictors of risk-taking behavior relevant to that domain (e.g., Weber et al. 2002; Dohmen et al. 2011). We therefore present results using both the general willingness to take risks and the domain-specific stated risk preference measures. We view these preferences as distinct from behavioral risk preferences. In particular, we expect stated risk preferences to be informed by past risk-taking behavior, particularly when measured in respect of specific domains.[9]

We estimate pooled linear regression models of the risk preference score — which is increasing in willingness to take risks — and present results in Table 3.[10] Our unconditional OLS estimates (panel A) reveal that overall depression is associated with significantly less willingness to take risks, both in general and across most domains. The exceptions are that depression is associated with a greater willingness to take health risks and is uncorrelated with occupational risk attitudes. These unconditional estimates are highly sensitive to the inclusion of controls, however. The link between the risk of depression and risk aversion is generally weaker — and sometimes changes sign — once we account for people's demographic and human capital characteristics (see panel B). In the health domain, however, the extent to which the depressive are more willing to take risks is amplified once we condition on controls. Conditionally, depression is linked to a greater, rather than lower, willingness to take risks in driving, finance, and occupation domains, although only the estimate for finance is statistically significant at the five percent level. Absolute effect sizes range from a 1.2 percent difference (occupation) to a 7.7 percent difference (general).

We conduct two robustness exercises. First, we regress stated risk preferences on the continuous MCS score. The conditional results are qualitatively consistent with those in Table 3 which are based on the depression indicator (see Table A9 in the Online Appendix). Second, we re-estimate our models using the stricter MCS threshold (MCS < 36.54) which classifies 10 percent of the SOEP sample as depressed. Estimates are similar (see Table A10 in the Online Appendix) with the exception that for finance, the depression indicator is negative; however, it is also statistically insignificant and small in magnitude.

Insert Table 3 Here

These results lead us to an important conclusion — the direction in which depression affects risk preferences depends on the context in which decisions are made. This result forms the basis of the theoretical and empirical investigations that follow. Health is a particularly interesting case in that those who are depressive report a greater willingness to take risks with their health than do the mentally well, irrespective of whether we account for other characteristics. At the same time, depression is associated with a significantly lower stated willingness to take risks in general.

C. Summary

We find that people's depressive state does not in general predict choices in an incentivized behavioral lottery choice task; evidence suggesting that the depressive are less risk averse is at best weak. However, people's mental well-being is related to their stated risk preferences. Conditional on demographic and human capital characteristics, those who are depressive report being more risk averse in general and with respect to leisure and trust; however, they report being less risk averse in the health and finance domains. We turn now to consider the link between people's depressive state and their risk-taking choices.

IV. Depression and Behaviors Involving Risk

What drives the patterns in stated risk preferences that we observe? We expect that when stating preferences for risk, people are likely to draw on current and past risk-taking behavior to inform their responses. Current and past risk-taking behavior is likely to be driven by 'trait' risk preference as well as other relevant factors. For example, when rating willingness to take risks over health, a person might think about their diet, whether they smoke, how much they exercise and so on. Preferences for each of these behaviors are likely to be driven by a variety of factors.

We move now to focus on the relationship between depression and behaviors involving risk. We limit our focus to the financial, health, and social risks because we find significant depression-gaps in stated risk preferences in these domains.[11] Our goal is to understand why the relationship between depression and risk preference is domain-specific. The analysis serves as a precursor to Section VI where we test for mediators between depression and risk-taking behaviors.

A. Method

Using SOEP data, we estimate a series of regression models of the form:

(1) $Y_{it}^{*} = c + \beta_1 D_{it} + \boldsymbol{X'_{it}\beta} + \varepsilon_{it}$.

In Equation 1, Y_{it}^{*} is the latent propensity to engage in the relevant risk behavior (e.g., poor diet), D_{it} is an indicator for being depressive (MCS < 45.6), $\boldsymbol{X_{it}}$ represents a set of controls, which for consistency are the same controls as in Section III, ε_{it} is a normally distributed error term, and all other terms are parameters to be estimated. Because our dependent variables are all either binary or ordinal, we estimate Equation 1 using either probit or ordered probit regression depending on the nature of the outcome variable.

B. Financial Risk-taking

We consider two behaviors related to financial risk-taking — owning risky assets (i.e., securities other than fixed interest securities, such as shares and variable bonds) and having supplementary health insurance.[12] We use indicators of these two financial decisions as dependent variables and estimate pooled probit regressions — with and without controls. The results are presented in Table 4. For consistency, we code all dependent variables to reflect greater risk-taking behavior, implying that we estimate the probability of not insuring, for example.

Insert Table 4 Here

Recall that there is a negative unconditional correlation between depression and stated willingness to take financial risks (see Table 3). We see the same negative unconditional relationship between depression and owning risky assets; the average partial effect is -4.6

percentage points (ppts) (14.6 percent difference relative to the mean). As with stated risk preferences, this disparity is greatly reduced once we condition on observables; however, it does not change sign and remains statistically significant (although economically unimportant) even after accounting for controls. It is therefore likely that the risk attitudes captured in people's stated risk preferences are informed by more than just their own choices regarding the purchase of risky assets.

Our health insurance results are consistent with our conditional stated risk preferences estimates. Those who are depressed are statistically more likely to be uninsured once we condition on controls, though the gap is modest.

C. Health Risk-taking

We study three health behaviors involving risk: (i) being a current smoker; (ii) having a poor diet; and (iii) adopting a sedentary lifestyle (exercising less than once per week).[13] We examine the relationship between depression and risky health behaviors using pooled probit (smoking, exercising) and ordered probit (diet) models. Our results are presented in Table 5. Definitions and descriptive statistics are reported in the explanatory notes to Table 5.

Insert Table 5 Here

All of our estimates are consistent with a greater willingness to take health risks among the depressive. Depressive people are more likely to smoke, maintain a poor diet and have a sedentary lifestyle. These differences are both statistically and economically meaningful. Before conditioning on controls, the depressive are 5.8 ppts more likely to smoke (18.8 percent); 1.2 ppts (20.0 percent) more likely to strongly disagree that they follow a health-conscious diet; 1.5 ppts (16.3 percent) less likely to strongly agree that they follow a health-conscious diet; and 7.8 ppts (13.4 percent) more likely to exercise less than once per week. Our estimates remain consistent, economically large, and statistically significant even after we include controls in the model.

D. Social Risk-taking

SOEP provides us with two key measures of social risk-taking: the frequency with which a person lends (i) his or her belongings or (ii) money to friends (both measured on a 1-5 scale [1 = never, 5 = very often]). Lending belongings or money to friends involves an element of risk because these loans may not be repaid. As those who are depressive state that they are less likely to take risks in the social domain (see Table 3), we would expect that they are less likely to engage in such behavior.

To investigate this, we again estimate ordered probit models with and without controls. The results are reported in Table 6. As predicted, the depressive are less likely to report lending belongings to friends. These effects are large enough to be economically meaningful — the depressive are 1.0 ppts (6.0 percent) more likely to never lend belongings to friends and 0.3 ppts (9.4 percent) less likely to lend belongings very often. However, in contrast to our expectations, they are also more likely to report lending money to friends. This effect is particularly strong for the probability of never lending money to friends — the unconditional average partial effect is -4.2 ppts (-7.8 percent). Both results are largely invariant to the inclusion of controls.

E. Summary

Taken together, our results highlight the complex relationship between depression and alternative risk-taking behaviors. Most results — particularly those in the health domain — are consistent with the depression-gap observed in stated risk preferences. However, those who are depressive are less likely than those who are mentally well to hold risky assets and more likely to lend money to their friends, despite reporting a greater (lower) willingness to take financial (social) risks (conditional on controls). These divergent findings indicate that there are complex relationships between depression and the drivers of risk-taking behavior, which may give rise to either more or less risk-taking depending on the nature of the choices being made.[14]

V. Framework for Risk-taking Behavior and Mechanisms

We develop a simple conceptual framework to understand the mechanisms linking depression to risk-taking behaviors. This is done in a step-by-step fashion starting with a standard neoclassical approach and then incorporating insights from behavioral economics. We draw on literature in economics, psychology, and neuroscience to make predictions about the mediating role of different mechanisms.

A. Financial Decisions: Insurance and Risky Assets

We begin by considering two closely related financial decisions: the purchase of insurance and investment in a risky asset, drawing heavily on Levin (2006). Consider an agent with wealth w who must decide whether to insure a potential financial loss L that occurs with probability p. She has the option of purchasing an insurance policy that will pay a if the loss occurs at a price of qa. Her optimization problem is:

(2) $\max pu[w - qa - L + a] + (1 - p)u[w - qa]$

If the insurance is actuarily fair (i.e., $q = p$), the agent will purchase just enough insurance to fully insure against the value of the loss (i.e., $a = L$) thereby equalizing wealth in loss and no-loss states. Agents do not fully insure their losses if $q > p$, however. In this case, a risk neutral agent will not insure at all, while a risk averse agent will buy some insurance with the insured amount increasing in the degree of risk aversion and decreasing in wealth everything else constant.

Now suppose the agent must decide between investing in a safe asset which returns r with certainty, or investing in a risky asset with a random return z. Her goal is to choose an amount a to allocate to the risky asset such that her expected utility is maximized, i.e.,

(3) $\max \int u[az + (w - a)r]dF(z)$

where $F(z)$ is the cumulative distribution function of z. Risk-averse agents will invest some of their wealth in the risky asset only if there is some positive rate of return (i.e., $E[z] - r > 0$) for doing so.[15] Conditional on wealth, differences in portfolio allocations are driven by differences in risk preferences. If agent A is more risk-averse than agent B, then it will be optimal for A to invest less in the risky asset than B. At the same time, people with decreasing absolute risk-aversion will invest more in the risky asset as their wealth increases.

Risk preferences and wealth play key roles in insurance and investment choices; each provides a theoretical link between depression and financial risk-taking. Our empirical analysis (see Section III), however, finds no evidence that behavioral risk preferences vary with depressive state.[16] The depressive do report a lower stated willingness to take risks in general which likely captures previous risk-taking behavior as well as trait-like risk preferences. Others have linked mental illness to reduced economic activity, lower earnings, less stable employment, and more financial insecurity (see Bubonya et al. 2019 for a review). Our framework suggests the depressive invest less in risky assets and purchase more insurance because they are less wealthy on average. Yet we find that while the depressive are less likely to invest in risky assets, they are also less (not more) likely to have health insurance (see Table 4).[17] Thus, these simple, static models cannot fully account for the patterns in depression and financial risk-taking that we observe.

More progress can be made by explicitly recognizing the inter-temporal nature of financial decisions and the importance of time preferences. People who are present-oriented (i.e., have high discount rates) will be less likely to give up current consumption to insure any future losses. On the other hand, if investing in risky assets today yields consumption benefits in the future, high discount rates will reduce the incentive to invest in risky assets.[18] Our finding that the depressive are less likely to have both risky assets and health insurance is therefore theoretically consistent with them having higher discount rates. The limited empirical evidence on this issue is mixed, however. Observational data indicate that there is a positive relationship between depressive symptoms and discount rates among college students (Eisenberg and Druss

2015). Bayer et al. (2019) and Pulcu et al. (2014) show the same in clinical samples of depressed individuals, though Pulcu et al. (2014) find the relationship is significant only for high rewards. Other clinical evidence suggests that depressed individuals have lower discount rates overall than the mentally well; but they also have more inconsistent preferences that can lead to less patient behavior in the near term (Takahashi et al. 2008).

We now turn to models of inter-temporal decision making — with richer notions of uncertainty — that explicitly account for people's consumption choices in order to develop a fuller understanding of the link between depression and risk-taking behavior.

B. Consumption Decisions: Risky Health Choices and Social Capital

Health Choices: Risky health choices (e.g., smoking, poor diet, sedentary lifestyles) are best modeled as intertemporal consumption choices made under uncertainty. Smoking, for example, generates current utility, but may result in future health problems, reducing future utility. Agents are assumed to choose in period *t* to consume a risk-related good (c_t) so as to maximize their utility:

(4) $U(c_t) = \sum_{\tau=t}^{T} \frac{1}{(1+\delta)^{\tau-t}} \left[\sum_{s \in S_\tau} p_\tau(.,s) u_\tau(c_t; s)\right]$

where τ indexes future periods and s indexes states of the world. Uncertainty is captured by state space S_τ which differs across time; in period τ each state of the world ($s \in S_\tau$) occurs with probability $p_\tau(.,s)$. Future utility is discounted by factor δ. If those experiencing depression are more present-oriented (i.e., have higher δ), they will discount any future health costs of their current risky consumption choices more heavily than those who are mentally well.

Equation 4 also highlights other key pathways linking depression to risky health behavior. Differences in taste preferences for the consumption good are captured in the shape of people's utility functions $u_\tau(c_t; s)$. Psychologists argue altered sensitivity to reward and punishment underpins poor decision making in depression (Cella et al. 2010; Eshel & Roiser 2010). Anhedonia — i.e., a lack of reaction to pleasurable stimuli — is "a cardinal feature of depression" (Pizzagalli et al. 2008, p. 76), for example. Kung et al. (2018) find that financial rewards to complete surveys are less effective for the depressive. At the same time, the marginal utility from smoking appears to be higher for those in poor mental health. Nicotine can relieve symptoms of depression and anxiety leaving smoking rates and smoking intensities higher in the mentally unwell population as people turn to smoking as a form of self-medication (see Lerman et al. 1998; Lawrence et al. 2009).

Numerous studies have linked depression to lower life expectancy. In one meta-analysis, depression was associated with a 50 percent increase in the risk of mortality (Cuijpers et al. 2014). Moreover, the association between depression and mortality persists over long periods of time (Gilman et al. 2017). The consequences of life expectancy on risky health decisions are captured by T. If depressive individuals expect to die sooner (i.e., have smaller T), they may have 'nothing to lose' and hence will be more prone towards risky consumption.[19]

Importantly, the future utility $u_\tau(.)$ from consuming c_t today is uncertain. Depression may influence people's expected utility by altering either: (i) $p_\tau(.,s)$ (the probability that state of the world s eventuates); or (ii) $u_\tau(c_t;s)$ (utility in that state). For example, major depressive disorders and other severe mental illnesses not only increase people's susceptibility to physical illness, but also compound the negative impact of that illness by increasing unhealthy lifestyle choices and reducing access to standard medical care (De Hert et al. 2011).

Finally, people's consumption of cigarettes, junk food, and sedentary activities are subject to both income and time constraints. Those who are mentally unwell are not only less likely to participate in the labor market, but also have higher unemployment rates and diminished productivity when they do (e.g., Kessler and Frank 1997; OECD 2012; Frijters et al. 2014; Bubonya et al. 2019). Thus, the depressed are likely to face a stricter budget constraint, but a potentially more relaxed time constraint.

Social Capital: A growing body of literature links low levels of social capital to poor mental health outcomes including depression, psychosis, and suicide (see McKenzie et al. 2002; Sartorius 2003; Kim et al. 2012). Sartorius (2003), for example, argues that the promotion of mental health and the treatment of mental disorders would add to the stock of social capital, while increasing social capital would support mental health.

Risk-taking social behavior can be modelled as an intertemporal consumption problem. Unlike the risky health behaviors we consider, our measures of risky social behavior (loaning money or possessions to others) are better seen as choices involving current costs and future benefits. People's current consumption is reduced when they loan money or belongings; however, their social capital — i.e., the strength of their relationships, support networks, etc. — may be greater in the future. Whether or not their trust is reciprocated is uncertain. If depressed individuals are more present-oriented than those who are mentally well, they will discount the future benefits of their social behavior more heavily, making them less likely to loan their possessions and money to others.

There are a number of other reasons that those experiencing depression may avoid social risk-taking. First, depression may be associated with lower levels of trust. Low interpersonal trust appears to be an independent risk factor for new-onset and long-term depression (Kim et al. 2012), while greater trust in ones' neighbors is linked to less depression in subsequent years (Fujiwara and Kawachi 2008). Second, it is plausible that depression impedes the conversion of social investments into social capital. The stigma attached to mental illness, for example, may undermine people's social networks and leave their future social capital unaffected by any social risk-taking they might engage in today. Finally, they may be less able to afford to loan their money or possessions to others because they have fewer economic resources.

C. Further Insights from Behavioral Economics

Thus far we have assumed that agents make intertemporal choices based on their expected *experienced* utility with known probability distributions. In reality, risk-taking decisions are also likely to be influenced by cognitive limitations, self-control issues, emotions, optimism, projection bias, and the like. Consequently, we adopt a more behavioral perspective and recast our conceptual framework using a *decision* utility function (Kahneman et al. 1997).

We begin by considering the role of self-control. "Depression can be seen as a set of related problems in self-control" (Rehm 1977, p. 787).[20] People's level of self-control influences the way they evaluate risk; low self-control shifts the balance towards shorter-run and away from longer-run options that are likely to involve different risks (see Gerhardt et al. 2017; Schildberg-Hörisch 2018). Consequently, a conceptual framework that accounts for self-control is important if we wish to understand the relationship between depression and risk-taking behavior.

Self-control issues result in a form of non-standard time preference; discount rates are relatively high over long time horizons and low over short time horizons (Laibson 1997; DellaVigna 2009). Following Shefrin and Thaler (1988), we adopt the following dual-self model to characterize this time preference inconsistency (i.e., their present focus):[21]

$$(5)\ U(c_t) = \varphi(.)u_t(c_t; s) + \big(1 - \varphi(.)\big)\left[u_t(c_t; s) + \sum_{\tau=t+1}^{T} \frac{1}{(1+\delta)^{\tau-t}}\left[\sum_{s \in S_\tau} p_\tau(., s)u_\tau(c_t; s)\right]\right]$$

where $\varphi(.)$ is the utility weight placed on immediate consumption and $(1 - \varphi(.))$ is the utility weight placed on the long-run consequences of that consumption. In effect, people are assumed to behave as if they have two co-existing, but mutually inconsistent, sets of preferences; one short-run and the other long-run (Shefrin and Thaler 1988). Lower trait (dispositional) self-control can be characterized as a greater emphasis on short-term outcomes, i.e., a higher $\varphi(.)$ (see Fudenberg and Levine 2012 for example).[22] Consequently, lower self-control in many cases is predicted to result in less risk aversion (see Schildberg-Hörisch 2018).[23] There is also psychological evidence that voluntary rather than automatic regulation processes are impaired in depressive episodes (Rive et al. 2013), while diminished self-control appears to result in more mental and physical health problems in part due to an increased tendency to engage in unhealthy coping strategies (Boals et al. 2011). To the extent that depression is associated with a reduced capacity for self-control, we would expect depressed individuals to engage in more risky health behavior, and less risky social behavior.

In addition, $\varphi(.)$ may also depend on other aspects of people's personalities. Locus of control, for example, can be characterized as "a generalized attitude, belief, or expectancy regarding the nature of the causal relationship between one's own behavior and its consequences" (Rotter 1966, p. 2). Those with an external locus of control believe that what happens in life is largely due to external forces (e.g., luck, powerful others) — rather than their own efforts — leading them to act as if their future outcomes are unrelated to their current choices. This can be modelled as a higher $\varphi(.)$. Meta-analysis indicates that greater externality is associated with greater depression (Benassi et al. 1988), while there is evidence that depressed people attribute good outcomes to luck and bad outcomes to themselves (Alloy and Ahrens 1987). Given this, we predict that — because they are more external — depressed individuals may engage in more risky health behavior, and less risky social behavior.

Finally, $\varphi(.)$ is likely to be linked to other dimensions of personality including impulsivity and conscientiousness. The behavior of people with low self-control is more strongly influenced by their impulses, for example, than is true for people with high self-control (Friese and Hofmann 2009). Self-control is a key facet of conscientiousness (Roberts et al. 2014; Mike et al. 2015) and mediates the role of personality traits (including conscientiousness) on impulsivity (Mao et al. 2018).

Although thought of primarily as a mood disorder, depression is characterized by deficits in cognition and decision making (Leykin et al. 2011; Blanco et al. 2013; Chen et al. 2015). Depression is not necessarily linked to biases in all forms of information processing; rather the issue is one of reduced executive functioning and capacity for selective attention (Gotlib and Joorman 2010). This has potentially wide-ranging implications. Takahashi et al. (2008), for example, find that depressive individuals are more impulsive and more time-inconsistent in their intertemporal choices than are healthy individuals; while healthy individuals discount gains and losses similarly, depressed individuals discount gains more than losses, making them more sensitive to losses in the distant future. The utility weight attached to current versus future consumption can therefore be conceptualized as:

(6) $\varphi(LoC, I, C, IQ)$

where LoC, I, C and IQ capture locus of control, impulsiveness, conscientiousness and cognitive capacity respectively.

Limitations in cognitive capacity are influential in risk-taking decisions in part because "cognition is the primary route through which emotions are regulated" (Gotlib and Joorman 2010, p. 301). In the face of risk and uncertainty, emotions compel us to take certain actions and avoid others. Psychologists are generally concerned with emotions that are experienced at the time a decision is made (i.e., anticipatory or immediate emotions). Neuroticism — a tendency to experience negative feelings such as anxiety, fear, anger, loneliness, etc. — is regarded as a key personality trait, for example. In contrast, economists have historically been more likely to focus on anticipated future emotions, such as disappointment and regret (Loewenstein 2000).[24] It is clear, however, that people react not only cognitively, but also emotionally and physiologically to the presence of risk. Moreover, anticipatory emotions (e.g., fear) associated with risk have the potential to explain decisions that are difficult to understand solely in cognitive-consequential terms (Loewenstein et al. 2001). Meta-analysis indicates that poor mental health is associated with emotion regulation strategies that involve less cognitive reappraisal and more expressive suppression (Hu et al. 2014).

Importantly, expectations over future utility (or future disutility) are likely to depend on the visceral emotions triggered by current circumstances. Gradin et al. (2011) provide evidence that the encoding (processing) of prediction errors is disrupted in depression, which contributes to anhedonia; depressed individuals learn less from reward signals (see also Pizzagalli et al. 2008; Must et al. 2013). People may, for example, be optimistic and over-estimate the utility gain from eating tomorrow if they are hungry today and fail to recognize that tomorrow they will be sated (see Gilbert and Wilson 2007). An inability to abstract from the current circumstances leads to projection bias — people fail to correctly predict their future preferences. Dispositional optimism is the general tendency to expect positive outcomes. We therefore extend Equation 5 by accounting for emotional response to risk, E_t, and optimism, *O,* in the utility function:

(7) $u_t(c_t; s, E_t, O)$

Projection bias, pessimism, and cognitive biases more generally, may result in the depressed consuming either more or fewer risk-related goods relative to the mentally well.

D. Putting It All Together

Our conceptual framework is useful in highlighting the ways that depression may influence people's propensities for risk-taking behavior. An overview of what these key mechanisms imply for the disparity in the risk-taking behavior of depressive vs. mentally well people is provided in Table 7. In particular, the direction of the observed depression-gap in risk-taking behavior is reported in panel A. Based on our reading of the literature, we then form hypotheses about the likely relationship between depression and each of the factors (mechanisms) that we consider; these are reported in Column 1 in panel B (i.e., the depressive are likely to have *lower* income/wealth). Finally, we use our conceptual framework to identify whether controlling for each mechanism would be expected to close the observed depression-gap in risk-taking behavior. Factors that, when controlled for in regressions, close the gap are shaded light grey; those that widen it are shaded dark grey (see panel B).

In the case of risky assets, for example, the depression-gap is potentially explained by many factors (i.e., budget constraints and discounting, cognitive limitations and optimism) whereas only differences in time horizons and patience are expected to explain the gap for insurance. Disparities in budget constraints, discounting, time-inconsistent preferences and emotions are all expected to contribute to the depression-gap in risk-taking health behaviors. Similarly, the gap in lending belongings to friends is potentially explained by this set of factors along with disparities in optimism and trust. In contrast to their observed behavior, however, we would predict those who are depressed to be more reluctant to lend money to their friends.

Insert Table 7 Here

VI. Explaining the Depression-Gap in Behaviors Involving Risk

We turn now to a mediation analysis which allows us to empirically assess how useful the mechanisms discussed above actually are in understanding the depression-gap in risk-taking behavior.

A. SOEP Measures of Potential Mechanisms

We proxy the different components of our theoretical framework by their observational equivalents in the SOEP data. To facilitate comparability across mediators, we recode them such that greater values can be (arguably) interpreted as more favorable, standardizing each to be mean zero with a standard deviation (std.) equal to one. Table 8 presents the means of all mediators, conditional on our standard controls, by depressive state along with the results of t-tests of differences in means.[25]

Insert Table 8 Here

We do not directly observe wealth; instead we proxy for permanent income by averaging annual net household income across all observations between 2002 and 2016. Naturally, this measure is correlated, but not perfectly, with log current income, which is included in all our analyses. Depressive individuals have 0.01 std. less log permanent income (0.63 percent). Time discounting is captured through people's self-reported level of patience; the depressive report 0.23 std. less patience.[26]

We capture the behavioral components of the dual-self model by controlling for three key personality traits that are related to people's capacity for self-control. The first is a measure of internal locus of control; depressive individuals score 0.49 std. lower indicating that they are less likely to believe that what happens in their lives is tied to their own choices (i.e., they are external). The second is an indicator for not being impulsive. People who are depressive are slightly less impulsive (0.09 std.) implying that they have less difficulty in resisting short-term pleasure. This may be the result of anhedonia, which mutes the stimulus the depressed experience in situations that others perceive as tempting. Our third measure captures self-reported conscientiousness which is also lower amongst the depressive. The disparity in non-impulsivity and conscientiousness suggests that, while it is easier for the depressive to resist short-term pleasure, they may nonetheless have self-control problems in the context of long-term goals and planning.[27]

We also account for the influence of emotions and expectations in risk-taking behavior using measures of emotional stability (the inverse of neuroticism) and optimism. Specifically, the depressive are 0.58 std. less emotionally stable suggesting that they may be more susceptible to risk-taking decisions that are driven by visceral emotions. In addition, we capture subjective expectations using two empirical measures. The first is self-reported confidence in the future which captures how optimistic an individual is with respect to the future in general. The depressive are 0.35 std. less optimistic. The second reflects how well people predict their future well-being. We construct this measure using respondents' answers to how satisfied with life in general they anticipate being in five years' time. We compare this value with their realized life satisfaction five years later and use the absolute difference to compute a measure of prediction accuracy. The depressive are 0.24 std. less accurate in their predictions. Finally, we control for the degree to which people believe that they can trust others; the depressive report being less trusting (0.26 std.).

B. Method

To investigate whether and to what extent the above mediators explain the depression-related disparity in risk-taking behavior that we observe, we follow Karlson et al. (2012). Their method allows us to recover the degree to which mediating variables, $\boldsymbol{Z_{it}}$, explain the relationship between depression, D_{it}, and risk-taking behavior, Y_{it}, using the following full model:

(8) $Y_{it}^{*} = \alpha_F + \beta_F D_{it} + \gamma_F \boldsymbol{Z_{it}} + \delta_F \boldsymbol{X_{it}} + \varepsilon_{it}$,

where Y_{it}^{*} is the unmeasured latent variable corresponding to Y_{it}. To be able to compare the resulting coefficient β_F to the corresponding coefficient from the reduced model excluding $\boldsymbol{Z_{it}}$, we add residuals $\boldsymbol{R_{it}}$, obtained by separately regressing the mediators $\boldsymbol{Z_{it}}$ on depression, to the reduced model:

(9) $Y_{it}^{*} = \alpha_R + \beta_R D_{it} + \gamma_R \boldsymbol{R_{it}} + \delta_R \boldsymbol{X_{it}} + \epsilon_i$.

These residuals, $\boldsymbol{R_{it}}$, reflect the component in $\boldsymbol{Z_{it}}$ that is uncorrelated with depression. Their inclusion circumvents the rescaling or attenuation bias that otherwise arises in cross-model comparisons of nonlinear models — like probit or ordered probit models in our case. Thus, the method allows us to estimate and compare β_R and β_F.[28] Karlson et al. (2012) show that the approach is considerably more robust to misspecification of the error terms than alternative approaches such as estimating linear probability models or decomposing average partial effects.

The Karlson et al. (2012) method relies on the usual assumptions in path-based mediation of conditional exogeneity for both the mediators and treatment (D_{it}) variables (see

Huber 2019). Since this is unlikely to hold in our case, our analysis is clearly a descriptive rather than causal exercise. The comparison of β_R and β_F nevertheless sheds light on the share of the overall depression-gap in risk-taking that is accounted for by the relationship between depression and the mediating factors that we consider. As such, the results provide a valuable guide to some of the potential mechanisms underpinning the relationship between depression and risk-related behavior.

C. Results

The results for each risk-taking domain are presented in Tables 9 through to 11. For each risk-taking behavior we show the estimated coefficient for the depression indicator, D_{it}, and the average partial effects for the reduced and full models, as well as the relative contribution (in percentage points) of each mediator to the depression-gap. These relative contributions are also presented graphically in Figure 1; budget constraint and discounting measures are displayed in checkered pattern, measures of time-inconsistent preferences are in solid pattern, and measures of emotions and expectations are in stripes.

Insert Tables 9 – 11 & Figure 1 Here

The ability of our mediators to explain the depression-gap in risk-taking behavior depends on the domain. Financial decisions are nearly completely explained by the mediating factors considered (see Table 9). The mediators explain 74 percent of the depression-gap in risky assets and 114 percent of the gap in lack of insurance.[29] Our mediators have varying power in explaining the gap in health behavior (see Table 10), however. The depression-gap in smoking is reduced by only 14 percent once we account for mediating factors; many factors in fact widen it. In contrast, the mediators explain around half of the gap in diet (50 percent) and exercise (42 percent). In the social risk-taking domain (see Table 11), the mediators successfully account for the entire depression-gap (146 percent) in the case of lending belongings. In contrast, almost all mediators contribute to a widening of the gap in money lending which is not surprising given that the observed depression-gap in lending money does not conform to our theoretical predictions to begin with.

The relative importance of different mediators is also context specific. The depression-gap in financial risk-taking is almost fully explained by differences in locus of control, confidence in the future, and trust. Consistent with our hypotheses, differences in permanent income also help explain the gap in holding risky assets (9 percent) or the purchase of insurance (6 percent) though to a smaller degree. The relative importance of our mediators in explaining the depression-gap is similar irrespective of the measure of financial behavior we consider. The gap in health behaviors also appears to be related to emotions and expectations, but to a lesser extent than for financial decisions. Interestingly, decisions around diets and exercise are primarily related to time-inconsistent preferences (locus of control or conscientiousness), whereas smoking is not. Depression-gaps in our two measures of social risk-taking (lending belongings and lending money) are influenced by a similar set of mediators. Lower levels of trust, patience, impulsivity, internal locus of control, confidence in the future, and prediction accuracy explain why the depressive lend less. Trust has the largest single effect across both behaviors.

D. Sensitivity Tests

We conduct three important sensitivity tests. First, we consider the role of cognitive ability using a small subsample of people who took a cognitive skills test.[30] The depressive score 0.13 std. lower on this test relative to the mentally well (conditional on controls), which may cause them additional difficulties in calculating the costs and benefits of intertemporal tradeoffs. We redo our analysis for this subsample of people, adding cognitive ability as an additional control in our models. Our qualitative results do not change. We find that cognitive abilities explain 9 percent of the depression-gap in holding risky assets and 21 percent of the gap in supplementary health insurance purchases, but less than 6 percent of the gap in all other risk-taking behaviors (see Table A18 in the Online Appendix).

Second, we test the robustness of our results to the inclusion of stated willingness to take risks in general as a potential mediator. Measures of stated risk preferences are likely to be endogenous since people may not fully isolate their reported willingness to take risks from their past behavior. However, our conclusions do not change when we consider stated risk preferences to be an additional mediator (see Table A19 in the Online Appendix). The willingness to take risks in general explains relatively little compared to other mediators (10 percent in the financial domain, between -9 and 3 percent in the health domain, and up to 18 percent in the social domain). Moreover, the proportions of the depression-gap explained by the mediators combined are largely unchanged. We thus conclude that differences in risk preferences alone do not explain the gaps in risk-taking behavior.

Finally, we rerun our estimations excluding log current income from the set of control variables in order to assess whether the relatively minor role of permanent income in risk-taking is due to its high correlation with log current income. This changes our baseline set of conditioning variables making these results informative, but not directly comparable to our main results. As expected, permanent income explains a relatively larger share of the depression-gap, especially in the financial domain, when current income is excluded from the model (see Table A20 in the Online Appendix). However, our conclusions about the relative importance of the other mediators remain largely unchanged.

E. Summary

Overall, these empirical results suggest the channels we propose do contribute to understanding the depression-gaps in risk-taking behavior — although to varying extents across the different domains. While we can fully explain the depression-gap in financial behaviors and in lending belongings, our proposed channels account for only half of the depression-gap or less in health risk-taking. In the health domain, there may be other factors that operate in addition to the behavioral traits we consider. In line with our expectations, most self-control related attributes do not help to explain the gap in financial behaviors. Locus of control is an exception, which matters greatly for financial but less for health and social risk-taking, in contrast to our hypotheses. Trust matters more in the social domain, as predicted. While trust explains between 8 and 24 percent of the depression-gap across financial and health behaviors, it explains almost 70 percent of the gap in lending belongings.

Some of our empirical findings challenge our theoretical predictions. Accounting for lower levels of patience, for example, widens the depression-gap in financial risk-taking. We also predicted that patience would in part explain gaps in health behaviors, but it has a negligible mediating effect.

VII. Conclusions

Impaired decision making is a core symptom of depression. Those who are depressed struggle, for example, to focus their attention on task-relevant information and cope with their negative automatic thoughts (Matthews and Macleod 2005; Gotlib and Joormann 2010). Despite this evidence, we know very little about the way that depressive symptoms influence the actual choices that people make. Our analysis makes a crucial contribution by using large-scale, representative data to analyze the way that depressive episodes shape both risk preferences and risk-taking behavior. To identify depressive episodes, we use a screening threshold based on general mental health rather than relying on clinically diagnosed depression. Given that our measure also captures less severe depressive episodes that go unreported and undiagnosed, we expect that our results are likely attenuated relative to those we might expect based solely on those with clinically diagnosed depression.

We find that depressive symptoms are generally unrelated to risk attitudes when those risk attitudes are measured using respondents' preferences over a series of incentivized, monetary lotteries. However, when asked directly, the depressive rate their own willingness to take risks differently to those who are mentally well. Importantly, the depression-related disparity in self-reported willingness to take risks is context specific. The depressed report a lower willingness to take risk in general, for example, and a greater willingness to take health risks. The context also matters for the disparity in the actual risk-taking behaviors that people engage in. The depressive are more likely to smoke, have a poor diet, adopt a sedentary lifestyle and loan money to others, but are less likely to lend their belongings. Our mediation analysis demonstrates that depression-related disparities in risk-taking behavior are largely explained by differences in the behavioral traits, e.g., locus of control, optimism and trust, of those who are depressive vs. mentally well, rather than differences in time preferences (patience) or financial resources. Overall, our analysis indicates that there is no common tendency towards either more or less risk-taking associated with depression. Further, the link between depression and risk-taking behavior is explained by people's behavioral traits rather than by differences in their risk preferences per se.

Our results lead us to several important conclusions. First, the way that risk preferences are measured matters. Standard behavioral risk measures based on preferences over monetary lotteries are not well-suited to explaining the relationship between depression and risk-taking behavior. This is true even in the case of related financial decisions such as the purchase of risky assets or insurance where — despite no significant difference in behavioral risk preferences — significant depression-related disparities in behavior exist. Survey-based measures of people's self-reported willingness to take risks in general also fail to completely capture the complexity of the relationship between depression and risk-taking behavior. Our simple conceptual framework makes it clear that the propensity towards risk-taking depends on many factors besides the curvature of the utility function. Like others, we conclude that domain-specific measures of the willingness to take risks more closely align with the disparity in relevant risk-taking behaviors that we observe than do behavioral risk measures (see Weber et al. 2002; Dohmen et al. 2011). At the same time, it is challenging to learn about depression-related differences in risk choices simply by examining the disparity in the risk preferences of those who are and are not mentally well. If researchers are interested in differences in the propensity to engage in risk-taking behaviors between groups, domain specific stated preferences may provide more useful information than behavioral measures of risk preference. Nevertheless, behavioral risk preferences have a strong theoretical foundation that makes them attractive to economists. Future research should explore the relative practical value of these measurement approaches.

Second, depression-related disparities in financial constraints, time preferences and stated risk preferences go only a limited way in explaining why those with depressive symptoms are more likely to take certain risks and avoid others. A more complete explanation can be found in the relationship between people's depression risk and their behavioral traits. While the depressive are less impulsive, they are also less internal, optimistic and emotionally stable. They report less trust in others and seem more susceptible to prediction errors. Much of the disparity in the risk-taking behavior of those who are depressive vs. mentally well disappears once these differences are accounted for. This implies that depression may influence risk-taking choices not by altering attitudes to risk directly, but rather by influencing the way people form expectations over and act on intertemporal tradeoffs. This would be consistent, for example, with the evidence that the willingness to take risks and actual risk-taking behavior both depend on people's disposition toward focusing on the favorable or unfavorable outcomes of risky situations (Dohmen et al. 2018).

Third, the relationship between depression and risk-taking behavior depends on the nature of the decision being made; there is no overarching tendency for the depressed to engage in either more or less risk-taking across the board. Further, the specific mechanisms linking depression to different forms of risk-taking behavior are generally consistent with our theoretical expectations. Given this, we believe there is a lot to be gained from understanding depression and risk through the lens of conceptual frameworks that account for the fundamentals of each risk-taking choice. At the very least, it is important to consider the relationship between depression and attitudes towards risk in the context of the broader decision environment. This has been a long-standing tradition in psychology which to date has not become standard practice in economics (see Schildberg-Hörisch 2018). Yet depression appears to influence people's proclivity towards risky choices by altering their behavioral traits, emotions and expectations — all of which are context-specific.

Finally, some forms of risk appear to be more nuanced in the depressed population. For example, the prevalence of smoking is higher among the mentally unwell in part because nicotine can relieve the symptoms of depression and anxiety making it an effective form of self-medication (Lerman et al. 1998; Lawrence et al. 2009). Thus, it is not surprising that smoking is not a good measure of general risk attitudes for the depressed. Similarly, while the depressive are less likely to lend their belongings to friends as expected, they are more likely to lend money. This is particularly puzzling given they have fewer financial resources and report being less likely to trust others. We can only speculate why this is the case. It may be that for the depressed, loaning money to friends acts as a form of social insurance in the way that resource sharing operates as an insurance mechanism in some migrant communities (see Besley et al. 1993).

These conclusions have important implications for public health efforts to address the challenges posed by poor mental health. Although our analysis is not causal, our descriptive findings are useful in understanding the relationship between depression and risk, prioritizing policy efforts, and identifying directions for future research.[31] Developing a conceptual framework that proposes channels in which the link between depression and risk can operate, we have identified several behavioral tendencies that may be helpful in screening for depression. Moreover, our results open up interesting directions for the design of interventions targeting less desirable risk-taking behavior. Those experiencing depression, for example, may fail to realize the additional financial returns associated with purchasing high growth assets. They also insure less. As our focus is on supplemental health insurance in Germany, not primary health insurance like in the United States, it is unclear whether the lack of such health insurance exposes the individuals we consider to substantial financial risks. At the same time, any financial costs of not insuring are likely to be compounded by the additional health risks they take. These financial penalties are not only a potentially important, but overlooked, component of the cost of depression. They might be mitigated through interventions targeting financial literacy for those experiencing depression. Future research exploring how depression is associated with other risk-taking behaviors — and what the broader consequences of these behavioral differences are — would be particularly valuable.

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Table 1

Payoffs and Probabilities Associated with the SOEP 2014 Risk Experiment.

	Option A	Option B	Option C	Option D
Scenario 1	3€, 100%	32€, 10%		
		0€, 90%		
Scenario 2	3€, 100%	4€, 80%		
		0€, 20%		
Scenario 3	3€, 100%	4€, 70%	32€, 10%	68€, 5%
		0€, 30%	0€, 90%	0€, 95%
Scenario 4	3€, 100%	4€, 80%	4€, 70%	34€, 10%
		0€, 20%	0€, 30%	0€, 90%

Notes: SOEP-IS.2016.2 2014. For each option, the cell shows the payoff and its probability (e.g., for scenario 1, option B there is a 10% chance of receiving 32€ and a 90% chance of receiving nothing).

Table 2

Depression and Behavioral Risk Preferences, Regression Results using the 2014 SOEP Risk Experiment.

	(1)	(2)	(3)
Panel A: Non-parametric logit regressions			
Depression	1.187	1.156	1.222*
	(0.126)	(0.127)	(0.146)
Controls	No	Yes	Yes
Observations	3,640	3,508	2,980
Clusters	910	877	745
Panel B: Structural model estimates			
Relative risk aversion ($\hat{r}$ equation)			
Depression	-0.095	-0.086	-0.101*
	(0.062)	(0.061)	(0.057)
Constant	0.182***	-0.107	-0.012
	(0.025)	(0.137)	(0.145)
Probability weighting factor ($\hat{\gamma}$ equation)			
Depression	0.093	0.091	0.111*
	(0.067)	(0.067)	(0.063)
Constant	0.832***	0.828***	0.730***
	(0.027)	(0.027)	(0.023)
Controls	No	Yes	Yes
Obs.	10,920	10,524	8,940
Persons	910	877	745

Notes: SOEP-IS.2016.2 2014. Controls include the following: sex, age, age^2, log monthly household income, own and parents' upper secondary education or higher, household type (single person; couple w/out children; single parent; couple with children <16y; couple with children 16y+; couple with children <16y and 16y+; multi-generation; other combination (ref. group)) and German born. Non-parametric regressions are binary logit regressions predicting whether the option chosen involved uncertainty (i.e., not option A). Odds ratios are presented. The $\hat{r}$ equation in the structural model is the coefficient of relative risk aversion for a CRRA utility function (see Appendix B in the Online Appendix, equation (B.1)); the $\hat{\gamma}$ equation is the probability weighting factor in equation (B.3). Results in column 3 exclude those who chose option C in scenario 4 (see Table 1). Standard errors are in parentheses and are clustered at the individual level. * $p < 0.10$, *** $p < 0.01$.

Table 3

Depression and Stated Willingness to Take Risks: General and Across Domains, Pooled OLS Results.

	General	Driving	Finance	Sport/ Leisure	Occupat-ion	Health	Trust
Panel A: No controls							
Depression	-0.443***	-0.084***	-0.072***	-0.173***	-0.051	0.099***	-0.242***
	(0.019)	(0.032)	(0.027)	(0.031)	(0.033)	(0.030)	(0.029)
Effect size	-0.096	-0.027	-0.032	-0.049	-0.014	0.033	-0.071
Panel B: With controls							
Depression	-0.354***	0.059*	0.078***	-0.082***	0.043	0.172***	-0.156***
	(0.018)	(0.030)	(0.026)	(0.028)	(0.031)	(0.029)	(0.028)
Effect size	-0.077	0.018	0.035	-0.023	0.012	0.058	-0.046
Obs.	117,029	34,344	35,955	36,081	32,258	36,535	36,581
Persons	37,774	27,927	29,107	29,308	26,860	29,626	29,661

Notes: SOEPv33.1i 2004-2016. Controls include: sex, age, age^2, log monthly household income, own and parents' upper secondary education or higher, household type (single person; couple w/out children; single parent; couple with children <16y; couple with children 16y+; couple with children <16y and 16y+; multi-generation; other combination (ref. group)), German born and year dummies. Effect sizes are calculated as $\hat{\beta}/\bar{y}$ where $\hat{\beta}$ is the estimated Depression coefficient and $\bar{y}$ is the pooled sample mean for the relevant stated risk preference (the effect size is the percentage change from the mean associated with depression). All dependent variables are measured on a 0-10 scale with higher values indicating greater risk willingness. For the general domain {T} = 2004, 2006, 2008, 2010, 2012, 2014 and 2016. For the other domains {T} = 2004 and 2014. Standard errors are in parentheses and are clustered at the individual level. * $p < 0.10$, *** $p < 0.01$.

Table 4

Depression and Risk-taking Behaviors in the Financial Domain.

	Risky assets	Risky assets	No supp. health ins.	No supp. health ins.
Depression	-0.131***	-0.029***	0.108***	0.034**
	(0.011)	(0.011)	(0.013)	(0.013)
Average partial effect	-0.046***	-0.009***	0.029***	0.008**
	(0.004)	(0.003)	(0.003)	(0.003)
Controls	No	Yes	No	Yes
Obs.	132,597	132,597	114,235	114,235
Persons	38,103	38,103	35,244	35,244
Pseudo R^2	0.002	0.127	0.001	0.100

Notes: SOEPv33.1i 2002-2016. Risky assets = 1 if household owns risky assets (i.e., securities other than fixed interest securities, such as shares and variable bonds). Mean = 0.314. No health insurance = 1 if not currently covered by a supplementary private health insurance policy. Mean = 0.805. Controls include: sex, age, age^2, log monthly household income, own and parents' upper secondary education or higher, household type (single person; couple w/out children; single parent; couple with children <16y; couple with children 16y+; couple with children <16y and 16y+; multi-generation; other combination (ref. group)), German born and year dummies. Average partial effects are the sample mean change in the predicted probability when going from Depression = 1 to Depression = 0. Standard errors are in parentheses and are clustered at the individual level. Standard errors for average partial effects are calculated using the delta method. ** $p < 0.05$, *** $p < 0.01$.

Table 5

Depression and Risk-taking Behaviors in the Health Domain.

	Smoker	Smoker	Poor diet	Poor diet	Sedentary	Sedentary
Depression	0.162***	0.103***	0.094***	0.105***	0.202***	0.177***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.024)	(0.024)
Average partial effect:						
Pr(Y = 1)	0.058***	0.033***	-0.015***	-0.016***	0.078***	0.064***
	(0.004)	(0.004)	(0.002)	(0.001)	(0.009)	(0.009)
Pr(Y = 2)			-0.023***	-0.024***		
			(0.002)	(0.002)		
Pr(Y = 3)			0.026***	0.027***		
			(0.003)	(0.003)		
Pr(Y = 4)			0.012***	0.012***		
			(0.001)	(0.001)		
Controls	No	Yes	No	Yes	No	Yes
Obs.	118,999	118,999	96,172	96,172	15,045	15,045
Persons	38,287	38,287	33,915	33,915	15,045	15,045
Pseudo R^2	0.003	0.112	0.001	0.042	0.004	0.068

Notes: SOEPv33.1i 2002-2016. Smoker = 1 if current smoker. Mean = 0.308. Poor diet is a categorical variable (1-4 scale) indicating agreement to the statement that they follow a health-conscious diet (1 = strongly agree, 4 = not at all). The distribution from 1-4 is 0.092, 0.419, 0.429 and 0.060. Sedentary = 1 if participates in sports/exercise less than once per week. Mean = 0.581. Controls include: sex, age, age^2, log monthly household income, own and parents' upper secondary education or higher, household type (single person; couple w/out children; single parent; couple with children <16y; couple with children 16y+; couple with children <16y and 16y+; multi-generation; other combination (ref. group)), German born and year dummies. Average partial effects are the sample mean change in the predicted probability when going from Depression = 1 to Depression = 0. For Poor diet, the average partial effects are the change in predicted probability for each of the four possible responses. Standard errors are in parentheses and are clustered at the individual level. Standard errors for average partial effects are calculated using the delta method. *** $p < 0.01$.

Table 6

Depression and Risk-taking Behaviors in the Social Domain.

	Lend belongings	Lend belongings	Lend money	Lend money
Depression	-0.041**	-0.055***	0.105***	0.099***
	(0.020)	(0.020)	(0.021)	(0.022)
Average partial effect:				
Pr(Y = 1)	0.010**	0.012***	-0.042***	-0.035***
	(0.005)	(0.005)	(0.008)	(0.008)
Pr(Y = 2)	0.006**	0.007***	0.018***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
Pr(Y = 3)	-0.005**	-0.006***	(0.018***	0.015***
	(0.003)	(0.002)	(0.004)	(0.003)
Pr(Y = 4)	-0.008**	-0.010***	0.005***	0.004***
	(0.004)	(0.004)	(0.001)	(0.001)
Pr(Y = 5)	-0.003**	-0.004***	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Controls	No	Yes	No	Yes
Obs.	15,015	15,015	15,011	15,011
Persons	15,015	15,015	15,011	15,011
Pseudo R^2	0.000	0.058	0.001	0.077

Notes: SOEPv33.1i 2008. Lend belongings is a categorical variable (1-5 scale) indicating the frequency at which the respondent lends belongings to friends (1 = never, 5 = very often). The distribution from 1-5 is 0.167, 0.296, 0.345, 0.160 and 0.032. Lend money is a categorical variable (1-5 scale) indicating the frequency at which the respondent lends money to friends (1 = never, 5 = very often). The distribution from 1-5 is 0.538, 0.319, 0.116, 0.023 and 0.004. Controls include: sex, age, age^2, log monthly household income, own and parents' upper secondary education or higher, household type (single person; couple w/out children; single parent; couple with children <16y; couple with children 16y+; couple with children <16y and 16y+; multi-generation; other combination (ref. group)) and German born. Average partial effects are the sample mean predicted probability for each of the possible responses when going from Depression = 1 to Depression = 0. Robust standard errors are in parentheses. Standard errors for average partial effects are calculated using the delta method. ** $p < 0.05$, *** $p < 0.01$.

Table 7

Predictions for Explaining the Depression-gaps in Risk-taking Behaviors.

	Financial risk-taking		**Health risk-taking**		**Social risk-taking**	
	Risky assets	**No insurance**	**Smoker**	**Poor diet /Sedentary**	**Lend belongings**	**Lend money**
Panel A: Observed behavior						
Depressed take … risk.	Less	More	More	More	Less	More
Panel B: Hypothesized behavior						
Budget constraints and discounting						
Lower income/wealth	Less due to less wealth to invest and DARA[a] in wealth.	Less due to DARA in wealth.	Less due to cigarette costs.	More due to healthier options more expensive.	Less due to less capacity to lend.	Less due to less capacity to lend.
Lower time horizon	Less due to undervaluing future returns.	More due to 'nothing to lose.'	More due to 'nothing to lose.'		Less due to undervaluing future returns.	Less due to undervaluing future returns.
Lower patience	Less due to discounting future returns.	More due to discounting future costs.	More due to discounting future costs.		Less due to discounting future rewards.	Less due to discounting future rewards.
Time-inconsistent preferences						
Lower self-control	---		More due to overweighing present.		Less due to overweighing present.	Less due to overweighing present.
Less internal locus of control						
Higher impulsivity						
Lower conscientiousness						
Cognitive limitations	Less due to avoidance of complicated tasks.	---				

Emotions and expectations					
Lower emotional stability	---		More due to stronger emotional drive.	?	?
Lower optimism	Less due to underestimation of future returns.	Less due to higher perceived need for insurance.	Less due to overvaluing future costs.	Less due to lower perceived future benefits.	Less due to lower perceived future benefits.
Lower prediction accuracy	?		?	?	?
Lower trust	---		---	Less.	Less.

Notes: Panel 1 reports the observed depression-gap in risk-taking behaviors from the results presented in Tables 4, 5, and 6. Panel 2 presents our hypothesis of how each factor (mediator) in Column 1 may affect each risk-taking behavior. Mediators that are expected to close the observed depression-gap in risk-taking behavior when controlling for them in regressions are shaded in light grey, while factors that are expected to widen the gap are shaded in dark grey.

[a] Decreasing absolute risk aversion.

Table 8

Summary Statistics of Potential Mediators.

	Means		Difference	Equality of means	
	Mentally well (1)	Depressed (2)	(2) - (1)	t-stat.	p-value
Budget constraints and discounting					
Log permanent income	0.038	0.026	-0.012	-2.227	0.026
Patience	0.064	-0.165	-0.229	-17.121	0.000
Time-inconsistent preferences					
Internal locus of control	0.155	-0.332	-0.488	-39.755	0.000
Non-impulsivity	-0.026	0.067	0.092	7.021	0.000
Conscientiousness	0.068	-0.173	-0.241	-18.749	0.000
Emotions and expectations					
Emotional stability	0.169	-0.411	-0.580	-47.265	0.000
Confidence in future	0.104	-0.248	-0.352	-28.414	0.000
Prediction accuracy	0.082	-0.162	-0.244	-18.580	0.000
Trust	0.098	-0.158	-0.255	-20.028	0.000
Obs.	43,427	16,770			

Notes: SOEPv33.1i 2008-2016. All measures are standardized to mean of zero and variance one. All cells are conditional on individual control variables (via linear regression) and account for clustering at the individual level. Controls include: sex, age, age^2, log monthly household income, own and parents' upper secondary education or higher, household type (single person; couple w/out children; single parent; couple with children <16y; couple with children 16y+; couple with children <16y and 16y+; multi-generation; other combination (ref. group)) and German born.

Table 9

Mediation Results for the Depression-gap in Risk-taking Behaviors in the Financial Domain.

	Risky assets	Risky assets	No supp. health ins.	No supp. health ins.
Depression	-0.047**	-0.012	0.030	-0.004
	(0.018)	(0.018)	(0.020)	(0.020)
Average partial effect:				
Pr(Y = 1)	-0.014**	-0.004	0.008	-0.001
	(0.005)	(0.005)	(0.006)	(0.006)
Percentage contribution to mediation:				
Budget constraints and discounting				
Log permanent income		9.06		5.78
Patience		-7.25		-13.41
Time-inconsistent preferences				
Internal locus of control		82.64		118.75
Non-impulsivity		-4.90		14.59
Conscientiousness		-33.36		-17.41
Emotion and expectations				
Emotional stability		-33.37		-28.73
Confidence in future		32.00		19.01
Prediction accuracy		4.87		0.44
Trust		24.01		15.10
Total		**73.69**		**114.13**
Model	Reduced	Full	Reduced	Full
Obs.	51,178	51,178	42,707	42,707
Persons	15,801	15,801	13,583	13,583

Notes: SOEPv33.1i 2008-2016. Controls are included in each estimation. Standard errors are in parentheses and are clustered at the individual level. ** $p < 0.05$, *** $p < 0.01$.

Table 10

Mediation Results for the Depression-gap in Risk-taking Behaviors in the Health Domain.

	Smoker	Smoker	Poor diet	Poor diet	Sedentary	Sedentary
Depression	0.092***	0.079***	0.116***	0.058***	0.173***	0.099***
	(0.019)	(0.019)	(0.014)	(0.015)	(0.027)	(0.029)
Average partial effect:						
Pr(Y = 1)	0.028***	0.024***	-0.018***	-0.009***	0.061***	0.035***
	(0.006)	(0.006)	(0.002)	(0.002)	(0.010)	(0.010)
Pr(Y = 2)			-0.025***	-0.013***		
			(0.003)	(0.003)		
Pr(Y = 3)			0.032***	0.016***		
			(0.004)	(0.004)		
Pr(Y = 4)			0.011***	0.005***		
			(0.001)	(0.001)		
Percentage contribution to mediation:						
Budget constraints and discounting						
Log permanent income		1.38		1.16		1.55
Patience		2.46		7.17		0.60
Time-inconsistent preferences						
Internal locus of control		-1.94		7.41		14.60
Non-impulsivity		-9.11		0.05		2.26
Conscientiousness		-0.49		26.08		-2.45
Emotion and expectations						
Emotional stability		-30.18		-6.62		0.23
Confidence in future		13.93		6.54		6.19
Prediction accuracy		17.58		0.56		7.14
Trust		20.13		7.56		12.33
Total		**13.76**		**49.91**		**42.45**
Model	Reduced	Full	Reduced	Full	Reduced	Full
Obs.	46,332	46,332	42,418	42,418	11,892	11,892
Persons	15,778	15,778	14,630	14,630	11,892	11,892

Notes: SOEPv33.1i 2008-2016. Controls are included in each estimation. Standard errors are in parentheses and are clustered at the individual level. *** $p < 0.01$.

Table 11

Mediation Results for the Depression-gap in Risk-taking Behaviors in the Social Domain.

	Lend belongings	Lend belongings	Lend money	Lend money
Depression	-0.051**	0.023	0.092***	0.145***
	(0.023)	(0.024)	(0.024)	(0.026)
Average partial effect:				
Pr(Y = 1)	0.011**	-0.005	-0.033***	-0.052***
	(0.005)	(0.005)	(0.009)	(0.009)
Pr(Y = 2)	0.007**	-0.003	0.016***	0.025***
	(0.003)	(0.003)	(0.004)	(0.005)
Pr(Y = 3)	-0.006**	0.003	0.013***	0.021***
	(0.003)	(0.003)	(0.003)	(0.004)
Pr(Y = 4)	-0.009**	0.004	0.003***	0.005***
	(0.004)	(0.004)	(0.001)	(0.001)
Pr(Y = 5)	-0.003**	0.001	0.001**	0.001***
	(0.001)	(0.002)	(0.000)	(0.000)
Percentage contribution to mediation:				
Budget constraints and discounting				
Log permanent income		2.95		-1.02
Patience		17.64		-12.47
Time-inconsistent preferences				
Internal locus of control		22.59		-12.15
Non-impulsivity		21.43		-9.73
Conscientiousness		-5.00		15.42
Emotion and expectations				
Emotional stability		-3.82		-3.18
Confidence in future		11.84		-9.62
Prediction accuracy		9.82		-1.42
Trust		68.57		-22.56
Total		**146.02**		**-56.71**
Model	Reduced	Full	Reduced	Full
Obs.	11,871	11,871	11,867	11,867
Persons	11,871	11,871	11,867	11,867

Notes: SOEPv33.1i 2008-2016. Controls are included in each estimation. Robust standard errors are presented in parentheses. ** $p < 0.05$, *** $p < 0.01$.

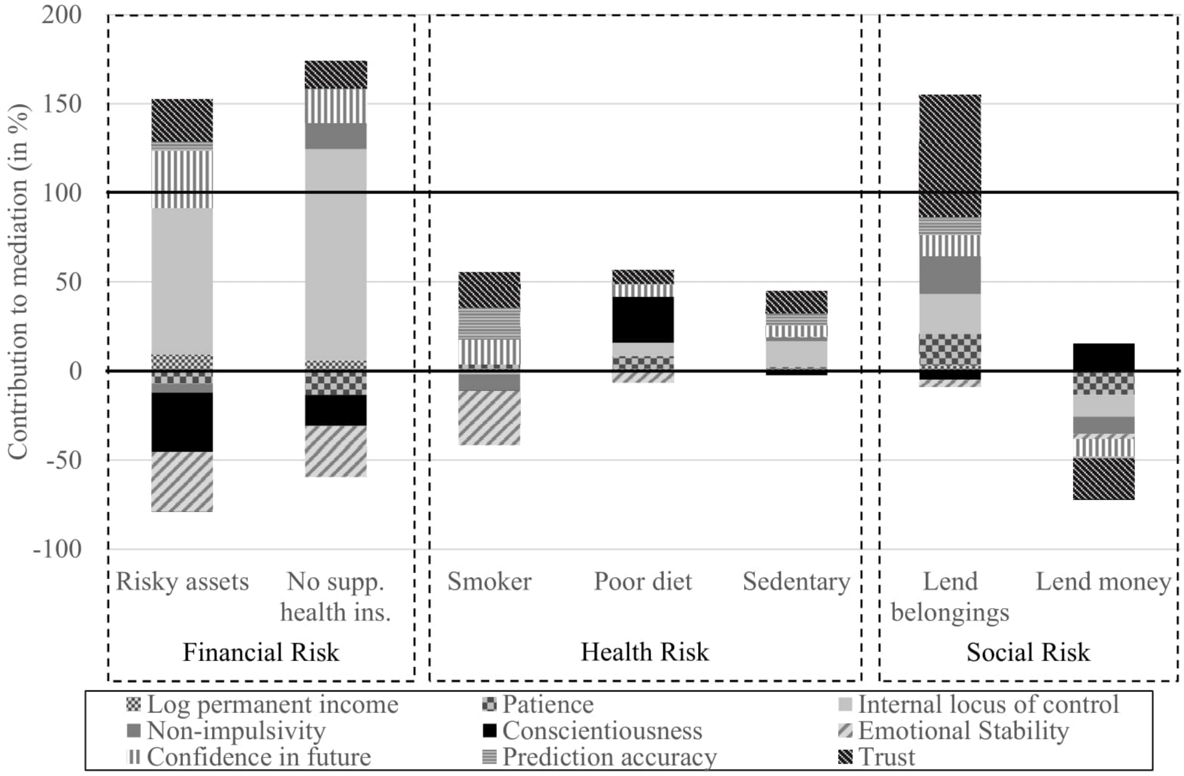

Figure 1

Percentage Contribution of Mediators to Depression-gap in Risk-taking Behaviors.

Source: Own illustration.

Notes: SOEPv33.1i 2008-2016. Graphical illustration of Tables 9 – 11.

[1] We distinguish between risk-taking behaviors (i.e., previous realized choices involving risk or uncertainty) and risk preferences (i.e., people's underlying risk aversion or risk tolerance). More specifically, behavioral risk preference measures elicit people's risk aversion through their choices among risky alternatives in an incentivized task or game, whereas stated risk preference measures are people's self-reported survey responses to questions about their degree of risk aversion. See Eckel (2019) for an overview and discussion of these two different measurement approaches.

[2] We use data from the International Scientific Use Version of the SOEP (data for years 1984-2016, version 33.1, SOEP, 2018, doi:10.5684/soep.v33.1i) and from the SOEP Innovation Sample (data for years 1998-2016, SOEP, 2018, doi:10.5684/soep.is.2016.2).

[3] These are likely lower bounds given the underrepresentation of the acutely depressed in the studies (Busch et al. 2013).

[4] Specifically, questions on medically diagnosed depression were asked in 2009, 2011, 2013, and 2015. We use data from 27,802 individuals in our sample, who we observe in at least one of these years. Due to the required clinical assessment and potential underreporting, the prevalence of medical diagnosis is naturally lower than the incidence of depressive episodes captured by our MCS score. The tetrachoric correlation in the two measures is 0.5.

[5] At the end of the experiment one choice scenario was randomly selected and played out with real monetary consequences.

[6] Using this threshold, none of the binary logit estimates are statistically significant (see Appendix Table A7).

[7] Frey et al. (2017) compare a battery of stated and behavioral risk preference measures and find that the stated preferences significantly outperform the behavioral measures in terms of both temporal (i.e., test-retest) and convergent stability (i.e., capturing a common underlying

trait). Dohmen et al. (2011) and Lönnqvist et al. (2015) provide evidence that these measures are better predictors of actual risk-taking behavior, even though self-reported measures of risk preferences are correlated with decisions in incentivized lottery experiments (Dohmen et al. 2011; Vieider et al. 2015; Gillen et al. 2019). Specifically, self-reported risk preferences are significant predictors of financial decisions (Barasinska et al. 2012), occupational choice (Bonin et al. 2007; Fouarge et al. 2014), and migration (Jaeger et al. 2010).

[8] In the smaller SOEP-IS subsample undertaking the risky choice experiment, this measure has a positive and statistically significant (although relatively small) polychoric correlation with selecting a choice involving risk in the lottery task described in the previous section (ρ=0.091, se=0.012).

[9] See Steiner et al. (2019) for a more extensive discussion of the cognitive processes underlying people's response behavior when asked about their risk preferences. Their analyses suggest that self-reports of risk preferences are rooted in people's idiosyncratic experiences and draw on their memory of past behaviors.

[10] We also estimate models controlling for individual fixed effects (see Appendix Table A8). However, we are cautious about over-interpreting these results since deviations in mental well-being may be caused by unobserved changes in personal circumstances that have independent effects on risk preferences, as well as by measurement error. While our fixed effects estimates are generally less precise, the overarching conclusion remains; whether depression is associated with a greater or lesser willingness to take risks depends very much on the domain in which decisions are being made.

[11] Preferences also differ in the sports/leisure domain but we lack corresponding measures of risk-related behavior.

[12] Germany has compulsory health insurance; everyone is covered by either public or private insurance that largely covers all medical essentials. Individuals can also purchase

supplementary health insurance voluntarily which covers additional medical (say dental) or hospital services.

[13] The SOEP has information about alcohol consumption, but no measures of risky alcohol use (e.g., binge drinking).

[14] In Tables A11-A16 in the Online Appendix we repeat the regressions in this section but replace the depression indicator with: (i) a continuous MCS score; and (ii) the stricter MCS threshold that isolates more severe depression. All results are qualitatively similar, with the exception that the estimates for the effect of depression on lending money are only significant after conditioning on controls in (i) and are not significant in (ii).

[15] In contrast, risk-neutral investors will allocate their entire wealth to the asset with the highest expected return.

[16] Chung et al. (2017) and Bayer et al. (2019) reach the same conclusion using clinical samples of depressed. Bayer et al. (2019) do, however, find that depressive symptomology is positively correlated with willingness to take risks in general, measured using a multi-item questionnaire.

[17] It is important to note that these relationships hold despite controlling for income levels.

[18] The discount rate may also affect wealth portfolios if risky assets take longer to mature than safe assets.

[19] See Harris et al. (2002) who make a similar argument with respect to adolescent risk-taking.

[20] Rehm (1977) provides a historical review of psychological theories of self-control and depression.

[21] We adopt a dual-self model for two primary reasons. First, this allows us to study dynamically inconsistent choices without making the maintained assumption that preferences themselves are dynamically inconsistent (see Ericson and Laibson 2019). Second, this model is flexible enough to allow us to consider how personality traits (locus of control, impulsiveness,

conscientiousness) and cognitive capacity affect intertemporal choice through the weight that they place on present versus future consumption.

[22] Shefrin and Thaler (1988) cast their model in terms of a “myopic doer” and a “long-term planner”, while Thaler and Sunstein (2008) refer to these as the “reflective” and “automatic” systems. See Tangney et al. (2004) for a discussion of dispositional versus state self-control.

[23] Note that current consumption choices are assumed to be independent of past consumption choices, ruling out addiction which would further increase decision failures (see Bernheim and Rangel 2004).

[24] See Tymula and Glimcher (2018) for a review of the history of emotions in economics and psychology.

[25] The description and availability of the mediators are described in Table A2 in the Online Appendix. Unconditional summary statistics can be found in Table A17 in the Online Appendix.

[26] We do not observe life expectancy in our data and therefore ignore the role of the time horizon in our mediation analysis.

[27] Self-control is a key facet of conscientiousness and is sometimes characterized as non-impulsivity (Mike et al. 2015). Since we condition on non-impulsivity, the independent variation in our control for conscientiousness may more strongly reflect other aspects of conscientiousness (e.g., orderliness, industriousness, responsibility) than self-control.

[28] For further details on the method see Karlson et al. (2012) and Breen et al. (2013); for a description of its implementation in Stata see Kohler et al. (2011). For other applications of this method in the economics and social sciences literature see, e.g., Tubeuf et al. (2012), Breen et al. (2014) and Haskins and Jacobsen (2017).

[29] To ensure we have information on all mediators, estimation is conducted over 2008 – 2016. The depression-gap in insurance purchase is not statistically different from zero, which may be

attributed to the loss in sample size. At the same time, the magnitude of the marginal effect is equal to the one based on the full (2002 – 2016) SOEP sample used in Section IV (both 0.008).

[30] All dimensions of cognitive abilities are assessed in short tests. Crystallized intelligence, obtained through learning, is measured either by the number of different animals people can list in 90 seconds or via the Multiple-Choice Vocabulary Intelligence Test, which takes around five minutes; fluid intelligence, an innate ability, is measured by the number of correct assignments in a symbol-digit-correspondence task within 90 seconds. See Richter et al. (2013) for details. Respondents usually complete two out of these three tests. We average the standardized results from each test available.

[31] See Loeb et al. (2017) for an extensive discussion on the value of descriptive analysis for public policy.