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Bouncing Back from Health Shocks: Locus of Control and Labor Supply

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NON-TECHNICAL SUMMARY

Many studies have demonstrated a causal effect of ill health on labour-supply, whereby individuals with poor health or who experience health difficulties are less likely to participate in the labour market. In this study, I explore whether the labour-supply of individuals with different personalities –measured by control beliefs– responds differently to health shocks (measured by whether was admitted to hospital for 10 nights or more).

To accomplish this, I follow the labour-supply trajectories of 649 initially full-time employed and healthy men who experience at some point in time an episode of ill health. The longitudinal data necessary to do so come from the German Socio-Economic Panel (SOEP), and spans years 1994 to 2012.

My findings provide clear evidence of personality differences in labour supply responses to health shocks amongst German men. When compared with men who have positive control beliefs, men with negative control beliefs are on average 100% more likely to drop out of the labour force after a health shock. This drop out is unrelated to early retirement. In addition, when compared with men who have positive control beliefs, men with negative control beliefs work on average 12% fewer hours per week over the year when experiencing a health shock.

These behavioural differences are strongest for men from low socioeconomic backgrounds, men who do not have access to private health insurance, and men who experience high intensity shocks to their health. Different labour-supply responses are also observed for conscientiousness and risk tolerance, traits that have been linked with willingness to invest and treatment compliance.

Teaching individuals the ability to interpret experiences in an optimistic fashion and to understand the importance of taking self-responsibility could be a cost-effective way to counter-balance rising health care costs associated with an aging society and with increasing prevalence rates of avoidable illnesses (such as obesity, diabetes and cardiovascular disease). This would require interventions at the person or community level, with the possibility that such interventions begin during infancy and teenage years.

ABOUT THE AUTHORS

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Abstract

Many studies have demonstrated a causal effect of ill health on labor-supply. In this study, I explore the personality-related heterogeneity - measured by differences in control beliefs - in the labor-supply response to health shocks. To identify such behavioral differences, I follow the labor-supply trajectories of 649 initially full-time employed and healthy men who experience at some point in time an episode of ill health. When compared with men who have positive control beliefs, men with negative control beliefs are on average 100% more likely to drop out of the labor force - a drop out unrelated to early retirement - and work on average 12% less hours per week the year after the health shock. These behavioral differences remain robust to alternative estimation samples and health-shock definitions. They are strongest for men from low socioeconomic backgrounds, who do not have access to private health insurance, or who experience high intensity shocks. Heterogeneous labor-supply responses are also observed for conscientiousness and risk tolerance, traits that have been linked with willingness to invest and treatment compliance. An important conclusion from the findings is that a small set of non-cognitive skills produces long term labor-market benefits in the advent of adversity.

Keywords: Non-cognitive skills; locus of control; resilience; labor supply; health shocks; SOEP

1 Introduction

During the course of a normal life span, most people will experience at least one traumatic life event. Although such traumatic events can be highly debilitating in the short run, it is now established that not all individuals will respond to life events in the same way. Decades of research conducted by the team of George Bonanno at Columbia University have demonstrated important individual differences in the psychological adjustment and coping strategies to severe life events (see Bonanno 2004; Bonanno et al. 2011). Psychological distress is a normal response to such events, but some individuals fall into a chronic dysfunction after an adverse life event, while others return to baseline levels after several months. Most of the research studying individual differences in the response to life events has focused on disasters, exposure to warfare, and loss of a loved one. In recent years, subsequent studies have identified similar individual differences in the response to health-related adversities, such as emergency surgery, health epidemics, breast cancer and physical trauma (see Bonanno et al. 2012, for an overviw of the literature).

The ability to cope with adversity is referred to as resilience in the Positive Psychology literature (See Seligman 2011). It is "the capacity to maintain, or regain, psychological well-being in the face of challenge. The definition underscores ... the capacity to flourish, develop, and function effectively despite difficult circumstances or events" (p. 12 Ryff et al. 2012). An important component of resilience are beliefs around whether one can influence the important outcomes of one's life. These *positive control beliefs* are often referred to in the literature as *sense of mastery* (Masten 2014), *self-efficacy* (Bandura 1990) or *internal locus of control* (Rotter 1966). Economists are increasingly interested in the health and labor-market benefits of positive control beliefs (see Cobb-Clark 2015, for a review), especially so in the presence of adversity. For instance, Buddelmeyer and Powdthavee (2016) study the psychological benefits of positive control beliefs when dealing with a series of negative life events ranging from the loss of a loved one to the experience of financial distress. Caliendo et al. (2014) and McGee (2015) show that positive control beliefs help workers, who have lost their job, to search more intensively for re-employment, and therefore are more likely to be re-employed.

In this study, I explore whether positive control beliefs can function as an insurance against episodes of ill health. Instead of investigating the psychological wellbeing trajectories following an adverse event, I measure functioning as the ability to stay in the labor market. I hypothesize that among individuals who experience a health shock those who exhibited positive control beliefs prior to the health shock are less likely to drop out of the labor market - or reduce their hours of work - than those who exhibited negative control beliefs. They do so, because their attitude helps them to undercut feelings of hopelessness which in turn allows them to exploit all possible resources to counterbalance the negative impact of the health shock. To test this hypothesis, I follow the labor-supply decisions of initially healthy and full-time employed men who experience an episode of ill health at some point in time using data from the German Socio-Economic Panel (SOEP), a nationally-representative longitudinal survey.[1]

Understanding the heterogeneity in coping mechanisms with health shocks is of paramount importance to public policy because ill health has long-term economic consequences for individuals (See Smith 2005, 1999; Currie and Madrian 1999, for an overview). Episodes of ill health may force older workers into early retirement (Disney et al. 2006; Wing Han Au et al. 2005; Bound et al. 1999; Riphahn 1999) and younger workers out of the labor market (García-Gómez et al. 2010; García-Gómez and López-Nicolás 2006). The employment effects of health shocks persist over many years (Crichton et al. 2011; García-Gómez et al. 2013). Public policy may utilize knowledge on the heterogeneity of coping behavior with health-related adversity to save public taxpayer money on health and social insurance pay-outs.

There are two alternative avenues through which public policy could utilize this knowledge. One avenue is to directly target individuals who experience adversity. For instance, life-coaching sessions that improve positive thinking could be offered alongside standard medical treatment during episodes of ill health. Such training is already provided in large scale to employees of the US American military upon return from traumatizing military interventions (Seligman 2011). Another avenue for public policy is to teach positive control beliefs as part of standard school curriculum. Governments in California (United States), Ottawa-Carleton (Canada), and Victoria (Australia) have already or are currently revising their school curricula to formalize resilience education for children. The effectiveness of these initiatives has not been evaluated yet, nor do we know which intervention strategies are most successful in teaching and evaluating these skills

[1] The analysis is conducted on men only because for women it is difficult to disentangle episodes of ill health and subsequent labor supply responses from pregnancy-related health problems and pregnancy-related labor supply decisions.

(see Schurer 2016, for evidence and discussion). Innovative methods to teach positive control beliefs have been evaluated by Bernard et al. (2014) in a developing country context.[2]

Theoretically, there are several alternative mechanisms that could explain heterogeneous labor-supply responses to health shocks, which are not caused by, but correlate with, control beliefs. On the one hand, it may be that negative control beliefs measured at some point in time just proxy latent health problems. Thus, instead of identifying true behavioral differences in response to health shocks, control perceptions may just capture more intense health shocks or worse childhood (ex ante) health that also explain labor supply trajectories. On the other hand, positive control tendencies may just proxy higher levels of human capital or socioeconomic advantage. If there is an education gradient in positive control beliefs, then they may just capture an individual's access to information, private health insurance, and high-quality care. I will present a theoretical model in the next Section that describes and justifies these alternative channels.

To identify heterogeneous labor-supply responses to health shocks that are truly linked to differences in control beliefs I will choose an empirical strategy that is able to shut off each of these alternative mechanisms. Using German data has multiple advantages of testing these heterogeneous labor-supply responses. On the one hand, Germany has an almost universal and relatively homogeneous health care system, with a high coverage of health care services, free provider choice, and a high density of physicians and hospitals, factors which ensure access to high-quality health care for all citizens (see Eibich and Ziebarth 2014). German labor-protection laws further protect most workers from short-notice lay-offs due to health problems. Both institutional settings reduce the possibility that observed heterogeneous labor-supply responses are reflections of unequal and difficult-to-observe access to care and past labor supply.

My estimation model is based on a standard specification used in the previous literature to identify the causal effect of health shocks on labor supply (e.g. García-Gómez 2011; García-Gómez and López-Nicolás 2006). I follow the health and labor-supply trajectories of a selected sample of working-age men who have experienced an episode of ill health over a three-year time window. In the benchmark model, episodes of ill health are defined as admission to hospital for at least

[2]The authors showed videos of successful people in randomly selected Ethiopian villages. They could then demonstrate that in those randomly-selected villages both aspirations and control perceptions changed significantly relative to villages where the videos were not shown, and improved control perceptions were associated with savings and investment behaviors.

10 nights. This measure provides variation in health that is more likely to be exogenous than, for instance, self-reported measures of changes in health status (see García-Gómez et al. 2013, for a similar approach and arguments). I estimate the probability of changes in labor supply in period t as a function of a binary health shock measure (t-1), a continuous measure of ex ante control perceptions (t=0), and an interaction term of the two. Similar specifications have been used to identify the moderating effects of control beliefs on the effect of job loss and re-employment (Caliendo et al. 2014; McGee 2015) or on the effect of life events on emotional health (Buddelmeyer and Powdthavee 2016).

Importantly, to ensure that the labor-supply responses in period t do not merely reflect a fixed propensity to work less that correlates with control beliefs and past health, I condition the analysis on a sample of full-time working and healthy men in period $t-2$. Thus, I de facto prune the data to make the treatment (negative control) and the control group (positive control) as comparable in terms of pre-treatment health and labor force outcomes. Any remaining long-term differences in labor supply and workplace entitlements are controlled for by conditioning the analysis on accumulated past unemployment experiences, past labor market productivity, years spent at the firm, and employer characteristics, a strategy that has also been used by Riphahn (1999). Moreover, control perceptions are measured strictly before health and labor supply trajectories are observed. I use an averaged measure derived from factor analysis (e.g. Piatek and Pinger 2015) over three time periods (1994-1996) to reduce error measurement error (Cunha and Heckman 2008; Cunha et al. 2010; Cobb-Clark and Schurer 2013; Cobb-Clark et al. 2014).

One could further argue that an adult measure of ex ante control perceptions is a reflection only of past health experiences. To date there is no empirical evidence that shows that past health shocks cause negative control perceptions in adulthood. The only available empirical evidence shows that in shorter time periods over four years, negative control perceptions of working-age men do not respond to health shocks (Cobb-Clark and Schurer 2013). To ensure that adulthood control perceptions are not merely reflections of childhood or adolescence health problems, I further control the analysis on an averaged health measure also derived from years 1994-1996.

To control for regional variations in labor-market conditions and access to care, I control for state fixed effects and state-by-year unemployment rates. Although not perfect proxies for regional variations in access to care, these have been shown to sufficiently capture regional variations in funding of care in Germany (see Eibich and Ziebarth 2014; Goepffahrt et al. 2015, for arguments).[3] Finally, a series of robustness checks will be conducted to shut off one-by-one alternative mechanisms – differences in human capital, ex ante health, and intensity of the health shock – that could equally explain heterogeneous labor-supply responses to health shocks.

The results show that men with negative versus men with positive control beliefs are on average 100% more likely to drop out of the labor force and work on average 12% less hours per week the year after experiencing a health shock. These behavioral differences remain robust to alternative sample and health-shock definitions. They are strongest for men from low socioeconomic backgrounds, who do not have access to private health insurance, or who experience high intensity shocks. Heterogeneous labor-supply responses are also observed for conscientiousness and risk tolerance, traits that have been linked with willingness to invest and treatment compliance in the previous literature. However, no heterogeneous responses can be found for any other non-cognitive skills observed in my data, thereby excluding the possibility that control perceptions just proxy some other unobservable heterogeneity not controlled for in the model. An important conclusion to draw from these findings is that there are long-term labor market benefits of a small set of non-cognitive skills in the advent of adversity, which in combination could be powerful proxies of resilience.

The remainder of the paper proceeds in the following way. Section 2 lays out a theoretical model that explains the various mechanisms through which control perceptions can lead to heterogeneous labor-supply responses to health shocks. Section 3 discusses the available data, the choice of outcome and treatment variables, and summary statistics of the sample. Section 4 presents the econometric model and the tests I conduct to control for alternative mechanisms. Section 5 presents the analysis and robustness checks. Section 6 discusses the findings. An online appendix presents supplementary material.

[3]Germany's hospital infrastructure is financed and regulated by the 16 German states. The average geographic region is smaller than for instance the average US Hospital Referral Region. High density of physicians and hospitals in international comparison, in addition to relatively low hospital occupancy rates of 80% (see Gesundheitsberichterstattung des Bundes (2012), www.gbe-bund.de). Copayments for ambulatory or hospital services are, with minor exceptions, moderate and equal for all insured (Goepffahrt et al. 2015, p. 2).

2 Theoretical framework

Why would individuals with positive control beliefs reduce their work hours less in response to a health shock than individuals with negative control beliefs? The following, brief theoretical framework and numerical example serve to demonstrate the potential pathways and motivates my identification strategy described in Section 4. To illustrate ideas, I build on Grossman's Health Investment Model (Grossman 1972), which allows individuals to invest in their health to off-set yearly depreciations in health or a sudden increase in the depreciation rate (health shock). The Grossman model embarks from an inter-temporal utility function and budget constraint. The total time available for work is determined by the individual's health status. Individuals choose the hours they want to work on the basis of their perceived health - including perceptions of bodily function and pain - which may imperfectly correlate with objective health. Perceived health affects the perceived disutility from work.[4] The Grossman model can be solved for labor supply (see Schurer 2008, for an application in a two-period model). In a two-period model, period-2 labor supply in the optimum (LS_2^*) depends on period-2 heath status (H_2):

$$LS_2^* = g(H_2) \tag{1}$$

Health status in period 2 is the outcome of past investment (I_1), past health status (H_1), and the depreciation rate δ ($0 < \delta < 1$). Investment enters the health function non-linearly to emphasize that depreciation in health can directly be off-set by investment, and the return of the investment can be boosted by a productivity parameter α:

$$H_2 = \left(1 - \frac{\delta}{\alpha I_1}\right) H_1 \tag{2}$$

In line with the original Grossman model, the productivity parameter α is a function of education (E) and access to high-quality medical care (M) such that $\frac{\partial \alpha}{\partial E} > 0$ and $\frac{\partial \alpha}{\partial M} > 0$. Investment leads to higher perceived health ($\frac{\partial H_2}{\partial I_1} > 0$). Individuals work less hours when they perceive their health to be too low to justify the effort to work (reductions in H_2), i.e. $\frac{\partial LS^*}{\partial H_2} > 0$. In the original Grossman model, δ is assumed to be constant, but an increasing δ is discussed as a special case of

[4]For similar arguments in the context of malaria testing, perceived health and labor supply/productivity, see Dillon et al. (2014).

aging. For the purpose of this study, I let the depreciation rate increase exogenously to represent a health shock. Health status in period 2 is reduced if the depreciation rate increases by one unit.

This framework points to a number of mechanisms that could explain why individuals with positive control beliefs have a higher health capital in period 2, after the experience of a health shock ($\uparrow \delta$), and therefore supply more hours of work in period 2. Let θ represent beliefs that are increasing in positive control perceptions. I will demonstrate the consequences of each alternative hypothesis on labor supply with a numerical example. Let δ change from 0.4 to 0.5 to indicate a 0.1 unit health shock, $H_1 = 100$ (%), $I_1 = 1$ (Unit) and $\alpha = 1$. Under each scenario, the value of one of the four parameters will be changed.

Mechanism 1: Investment in health is a positive function of control beliefs ($\frac{\partial I(\theta)}{\partial \theta} > 0$). Let $I_1^{NEG} = 1$ unit and $I_1^{POS} = 2$ units. Health levels for the two groups will vary as follows:

$$H_2^{POS} = \left(1 - \frac{0.5}{2}\right)100 = 75, \tag{3}$$

$$H_2^{NEG} = \left(1 - \frac{0.5}{1}\right)100 = 50. \tag{4}$$

As a consequence, individuals with positive control beliefs will experience better (perceived) health in period 2, and therefore experience lower disutility of work, and will provide more hours of work than individuals with negative control beliefs. The tendency to invest in health to counterbalance adverse health events is a main characteristic of resilient behavior. It can be understood as the ability and the effort to adhere to strict treatment regimes and to establish healthy habits. Evidence on myocardial infarction survivors suggest perceptions of personal control are linked with a better adherence to recommended medication and behavioral regimes and a higher rate of returning to work following the recuperative period (See Strudler Wallston and Wallston 1978; Fitzgerald et al. 1993, for an overview of the literature). Previous research has also documented that individuals with positive control beliefs invest more in their health (Cobb-Clark et al. 2014; Chiteji 2010).

Mechanism 2: The productivity of health investments is higher for individuals with higher levels of education or better access to high-quality health care, and it is individuals with positive control beliefs who have higher levels of education and access to health care ($\frac{\partial \alpha(E(\theta)}{\partial E}\frac{\partial E}{\partial \theta} >$

$0, \frac{\partial\alpha(M(\theta)}{\partial M}\frac{\partial M}{\partial\theta} > 0)$. Therefore, individuals with positive control beliefs are more effective in transforming the same level of investment into health outcomes than individuals with negative control beliefs. Let $I_1^{POS} = I_1^{NEG} = 1$ unit, and $\alpha^{POS} = 1$ and $\alpha^{NEG} = 0.75$. Health levels for the two groups will vary as follows:

$$H_2^{POS} = \left(1 - \frac{0.5}{1 \times 1}\right)100 = 50, \tag{5}$$

$$H_2^{NEG} = \left(1 - \frac{0.5}{0.75 \times 1}\right)100 = 25. \tag{6}$$

Once again, the implication is that despite the same amount of investment, perceived health will be lower in period 2 for individuals with negative control beliefs than for individuals with positive control beliefs, because they differ in their access to high-quality medical care or information. This would lead to an observationally equivalent outcome as suggested by mechanism 1, although the underlying mechanism is different. Previous research has shown that individuals with positive control beliefs invest more in their own education (Coleman and Deleire 2003; Hadsell 2010) and in the education of their children (Lekfuangfu et al. 2014), and adolescents' control beliefs are associated with parental socioeconomic status (Schurer 2015; Anger and Schnitzlein 2015). Lundborg et al. (2015) show evidence on the education-related heterogeneity in the response to health shocks using Swedish administrative data, although the authors do not discuss the mechanisms.

Mechanism 3: Control beliefs are positively associated with ex ante health ($\frac{\partial H_1(\theta)}{\partial\theta} > 0$) and therefore individuals with positive control beliefs have better health at the outset. Let $H_1^{POS} = 100$ and $H_1^{NEG} = 50$. The health outcomes in period 2 for the two groups are:

$$H_2^{POS} = \left(1 - \frac{0.5}{1}\right)100 = 50, \tag{7}$$

$$H_2^{NEG} = \left(1 - \frac{0.5}{1}\right)50 = 25. \tag{8}$$

Hence, individuals with positive control beliefs will experience better health in period 2 than individuals with negative beliefs, even in the presence of the same health investment, the same access to high-quality care, and the same health shock. This mechanism raises the important concern that control beliefs measured in adulthood may be a proxy for long-term health problems. Adults with negative control beliefs may have experienced early-life health problems that cause adulthood negative control beliefs. There is evidence in the literature that control beliefs correlate with health status assessments in adulthood (e.g. Mackenbach et al. 2002; Klonowicz 2001), yet Cobb-Clark and Schurer (2013) have shown that persistent health shocks and chronic pain do not significantly boost negative control beliefs in adulthood (ages 25 to 60). This evidence does not invalidate the possibility that early life health conditions shape an individual's control beliefs. Some evidence suggests that children from low socioeconomic status (Schurer 2015) or unstable families (Anger and Schnitzlein 2015) are more likely to express negative control beliefs by adolescence. This evidence, in combination with evidence on social inequalities in child health outcomes (Pillas et al. 2014), points to the possibility that adulthood control beliefs may reflect an unhealthy start into life. Hence, despite the same increase in the health depreciation rate, investment, and productivity, individuals with negative control beliefs will have a lower absolute[5] level of health in period 2 than individuals with positive control beliefs.

Mechanism 4: Positive control beliefs are associated with lower depreciation rates ($\frac{\partial\delta(\theta)}{\partial\theta} < 0$). If individuals with negative control beliefs experience an episode of ill health that increases their health depreciation rate, then this shock would occur at a higher overall level of depreciation, while the change would occur at a lower level of depreciation for individuals with positive control beliefs. If there is a concave relationship between the depreciation rate and positive control beliefs ($\frac{\partial\delta}{\partial\theta} < 0$; $\frac{\partial^2\delta}{\partial\theta\partial\theta} < 0$) - which is a reasonable assumption because δ is upward bounded at 1 - then individuals with positive control beliefs will have a higher health status in period 2, even in the presence of the same health investment, initial level of health, and productivity. Let's assume the health shock increases δ for both groups by 0.1 units, but the long-term $\delta^{POS} = 0.1$ and $\delta^{NEG} = 0.4$, hence $\delta^{NEG} = 0.4 + 0.1 = 0.5$ and $\delta^{POS} = 0.1 + 0.1 = 0.2$, which results in the following two health outcomes in period 2:

$$H_2^{POS} = \left(1 - \frac{0.2}{1}\right)100 = 80, \tag{9}$$

[5]Note that individuals with higher levels of health in period 1, who experience an increase in the health depreciation rate, experience a larger marginal decline in health in period 2. However, in absolute terms, the health level in period 2 is still higher for individuals who were in better health in period 1, and therefore they can provide more hours

$$H_2^{NEG} = \left(1 - \frac{0.5}{1}\right)100 = 50. \tag{10}$$

If individuals with positive control beliefs experience weaker health shocks, even in the presence of the same health investment, ex ante health and access to care, then they will experience better health in time period 2. To the best of my knowledge, there is no empirical evidence that would support this hypothesis, although theoretically it is possible.

While mechanism 1 is the mechanism I seek to explicitly test for, all four mechanisms lead to an observationally equivalent outcome. Each mechanism predicts that individuals with positive control beliefs will have a better health status in time period 2 after experiencing a health shock, and therefore provide more hours of work, although the underlying causes are different.[6] Thus, it is important to choose an identification strategy that can separate out the heterogeneous labor-supply responses to health shocks due to differences in investment that result from differences in control beliefs (mechanism 1), from heterogeneity in access to high-quality care or information (mechanism 2), heterogeneity in initial health (mechanism 3), or heterogeneity in the health depreciation rates (mechanism 4).

Since at no point in the empirical analysis will I be able to observe the actual health investment behavior of individuals who experienced a health shock, I will show that mechanism 1 is likely by proof of exclusion by systematically turning off mechanisms 2, 3, and 4. Proof by exclusion of alternative mechanisms is valid under the assumption that the above theoretical model captures all relevant channels via which control beliefs affect health and labor supply.[7]

[6]Note, more complex scenarios can be thought of, e.g. that each of δ, I_1, H_1, α depend on θ. If individuals with positive control beliefs are simultaneously investing more in their health, start out with better perceived health, experience smaller health depreciations and have better access to high-quality care, then the differential responses to a health shock will be even larger.

[7]Some may argue that there is a fifth mechanism, namely that it is unobserved ability that drives labor supply decisions after the experience of a health shock. Such a competing hypothesis was discussed in Caliendo et al. (2014) and Coleman and Deleire (2003). In both studies, the alternative hypothesis is that for highly intelligent individuals jobs will arrive at a higher rate, and therefore highly able individuals are more likely to find a job. Unlike Coleman and Deleire (2003) and Caliendo et al. (2014) who model the heterogeneous behavior of high school students and the unemployed, respectively, I focus on individuals who are full-time employed and hence do not apply for a (new) job.

3 Data, identification strategy, and variable definition

3.1 The German institutional context

Germany provides an ideal setting to test the medium-term responses to health shocks, because Germany's generous social security system ensures almost universal access to health care and allows individuals to stop working, or reduce hours of work, when experiencing a debilitating illness while maintaining a regular income flow for at least 1 1/2 years thereafter. In the case of illness, German employees can rely on income provided by various insurance funds.[8] The sickness funds give cash benefits to their members during the first six weeks of sickness while employers pay 100% of the employee's last net income. Afterwards, sickness funds continue to pay for up to 78 weeks 80% of the last net income (Johnson and Stoskopf 2010).

In addition, medical health care is universally provided independent of employment status, in contrast to the United States, where health insurance is mainly tied to the employer. The latter implies that individuals may have to continue to work in case of illness, just to be able to afford health care (Bradley et al. 2007). This does not mean that employees do not have private health insurance, in fact 10% of the population have private cover in Germany. Private health insurance coverage is less strictly regulated and subject to individual underwriting with risk-based premiums. It is especially attractive to healthy and high-income individuals, but the evidence is mixed with respect to whether there is positive or negative selection into private health insurance (Schmitz 2011). More importantly, Germany has the advantage of a highly homogeneous health care system. Co-payments for ambulatory or hospital services - with minor exceptions - are small and equal for all insured. There are regional differences in base rates, but these differences can be controlled for by regional fixed effects or measures of local economic activity (see Goepffahrt et al. 2015).

Even though the German Termination Protection Act allows employers to lay off employees who are on long-term sick leave, employers must abide with strict notice periods of seven months. Notice periods - independent of the reason of dismissal - increase with seniority of the employee. For instance, employees who have worked for 15 years in the same company enjoy a six-month

[8]The German Social Security System consists of health insurance, home care and nursing insurance, pension insurance and unemployment insurance and it is mandatory to all employees.

notice period. Very strict guidelines apply also for workers with disabilities who enjoy special protection.[9] To this extent, short-term changes in employment due to illness-related layoff are unlikely to be observed in the time-frame of this analysis. This means that the German case allows me to study the medium-term effects of ill health on labor supply that result from individual choice rather than from budget constraints or health-related lay offs.

3.2 Identification strategy

The analysis is conducted with data from years 1994-2012 extracted from the German Socio-Economic Panel (SOEP Data Release 1984-2012). The SOEP is a longitudinal survey of private households established in West Germany in 1984, which extended its sample after Germany's reunification to include the new Bundeslaender.[10] In its first year the study included 5,921 households from which 12,245 individuals from age 17 onwards were successfully interviewed ("German West" and "Foreigner" sample). Further samples were added in consecutive years from which my study uses the "German East" (1990), "Immigrant" (1994/1995) and the "Refreshment" (1998) samples. The SOEP achieved a reasonably high first wave cross-sectional response rate of 64.5% and has an average longitudinal response rate of 92.2% (Wagner et al. 2006).

My identification strategy relies on selecting a sample of men from the SOEP with the following characteristics: (1) complete data is available on ex ante positive control beliefs and ex ante health status, both measured as average over three time periods between 1994-1996; (2) aged between 25 and 60 years between 1997 and 2012; (3) admitted to hospital for at least 10 nights at some point in time between 1998 and 2011; and (4) being in good health and in full-time employment one year before experiencing an episode of ill health. Starting in 1997, I draw three-year intervals repeatedly from the data which I use to condition the sample on healthy and fulltime employed men in period $t-2$, but who experience a health shock in the second time period of the interval ($t-1$). I then explore whether labor supply changes in time period t and whether this change is linked to negative control beliefs. In total, there are 14 three-year intervals (See

[9] For an overview of the German Employment Law, see `http://www.iclg.co.uk/practice-areas/employment-and-labour-law/employment-and-labour-law-2016/germany` and `http://www.ilo.org/ifpdial/information-resources/national-labour-law-profiles/WCMS_158899/lang--en/index.htm`.

[10] The data used in this paper was extracted from the SOEP Database provided by the DIW Berlin (http://www.diw.de/soep) using the Add-On package SOEP Info for Stata(R). It uses the 95% Scientific sample obtained from Cornell University.

Table A.1 in the Appendix).[11] Some individuals experience multiple hospital admissions during 1998 and 2011.

Importantly, I consider the labor-supply responses of men only due to the difficulty in modeling female labor supply, and separating out health shocks and labor-supply responses from pregnancy experiences. The age restriction of my sample to men who are no younger than 25 years and no older than 60 years of age at any point within the three-year intervals is chosen to more cleanly identify health-related labor-supply responses. The upper bound is chosen to ensure that short-term labor supply decisions are not driven by retirement decisions, which depend on superannuation availability and savings. In fact, there is no case of retirement in the estimation sample. The lower bound is chosen to ensure that short-term labor-supply decisions are not driven by frequent transitions in-and-out of education.

Between 1994 to 1996, there are 6930 men present in at least one of the years. Out of these, 6703 or 96.6% have at least once information available on control perceptions and health status. By restricting the sample to be at least 25 years of age from 1997 onward and not older than 58 years in 1997, another 24.4% of the sample is lost. Of the remaining 5065 individuals, 89% provide at least once information on whether they have experienced a health shock, leaving a sample of 4510 individuals. Another 11.7% of individuals are lost because they do not have information available at least once about their labor force status. Restricting the analysis on individuals who are not in bad or poor health in period $t-2$ and who are employed generates a final sample of at least 3730 individuals.[12] Of these 3730 individuals, 649 experienced an episode of ill health that I define as a health shock (10 nights at hospital). Alternative definitions of a health shock constructed using self-assessed health measures yields a sample of 771 individuals. About 16% of these individuals remain in the sample until 2012 (T=16), and the median length of stay in the sample is seven years. 117 individuals ultimately drop out of the sample due to death, 31 of which have experienced a health shock.

Because of the specific sample definitions, health and labor-supply related attrition from the

[11] This strategy of constructing three-year intervals for the analysis is adapted from García-Gómez (2011) and García-Gómez and López-Nicolás (2006).

[12] Most basic control variables are available for this sample. I flag missing observations for the following control variables: Big-Five personality traits and risk tolerance, years of education, sector and industry. When conditioning the sample on no missing values of the Big-Fiver personality traits and risk tolerance, that were measured in 2005, the treatment effects of interest would be stronger.

panel may be of concern. I tested for the possibility of systematic attrition, and conclude that my sample selection - at worst - is likely to downward bias my estimates of interest. Estimating a probit model of the probability of dropping out of the sample at some point in time, I find that men are more likely to drop out of the sample who had weaker ex ante health and labor force attachment, and who have ex ante negative control perceptions (marginally significant). Men who experienced a health shock are almost 200% more likely to dropout of the sample than men who did not experience a health shock (see Table A.2, Online Appendix). There are no statistically significant interaction effects between health shock and ex ante control perceptions.

If these are also the individuals who would experience the strongest health deteriorations in the future and the weakest labor force attachment, then this would flatten the negative relationship between changes in health and labor supply responses for individuals with negative control beliefs. As a consequence, the difference in labor-supply responses at any level of health deterioration between men with positive and negative control beliefs would be artificially reduced.

3.3 Variable definitions

3.3.1 Labor supply

The many studies that investigate the effect of ill health on labor market outcomes find that a strong negative impact operates through employment and work hours rather than wages (Bound et al. 1999; Smith 1999; Riphahn 1999; Disney et al. 2006; Lindeboom and Kerkhofs 2009). Therefore, I will use in the analysis four different labor-supply outcome measures: (1) a continuous variable of weekly hours worked including zero; (2) a binary indicator of whether the individual has dropped out from the labor force, but not due to retirement; (3) a binary indicator whether the individual works part-time; and (4) a binary indicator of whether the individual is unemployed. Part-time employment takes the value 1 if the individual works 20 hours or less per week (excluding zero hours).[13] On average, individuals in the full sample work 42 hours per week, while 1.42%

[13]This is an arbitrary cut-off, but in Germany there is no uniform definition of part-time work. An employee is considered to be part-time employed if his or her weekly working hours fall short of the fixed working hours arrangement of the particular industry and business. For instance, if the fixed working hours arrangement is 38.5 hours per week, then someone working 35 hours per week is considered to be working part-time. According to the Working Hours Legislation (Paragraph 3 ArbZG), the upper limit of work-hours is eight hours per day, hence someone who works 20 hours per week or less could work at maximum 2 1/2 days during the week. For simplicity, however, the measure will be referred to as part-time work.

drop out of the labor market, 3.4% become unemployed, and 6.4% work part-time at some point in time. In contrast, average labor supply in the years following the health shock is significantly lower for the 649 men who experience a health shock (see Table 2).

3.3.2 Health shock

To assess the effect of health on labor supply it is common in the literature to use a binary measure of a health shock. Smith (1999) and Smith (2005) argue that unanticipated, or at least significantly large, changes in health could serve as exogenous variation in health that aids identification of a causal impact of health on labor supply. I will follow this method, but instead of constructing the health shock from self-assessed health data,[14] I use information on hospital admissions which indicate acute health problems, a strategy that was also used in García-Gómez et al. (2013).[15] My health-shock measure takes the value 1 if the individual was admitted to hospital for 10 nights or more, which represents more than two sample standard deviations, and 0 otherwise (2.3%, 649 individuals). In the sample, the largest number of hospital admissions is 140 nights, but only 32 individuals exceeded 50 nights (Figure A.1, Online Appendix). In a robustness check, I further explore alternative health shock definitions such as changes in hospital admissions from one year to the other by more than 2 sample standard deviations, an increase in total health care utilization by 21 visits (> 2 sample standard deviation), or a drop in self-assessed health by two or more points (> 2 sample standard deviations).

In Germany, as in many OECD countries, patients have little influence over the number of nights they can spend in hospital for treatment, especially since the introduction of diagnosis-related groups (DRGs)-type payment system in 2000, which classifies patients into groups according to the consumption of resources required to treat their condition. Optimally, I would use

[14] E.g. Riphahn (1999), García-Gómez (2011), and García-Gómez and López-Nicolás (2006) construct a health shock from subjective health data, which will be considered in a sensitivity analysis. However, it is not the preferred solution in my setting to use self-assessed health for the construction of the health shock, because large variations in self-reports of health have been linked to variations in the personality trait of locus of control (Klonowicz 2001). In such a case, individuals with negative control beliefs would report a health shock despite having the same 'objective' level of health as individuals with positive control beliefs and thus would not be more likely to change their labor supply than a comparable positive-controlled individual. An optimal health shock measure would be a purged health measure, which is the predicted value from an estimated model of self-assessed health that controls for specific medical conditions (e.g. Bound et al. 1999; Disney et al. 2006; García-Gómez et al. 2010), which is not available in SOEP.

[15] García-Gómez et al. (2013) define their health shock in terms of acute hospital admissions of at least three days.

evidence based on diagnoses that underlie the health shock, but this information is not comprehensively available in my data. Since the number of nights spent at hospital is highly regulated, I can provide an approximate idea of what type of illnesses or injuries my health shock measure proxies. Data on German in-patient length-of-stay by diagnosis provided by the European Commission and OECD suggest that diseases of the circulatory system require ten days, of the respiratory system require less than nine days, of the muskoskeletal system and connective tissue require 11 days, and lung cancer 12 days. More severe conditions entail longer spells at hospital. For instance, obstructive pulmonary disease require on average 120 days, acute myocardial infarction 105 days, asthma 80 days, and cerebrovascular disease 270 days.[16]

In addition, the SOEP data provide for a small sample of individuals information on health diagnoses (nine health conditions) that was collected in two special modules in 2009 and 2011 only. I regress each of the health conditions on the lagged health shock measure and control for five quantile indicators of negative control beliefs (base: positive control), age-group indicators and private health insurance (Table A.3 Online Appendix). Individuals who spent at least 10 more nights at hospital last year are 183% more likely to be diagnosed with cancer, and between 112%-190% more likely to be diagnosed with cardiovascular disease, diabetes, or depression, while no effect is found for asthma, stroke, or megrim. Generally, there is no link between these health conditions and control perceptions with two important consequences. Men with negative control beliefs are almost 100% less likely to suffer from cancer relative to men with positive control beliefs, but 67% and 100% more likely to suffer from cardiovascular disease and depression, respectively.

From these data, one cannot say with certainty whether any of these illnesses are more or less under the actual control of the individual. Cancer, cardiovsacular disease, and depression are the most common and most costly chronic diseases in OECD countries. Some cancer can be well managed if diagnosed in early stages, and treatments are more effective if the patient exercises and eats healthily. Similarly, cardiovascular disease can be managed through life-style changes such as healthy diets and exercise. However, it would be purely speculative to say that any of these conditions are more or less endogenous to the behavior of the individual, or that individual health

[16] Data collected between 1998 and 2000 are accessible at: `www.ec.europa.eu/health/ph_information/dissemination/echi/echi_4_en.htm#37` and `www.euphix.org/object_document/o5579n27121.html`.

investments are more effective in let's say in cardiovascular disease management versus cancer management. All we can say is that the main health shock proxy is associated with important chronic illnesses in my data.

3.3.3 Control beliefs

In 1994, 1995, and 1996, the SOEP included a personality questionnaire that contains eight of the original 23-items of the Locus of Control Scale developed by Rotter (1966) (See Table 1 for item description). The scale assesses the extent to which one regards opportunities in life as being under one's control (positive control beliefs) versus being chance-determined, incidental, and unpredictable (negative control belief). Participants were asked to indicate their agreement with each of the eight items on a scale ranging from 1 (applies completely) to 4 (does not apply). The answers to items Q1, Q3, and Q6 were reversed so that high values of each item indicate external control tendencies. An exploratory factor analysis reveals that all eight items load unambiguously on one principal factor. I dropped item Q3 from the overall inventory as its exclusion enabled the internal consistency, measured by Cronbach's α (Cronbach 1951), to be improved from 0.726 to 0.739.[17] To achieve higher construct validity, I predict this first principal factor from factor analysis in each year.[18] Using a predicted first factor as index of negative control beliefs allows each item to contribute to the index with a different weight. To construct a time-invariant measure of control beliefs, I average the score for each individual across 1994-1996. Averaging across repeated measures reduces the likely measurement error in self-assessed non-cognitive skills (see Cobb-Clark et al. 2014).[19] A binary measure of negative control beliefs, that will be used in some of the descriptive analysis, is defined to take the value 1 if the index is greater than the 75^{th}

[17]Cronbach's α measures how closely related are the eight items as a group by considering the proportion of the average inter-item covariance in the total variation in the data. Higher levels of α are usually an indicator for one underlying concept. A level of 0.7 or above is usually accepted as satisfactory. Heineck and Anger (2010) also use SOEP data and calculate Cronbach α reliability measures for, among others, locus of control data measured in 2005. They exclude Q1, Q4, Q6, and Q7, however, a principal component analysis of Q2, Q3, Q5, Q8, Q9, and Q10 yields two factors upon which all remaining questions load and the resulting Cronbach's α is .62, which is significantly lower than the Cronbach's α obtained when excluding Q4, Q6, and Q9.

[18]Similar definitions have been used in Cobb-Clark et al. (2014); Piatek and Pinger (2015). Cobb-Clark and Schurer (2013) compared the performance of the factor-analytically derived measure against a measure that simply sums up all items, which has been used in e.g. Caliendo et al. (2014). The method for index aggregation does not affect the estimation results.

[19]Cobb-Clark and Schurer (2013), Cunha and Heckman (2008) and Cunha et al. (2010) emphasize the importance of measurement error in non-cognitive skills in their analysis of the determinants and the evolution of non-cognitive skills in early childhood and adolescence.

percentile, and 0 if it is smaller or equal to the 75^{th} percentile (positive control beliefs). The 75^{th} percentile cut-off value takes into account the left-skewed nature of external control tendencies.[20]

Choosing a measure of control beliefs that is averaged over three time periods and is measured strictly before all outcome and shock measures are observed reduces the risk of endogeneity in control beliefs. Even so, endogeneity in control beliefs may not be a large problem. Cobb-Clark and Schurer (2013) investigated in detail whether control perceptions respond to unanticipated life events. They conclude that for a working-age population control perceptions are surprisingly stable. At most, individuals change their answers by three points on a scale from 7 to 49. These small changes cannot be explained by life events, and most importantly, they cannot be explained by prolonged experiences of illness. Similar results on the stability of locus of control beliefs in adulthood are found for longer time periods using British cohort data (Schurer 2015). However, Schurer (2015) also finds that childhood socioeconomic status and parenting behavior are significant predictors of persisting negative control beliefs in adolescence. Since childhood socioeconomic status determines health outcomes over the lifecycle, it could be that adulthood control beliefs capture either socioeconomic status or long-term health problems.[21] I will explicitly deal with this possibility in the empirical analysis.

3.4 Descriptive analysis

Before moving on to outline the econometric models and the full data analysis, I will describe in this section the changes in labor supply, health care utilization and health outcomes for my main estimation sample by differences in control beliefs. A first glance at the SOEP data reveals that male labor-supply responses to health shocks do indeed differ by control beliefs. Figure 1 shows the average work-hours (and their 95% confidence intervals) separately for men with positive (solid line) and negative control beliefs (dashed line) over six time periods: two time periods before the health shock occurred ($t-3, t-2$), during the health shock ($t-1$), and three time periods after the health shock occurred ($t, t+1, t+2$). The sample is conditioned on men who were in

[20]There is no generally accepted threshold to categorize individuals into positive or negative control beliefs. Caliendo et al. (2014) use the sample mean as a cut-off value.

[21]It is further possible that control beliefs measured as an average across 1994-1996 are the result of age-specific variations in non-cognitive skills. In a robustness check, I adjusted the control beliefs scores by age (e.g. Heineck and Anger 2010). None of my conclusions change by using the age-adjusted measure, likely because in my sample control beliefs do not co-vary by age (correlation coefficient: 0.06). These results are provided upon request.

good health and worked full-time in period $t-2$ (N=649). There are two important conclusions to be drawn from this figure. First, all men reduce their work hours during and following the year of the health shock $(t-1)$. This is a standard finding in the literature and holds for various age groups (Crichton et al. 2011; Disney et al. 2006; Wing Han Au et al. 2005; Bound et al. 1999; Riphahn 1999; García-Gómez et al. 2010; García-Gómez and López-Nicolás 2006). Second, men who expressed negative control beliefs many years before the experience of a health shock are more likely to experience stronger reductions in hours worked than men who expressed strong positive control beliefs. In this example, men with negative control beliefs work only 32 hours per week, while men with positive control beliefs work 38 hours, a statistically significant difference of 6 hours on average, in period $t+3$.

Figures 2(a) to 2(d) describe in a similar way the evolution of doctor visits, number of nights spent at hospital, combined doctor visits and nights spent at hospital, and self-assessed health before and after the experience of a health shock by control beliefs. Again, dotted lines represent the 95% confidence interval bands. Before the health shock occurs, individuals with negative and positive control beliefs look very much alike in terms of health-care utilization and health status. Both groups, on average, visit a doctor about ten times a year, and spend less than two nights in hospital.[22] Both groups are also on average in good health before the health shock with an average health score of 2.5, which indicates good health or better.[23] In the year of the health shock $(t-1)$, by definition both groups increase their nights spent at hospital to 19 (positive control) and 22 (negative control) (Figure 2(b)), and their annual doctor visits to 18 and 23 visits, respectively (Figure 2(a)). These differences in health care utilization by control beliefs are not statistically significant at the 5% level or better. A year after the health shock both groups reduce their health care utilization to the baseline level, and no statistically significant differences emerge.

However, the evolution of health during and after the health shock is significantly different between the two groups (Figure 2(d)). During the health shock, men with negative control beliefs rate their health at 3.2, while men with positive control beliefs rate their health at 2.9, a difference

[22]One could argue that my sample is already chronically ill before the health shock, because its members spend already two nights in hospital and consult a doctor around ten times per year. However, health care utilization of my sample members is in line with the average German health care utilization. Data from the European Community Household Panel (1996) reveal that on average Germans consult a GP 5 times a year, a specialist 3 times a year, and spend 2 nights in hospital (Van Doorslaer and Masseria 2004). Further, for my research study it is important that men with positive and negative control beliefs do not differ in their pre-shock health care utilization.

[23]The health scale is increasing in ill health and ranges between 1 (excellent) and 5 (poor).

that is statistically significant at the 5% level. Importantly, three years after the experience of the health shock, the perceived health of men with negative control beliefs is still significantly worse than the perceived health of men with negative control beliefs (2.8 versus 3.1).

Table 2 shows the means of observable characteristics for men with positive (column 1) and negative control beliefs (column 2), and the p-values of the hypothesis test of no difference in means (column 3). Men with negative control beliefs have significantly lower levels of education (11 versus 13 years) and are significantly less likely to have private health insurance (4% versus 12%). This suggests that mechanism 2 could explain the heterogeneous labor-supply responses. It is also true that men with negative control beliefs have slightly lower levels of self-assessed ex ante health (2.3 versus 2.5), which would be evidence of mechanism 3. Finally, men with negative control beliefs are more likely to cluster in the higher end of the hospital night distribution, which is evidence for mechanism 4. In Figure 3 I display the relationship between negative control beliefs and the number of nights spent at hospital (bivariate kernel estimate with 95% confidence interval). There is no systematic relationship between control beliefs and the number of nights spent at hospital up until 19 nights. However, men with negative control beliefs are significantly more likely to have spent 20 or more nights at hospital (20-24 nights, 25-34 nights, and 35+ nights; N=195).

Table 2 also presents summary statistics of important determinants of labor supply by positive and negative control beliefs. Individuals with negative control beliefs are significantly less likely to work in professional and technical occupations, which is also reflected in a lower wage in period $t - 2$. They also differ significantly in other non-cognitive skills. They tend to be less risk tolerant, extraverted, and open to experiences, but they tend to be more neurotic. They also have accumulated more unemployment experience up until period $t-2$ (0.4 versus 0.8 of a year). They are less likely to work in very large companies, and are more likely to be a foreigner. These descriptive statistics emphasize that the main estimation strategy must account for the remaining differences in observable characteristics between individuals with negative and positive control beliefs.

4 Estimation methods

4.1 Modeling labor supply

To estimate the heterogeneity in the response to health shocks, I specify two separate models: (1) a tobit model in which weekly work hours - including 0 - is the outcome variable (censored from below at 0); and (2) a probit model in which a dummy variable that captures whether the individual has dropped out of the labor force is the outcome variable.[24] In both cases, I estimate the reduced form equation that is commonly used in the literature, and that can be directly derived from Eqs. (1) and (2). The estimation model will be illustrated for a probit model of the probability of dropping out of the labor market, that is similar to the specification in Riphahn (1999). Let Y^*_{it} be the true, but unobserved propensity to drop out of the labor force:

$$Y^*_{it} = \alpha_0 + \alpha_1 \bar{CB}_i + \alpha_2 HS_{it-1} + \alpha_3 \bar{CB}_i \times HS_{it-1} + \gamma \bar{H}_i + NCS'_i \mu + X'_{it} \beta + Z'_{it-2} \phi + \varepsilon_{it}. \quad (11)$$

Individual i is observed in time period t for $t \in \{1997, \dots, 2012\}$. In the data, a binary measure Y_{it} is observed which takes the value 1 if $Y^*_{it} > 0$, and 0 otherwise. The parameter α_0 is the average probability of dropping out of the labor force and α_1 represents the deviation from this mean by negative control beliefs ($\bar{CB}_i$). The variable HS_{it-1} is a binary indicator of the health shock, lagged by one time-period to ensure that changes in health are not the result of contemporaneous work conditions. Importantly, the health shock also enters the equation as an interaction with the continuous measure of control beliefs ($\bar{CB}_i \times HS_{it-1}$). The parameter α_2 measures the effect of the health shock on the probability of dropping out of the labor force for an individual with average control beliefs ($\bar{CB}_i = 0$), while α_3 indicates whether this effect differs by control beliefs. The main hypothesis of interest is $H_0 : \alpha_3 = 0$ against the one-sided alternative $H_a : \alpha_3 > 0$. The interaction effect is expressed as a movement from the lowest to the highest 10^{th} percentile of negative control beliefs, which is a common strategy used in the literature to represent the effects of non-cognitive skills on an outcome of interest (e.g. Heckman et al. 2006).

To be able to interpret the moderating effect of α_3 as causal, it is important to control for a variety of observable characteristics as suggested by the theoretical model in Section 2. Most

[24] In the empirical section, I will also estimate the probability of being registered as unemployed and working part-time ($\leqslant$ 20 hours, excluding 0).

importantly, I condition the analysis on ex ante trends in underlying health, where $\bar{H}_i$ is a measure of average health between 1994 and 1996. The parameter γ measures the influence of ex ante health on labor supply. The vector NCS_i' includes measures of other non-cognitive and cognitive skills that are likely to influence labor-supply decisions such as the Big-Five personality traits (Agreeableness, Conscientiousness, Extraversion, Neuroticism, Openness to Experience), willingness to take risks, and a measure of cognitive ability (Symbol digits modality tests) that were used in the same way by Heineck and Anger (2010).

The vector X_{it}' captures personal characteristics such as age (age groups in five-year intervals), private health insurance, years of education, being a foreigner, marital status, number of children below the age of 16, and the partner's labor force and health status. It also includes proxies for current labor market conditions such as the state-by-year unemployment rates,[25] state fixed effects, and time fixed effects that may affect contemporaneously the probability of leaving the labor market. State fixed effects and local unemployment rates in combination are also capturing regional variations in health care expenditures that have been reported for Germany (see Goepffahrt et al. 2015; Eibich and Ziebarth 2014, and references therein) and that may influence access to high-quality care. Z_{it-2}' is a vector of variables that proxy the individual's productivity potential, life-time earnings and benefit entitlements when employed (cumulative unemployment experience since working, prior wage, size of firm, occupational status, and tenure and tenure squared at firm of employment).[26] The error term ε_{it} is assumed to be normally distributed with a mean 0 and a variance of 1 (binary probit). Due to repeated observations across time, the standard errors are clustered by individual identifiers.

For a better overview of which assumptions apply to identify a causal interaction effect, the identification strategy is graphically depicted in Fig. 4.[27] The parameters of interest, α_2 and α_3, will be consistently estimated with Maximum Likelihood under the following assumptions: (1)

[25]Data on local unemployment rates are taken from the German Labor Agency Statistics and merged to the SOEP data on the basis of state and year identifier. These data are accessible at: `http://www.pub.arbeitsamt.de/hst/services/statistik/detail/z.html`.

[26]These measures are noisy proxies of what Blundell and MaCurdy (1999) stress should be included in labor supply models such as life-time wages, non-labor income (property income), and initial wealth. The authors admit that usually these are not included in survey data or measured with error. However, in my empirical specification, main interest is not to estimate consistently wage elasticities, but the effect of health and locus of control.

[27]This depiction is adapted from Decker and Schmitz (2015), who use a similar identification strategy with SOEP data.

$\bar{CB}_i$ and NCS_i' pick up all relevant individual-specific heterogeneity that correlates with episodes of ill health and labor supply; (2) conditional independence, which means that all remaining differences in the propensity to experience an episode of ill health and to drop out of the labor market are adequately accounted for by observable characteristics; and (3) a correct functional form is specified.

4.2 Testing for alternative mechanisms

As outlined in Section 2, there may be three alternative mechanisms which could explain a significant interaction effect between control beliefs and ill health on labor supply. I will address each mechanism one-by-one in a series of robustness checks to the benchmark model. To control for mechanism 2, I will first re-estimate Eq. (11) separately by educational qualification groups. Educational groups are defined according to Germany's three-tiered education system. This system separates students at age 10 into university school pathways, a process often blamed for creating an education system that allows for little upward mobility (See Heineck and Riphahn 2009, for an overview). Children who go through the minimum schooling pathway (Hauptschule) will end up mainly in manual labor occupations, whereas individuals going through the intermediate schooling pathway select into administrative, low-level public sector, and service occupations, although some can go on to obtain a degree from a polytechnic university. Students who go through the highest level of schooling (Gymnasium) usually go on to university and take up managerial, professional or technical occupations. Therefore, three groups are distinguished: Minimum schooling (N=265), intermediate schooling (N=245), and university education (N=111).[28] If the buffering effects of control beliefs reflect a general principle, not just an occupation- or education-specific phenomenon, then we should observe heterogeneity in the treatment effect by control beliefs within each group. Second, I will also re-estimate Eq. (11) using a sample of men who have public health insurance only (N=393), excluding the possibility that heterogeneous labor-supply responses are caused by access to higher-quality health care through private health insurance.

Mechanism 3 suggests that negative control beliefs are associated with lower levels of ex ante health. I have controlled for this in the benchmark specification by conditioning the sample on

[28]The estimation sample is reduced from 649 men to 621 men because the the variable describing educational pathways is not available for all sample members.

healthy men in period t-2 and by controlling for long-term, ex ante differences in health. To go a step beyond these controls, I additionally conduct the following sample restrictions: (1) men of age 56 or younger (N=525), because older age is associated with frail health; (2) men without chronic illnesses by dropping all men who experienced multiple health shocks (N=448); (3) men who survive the health shock (N=618); and (4) men who were already in good health ex ante (N=615).

According to mechanism 4, men with negative control beliefs experience worse episodes of ill health, and this could suggest that their health is worse in the next time period. To deal with belief-related heterogeneity in the intensity of the health shock, I re-estimate Eq. (11) by distinguishing seven intensities of the health shock: (1) 1-4 nights at hospital (N=560);(2) 5-9 nights (N=555); (3) 10-14 nights (N=333); 15-19 nights (N=85); 20-24 nights (N=89); 25-34 nights (N=69); and 35 or more nights (N=73). Each of these intensity indicators enters the regression model in levels and as an interaction with negative control beliefs.

Finally, one could argue that control beliefs capture other individual-specific heterogeneity that the theoretical model does not capture. To test for this possibility, I re-estimate Eq. (11), but I interact the health shock - sequentially - with one of the above defined non-cognitive skills (Risk tolerance, Conscientiousness, Extraversion, Agreeableness, Openness, Neuroticism). If control perceptions capture differences in investment behavior, then I should find significant interaction effects with non-cognitive skills that are also associated with resilience, persistence, and investment behavior (e.g. risk tolerance, conscientiousness), but not with non-cognitive skills that proxy altruism (agreeableness), sociability (extraversion) or openness to cultural experiences. I refer to this additional analysis as mechanism 5.

5 Estimation results

5.1 Main specification

Table 3 presents the estimation results from both tobit (outcome: "weekly work-hours") and probit models (outcomes: "out of the labor force", "part-time work", "unemployment"). Reported are marginal effects of the main variables of interest. Coefficients from the full model are reported in Table A.4 (Online Appendix). All marginal (probability) effects are calculated for a 1 standard deviation increase in the respective variable, or, as in the case for the interaction effects, for a move from the bottom to the top 10^{th} percentile in negative control beliefs.[29] As pointed out in Ai and Norton (2003), computing the correct marginal probability effect of α_3 is not straightforward in nonlinear regression models. Even if this coefficient is statistically indistinguishable from 0, the cross-partial derivative can still be different from 0. To compute the marginal interaction effect in the nonlinear models, I follow the computation method suggested in Karaca-Mandic et al. (2012).

For the average individual in the sample ($\bar{CB}_i = 0$), experiencing a health shock in period $t-1$ leads to a reduction in work hours by almost 4 hours (significant at the 1% level) and an increase in the probability of dropping out of the labor market or becoming unemployed by 1.6 and 1.1 percentage points, respectively (significant at the 1% and 5% level). There is substantial heterogeneity in this effect by control beliefs on both work hours and inactivity. On average, men with negative control beliefs (90^{th} percentile), who experienced a health shock, work 4.6 hours less per week (significant at the 5% level) than men with positive control beliefs (10^{th} percentile). These interaction effects imply a 12% reduction in work hours relative to the mean work hours of men with positive control beliefs who also experienced a health shock. The difference in the effect of ill health on inactivity for men with positive control and men with negative control control beliefs is 0.043 (significant at 1% level). This means that initially full-time employed and healthy men with negative control beliefs who experienced a health shock in period $t-1$ are 4.3 percentage points more likely to drop out of the labor force a year after the health shock than comparable men with positive control beliefs, ceteris paribus. Relative to the mean probability of 4.2% in the sample of men with positive control beliefs who also experienced a health shock, this implies a 103% increase in the probability of dropping out of the labor force. The heterogeneous response to a health shock is sizeable in comparison to the marginal effects calculated for other important determinants of labor supply. For instance, older individuals (55-60 years) are 1.8 percentage points more likely to drop out of the labor force than young individuals (25-29). Given that none of the changes in labor supply are associated with unemployment or retirement, they are likely to be associated with movements into disability insurance.

[29] The estimated models with interaction effects between control beliefs and the health shock are preferred over a specification without interaction term for the outcomes "out of the labor force" and "work-hours" according to both AIC and McFadden's R-squared criteria (See Table 3, bottom panel). The models pass a functional form test (Pregibon's Link) at the 5% level of significance or better for all models except for the outcome "part-time".

Choosing an alternative definition of the binary measure of a health shock does not change this conclusion. For instance, increasing the threshold of hospital admissions to 20 or more days or using deteriorations in self-assessed health by two or more units (2 sample standard deviations) - increases the marginal probability effect of interest from 4.3 percentage points to 8.1 percentage points and 6.5 percentage points, respectively and both interaction effects are significant at the 1% level. Using annual changes in health care utilization that exceed 2 sample standard deviations - for instance changes in health care visits that exceed 21 visits or changes in nights spent at hospital that exceed 20 - as a basis for constructing the health shock yields marginal probability effects of interest of 4.3 percentage points (significant at the 1% level) and 4.9 percentage points (significant at the 10% level), respectively. Hence, using alternative health shock definitions yield interaction effects that are equivalent or exceed the interaction effects obtained from the benchmark model. Finally, restricting the sample to individuals who have no missing values on education and non-cognitive skills (544 individuals with a health shock), increases the marginal probability effect from 4.3 to 5.4 percentage points. Due to systematic dropout of the sample for individuals with worse ex ante health, ex ante labor force attachment, and control perceptions, the presented estimates are likely to be a lower bound.

5.2 Controlling for alternative mechanisms

The results of the previous section demonstrate that the moderating effects of positive control beliefs are significant and sizeable. They continue to persist when controlling in a rigorous way for mechanisms 2 to 5. Figure 5 summarizes all treatment effects of interest for the outcome "dropping out of the labor force" for alternative specifications that seek to turn off one-by-one mechanisms 2-5. The boxplots report the marginal probability effect (black dot) and their 95% confidence intervals (capped lines). The numbers on the upper horizontal axis indicate the Model. For comparison, each boxplot also reports the benchmark effect from the main specification (Model 1).

Figure 5(a) reports the robustness checks regarding mechanism 2. The interaction effect of the health shock with control beliefs remains large for both men with minimum schooling (Model 2) and men with intermediate levels of schooling (Model 3), while there is no statistically significant interaction effect for men with university education (Model 4). Men with minimum schooling who have strong negative control beliefs are almost 7 percentage points more likely to drop out of the labor market after the experience of a health shock than men with the same level of schooling but who have strong positive control beliefs. The difference in the dropout probability is 4 percentage points for men with intermediate levels of schooling (both significant at the 10% level). In addition, among all men who have no private health insurance, the interaction effect is over 6 percentage points, and significant at the 1% level. This suggests that heterogeneous labor-supply responses to health shocks are not driven by an education or insurance gradient in control perceptions.

Figure 5(b) reports the robustness checks regarding mechanism 3. Models 2 and 3 show that the treatment effect becomes slightly larger (5 percentage points) when not controlling for ex ante health and not conditioning the sample on men in good health in period t-2, respectively. Restricting the sample to younger men (Model 4), reduces the treatment effect to 3.2 percentage points, but it is still significant at the 10% level. The treatment effect remains around 3 and 5 percentage points when restricting the sample to men who are not chronically ill (Model 5), who survived the health shock (Model 6), and who were in good ex ante health between 1994 and 1996 (Model 7).

Figure 5(c) reports the robustness check regarding mechanism 4. Instead of using a binary measure of the health shock that takes the value 1 if the individual spent 10 or more nights in hospital, I use seven binary variables, which each indicates a specific range of nights spent in hospital. There are no significant interaction effects of negative control beliefs and episodes of hospital admissions at the lower range (Models 2 to 5). However, I find strong and significant interaction effects for the higher intensities of hospital admissions (Models 6 to 8). For instance, men who were admitted to hospital for 20 to 24 nights and who score high on negative control beliefs are 7 percentage points more likely to drop out of the labor market than men with the same number of hospital admissions and strong positive control beliefs (significant at the 1% level). These interaction effects are 7 and 10 percentage points, respectively, for men who were admitted to hospital for 25 to 34 nights (Model 7) and for 35 or more nights (Model 8). Due to a smaller number of observations, these effects are estimated more imprecisely.

Finally, I test whether control beliefs merely proxy other individual-specific heterogeneity that may be equally well be proxied by any other non-cognitive skills that have been deemed important determinants of health and labor-market outcomes in the previous literature. Figure 5(d) depicts the interaction treatment effects of interest for risk tolerance and the Big-Five personality traits. As these personality traits are only observed for a smaller sample of men who experienced a health shock (N=544), because they are measured ten years after control perceptions were measured, I have re-estimated the interaction effect of control perceptions. In this selected sample, this interaction effect is 5.4 percentage points (significant at the 1% level).

Each marginal effect depicted in 5(d) is interpreted for a move from the bottom to the top 10^{th} percentile of the respective trait distribution. I find equally strong interaction effects for both willingness to take risks and conscientiousness, but no significant interaction effects for any of the other personality traits. Men at the bottom end of the risk tolerance and conscientiousness distribution are 4 and 5 percentage points, respectively, more likely to drop out of the labor market after the experience of a health shock than men at the top end of the risk and conscientiousness distribution. These alternative interaction effects are statistically significant at the 10% and 5% level, respectively. The implications of this finding are discussed in the next section.

6 Discussion and conclusion

In this study, I tested whether men with positive control beliefs are better in buffering the experience of episodes of ill health than men with negative control beliefs. The main hypothesis for why resilient behavior is observed for individuals with positive control beliefs is a theoretical argument: positive control beliefs help individuals to invest in their health - or remain psychologically functional - in the advent of health-related adversity. This causal channel was referred to as mechanism ♯ 1. Using longitudinal survey data from Germany, a country with an almost universal and homogenous health care system, I find robust evidence that men with positive ex ante control beliefs are significantly less likely to drop out of the labor force or reduce their hours of work than men with negative control beliefs following a long episode of ill health, ceteris paribus.

It is also true that men with positive control beliefs are on average better educated and more likely to have private health insurance (alternative mechanism ♯ 2), in better long-term, ex ante health (alternative mechanism ♯ 3), and less likely to experience more severe episodes of ill health (alternative mechanism ♯ 4). However, controlling for these alternative channels through which control beliefs could affect labor-supply responses does not change my conclusions. The beneficial effects of positive control beliefs are strongest for men from disadvantaged backgrounds, for men without access to private health insurance, or for men who experience extremely long episodes of ill health. Importantly, the buffering effects of positive control beliefs also hold for younger and overall healthier men.

Having shut off one-by-one alternative mechanisms 2, 3, and 4, leaves mechanism 1 as a likely explanation for heterogeneous labor-supply responses to episodes of ill health. The proof-by-exclusion approach is valid under the assumption that my theoretical model that links labor supply with health status and health investment adequately reflects all behavioral channels. There is still no certainty that men with positive control beliefs truly invest more in their health in the advent of a health shock. It could also be that men with negative control beliefs invest just the same as men with positive control beliefs, but that the positive effects of their investment are neutralized through increased levels of ill mental health, which has been hypothesized and tested for in Buddelmeyer and Powdthavee (2016). In the absence of better data it will be hard to tease out these differential pathways, but both are consistent with the notion of resilience.

Yet, the argument that individuals with positive control beliefs are more likely to invest in the face of adversity is strengthened by the observation that risk aversion and conscientiousness also act as buffer against health shocks. Risk tolerance correlates significantly with control beliefs both in my sample[30] and in other longitudinal data (e.g. Becker et al. 2012). Risk tolerance has been associated with higher willingness to invest in financial markets and physical activity (e.g. Dohmen et al. 2011). This would be consistent with mechanism 1 which says that individuals with better coping skills invest more to counterbalance episodes of ill health. Similarly, conscientiousness may also function as a buffer against ill health because highly-conscientious individuals are more effective at following protocols and treatment advice from their doctors (See Christensen and Johnson 2002, for an overview). Many studies found that conscientiousness is also associated with control beliefs (Marshall et al. 2014) and with active problem-focused coping behavior (Watson and Hubbard 1996). In my data, I cannot find significant interaction effects for any other non-cognitive skill, ruling out the possibility that self-assessed control perceptions measure just any unobserved heterogeneity. Other studies that have explored the interaction effects of control

[30] Willingness to take risks correlates negatively in my sample with negative control beliefs (-0.249, standard error .052).

perceptions with life events (Buddelmeyer and Powdthavee 2016; Caliendo et al. 2014; McGee 2015) have not tested for such alternative interaction effects. Therefore, my robustness-check findings cannot be compared.

The important conclusion of my analysis is that despite the many sources of confounding factors *control beliefs* have real labor-market consequences and - in combination with risk aversion and conscientiousness - they stand out as good observable measures to approximate what the positive psychology literature would call resilience (Seligman 2011). Although it is difficult to draw conclusions for other countries, one could expect that personality-related differences in labor-supply response behavior could be similar in countries which have comparably generous welfare systems such as France, Italy, Sweden or Britain. One would expect smaller differences in personality-related response behaviors in countries with less generous welfare systems, such as the US or Australia, where copayments for health care utilization are higher, sick-leave arrangements are less generous, and work-place protection is less secure than in Germany.

Teaching individuals resilience - the ability to interpret experiences in an optimistic fashion and to understand the importance of taking self-responsibility - could be one cost-effective way to counter-balance rising health care costs associated with an aging society and with increasing prevalence rates of avoidable illnesses such as obesity, diabetes and cardiovascular disease (Cobb-Clark et al. 2014). Teaching positive control beliefs in adulthood is not easy - many interventions that sought to change control beliefs in adulthood as one method of improving life-style choices have tended to fail (see Ashford et al. 2010, for an overview). One reason could be that control beliefs do not dramatically change in adulthood, even in the presence of severe life events (Cobb-Clark and Schurer 2013; Schurer 2015). This does not mean that the way individuals perceive the world is hard-wired,[31] but it is consistent with the suggestion that adulthood interventions would require more heavy artillery to tweak belief systems. Such heavy artillery was imposed on long-term recipients of income support from two regions in Canada (Self Sufficiency Project), by paying income subsidies that aimed at increasing labor supply (See Gottschalk 2005). Although not aimed at improving control beliefs per se, Gottschalk (2005) showed that they changed for individuals over the 36-month duration of the intervention. There are also promising interven-

[31]For evidence against the hypothesis that character traits are hard-wired from young adulthood onwards, see Roberts et al. (2006).

tions in developing countries that aim at improving the way community members think about the future, and which were shown to be effective (Bernard et al. 2014). Seligman (2011) discusses a promising new approach to teach at large scale US military staff skills suitable for dealing with traumatizing events.

Alternatively, interventions could directly target children or adolescents to improve perceptions of control (e.g. Schurer 2016; Almlund et al. 2011; Cunha and Heckman 2009; Heckman and Masterov 2007, for possible routes of intervention). Some promising initiatives are emerging world-wide that aim at strengthening resilience in school children. For instance, the Penn Resilience Program teaches elementary and middle school students to detect inaccurate thoughts, to evaluate the accuracy of their thoughts, and to challenge negative beliefs by considering alternative interpretations.[32] Similar resilience programs are currently experimented with in Victoria (Australia),[33] in Britain (Challen et al. 2011), and in Canada.[34] Preliminary evidence from randomized controlled trials of the UK resilience program suggest that, at least in the short-run, students depression scores, school attendance and performance improved (Challen et al. 2011).

To conclude, the empirical findings in this study offer a new understanding of how differences in control perceptions can significantly and beneficially affect the way in which men from one advanced continental European economy respond to episodes of ill health, and therefore influence life-cycle work trajectories. Future research is needed to better understand whether beneficial economic consequences of resilience are gender-specific or specific to the nature of welfare regimes. Thus, the role and development of control perceptions deserve greater emphasis in education and health policy.

References

Ai, C., Norton, E., 2003. Interaction terms in logit and probit models. Economics Letters 80, 123Ű129.

Almlund, M., Lee Duckworth, A., Heckman, J.J., Kautz, T., 2011. Personality psychology and

[32]See Seligman et al. (2009) and www.ppc.sas.upenn.edu for a description of the program and its preliminary successes.

[33]For an overview of initiatives see www.is.vic.edu.au.

[34]See an overview of the Ottawa-Carleton School District Board Annual Report: http://www.ocdsb.ca/ab-ocdsb/annual_Reports/Pages/default.aspx

economics. In S.M. Eric A. Hanushek, L. Woessmann (Eds.), Handbook of the Economics of Education, vol. 4. North-Holland, pp. 1–181.

Anger, S., Schnitzlein, D., 2015. Cognitive skills, non-cognitive skills, and family background: Evidence from sibling correlations. Unpublished working paper, University of Hannover.

Ashford, S., Edmunds, J., French, D., 2010. What is the best way to change self-efficacy to promote lifestyle and recreational physical activity? A systematic review with meta analysis. British Journal of Health Psychology 15, 265–288.

Bandura, A., 1990. Reflections of non-ability determinants of competence. In R. Sternberg, John Kolligan Jr (Eds.), Competence Considered. Yale University Press, New Haven, Conn.

Becker, A., Deckers, T., Dohmen, T., Kosse, F., Falk, A., 2012. The relationship between economic preferences and psychological personality measures. Annual Review of Economics 4, 453–478.

Bernard, T., Dercon, S., Orkin, K., Seyoum Taffesse, A., 2014. The future in mind: Aspirations and forward-looking behaviour in rural ethiopia. Working paper, Centre for the Study of African Economies.

Blundell, R., MaCurdy, T., 1999. Labor supply: A review of alternative approaches. In O.C. Ashenfelter, D. Card (Eds.), Handbook of Labor Economics, vol. 3. Elsevier, pp. 1559–1695.

Bonanno, G.A., 2004. Loss, trauma, and human resilience: Have we underestimated the human capacity to thrive after extremely adverse events? American Psychologist 59, 20–28.

Bonanno, G.A., Kennedy, P., Galatzer-Levy, I.R., Lude, P., Elfstroem, M.L., 2012. Trajectories of resilience, depression, and anxiety following spinal cord injury. Rehabilitation Psychology 57, 236–247.

Bonanno, G.A., Westphal, M., Mancini, A., 2011. Resilience to loss and potential trauma. Annual Review of Clinical Psychology 7, 511–535.

Bound, J., Schoenbaum, M., Stinebrickner, T., Waidman, T., 1999. The dynamic effects of health on the labor force transitions of older workers. Labour Economics 6, 179–202.

Bradley, C.J., Neumark, D., Luo, Z., Bednarek, H.L., 2007. Employment-contingent health insurance, illness, and labor supply of women: Evidence from married women with breast cancer. Health Economics 16, 719–737.

Buddelmeyer, H., Powdthavee, N., 2016. Can having internal locus of control insure against negative shocks? Psychological evidence from panel data. Journal of Economic Behavior & Organization 122, 88–109.

Caliendo, M., Cobb-Clark, D., Uhlendorff, A., 2014. Locus of control and job search strategies. Review of Economics and Statistics Forthcoming.

Challen, A., Noden, P., West, A., Machin, S., 2011. UK resilience programme: Evaluation: Final report. Tech. rep., Department of Education.

Chiteji, N., 2010. Time preference, noncognitive skills and well being across the life course: Do noncognitive skills encourage healthy behavior? American Economic Review: Papers & Proceedings 100, 200–204.

Christensen, A.J., Johnson, J.A., 2002. Patient adherence with medical treatment regimens: An interactive approach. Current Directions in Psychological Science 11, pp. 94–97.

Cobb-Clark, D., Kassenboehmer, S., Schurer, S., 2014. Healthy habits: What explains the connection between diet, exercise, and locus of control? Journal of Economic Behavior and Organization 98, 1–28.

Cobb-Clark, D., Schurer, S., 2013. Two economists' musings on the stability of locus of control. The Economic Journal 123, F358–F400.

Cobb-Clark, D.A., 2015. Locus of control and the labour market. IZA Journal of Labor Economics 4.

Coleman, M., Deleire, T., 2003. An economic model of locus of control and the human capital investment decision. Journal of Human Resources 38, 701–721.

Crichton, S., Stillman, S., Hyslop, D., 2011. Returning to work from injury: Longitudinal evidence on employment and earnings. Industrial and Labor Relations Review 64, 763–783.

Cronbach, L.J., 1951. Coefficient alpha and the internal structure of tests. Psychometrika 16, 297–334.

Cunha, F., Heckman, J.J., 2008. Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. Journal of Human Resources 43, 738–782.

Cunha, F., Heckman, J.J., 2009. The economics and psychology of inequality and human development. Journal of the European Economics Association 7, 320–364.

Cunha, F., Heckman, J.J., Schennach, S.M., 2010. Estimating the technology of cognitive and noncognitive skill formation. Econometrica 78, 883Ű931.

Currie, J., Madrian, B., 1999. Health, health insurance and the labour market. In O. Ashenfelter, D. Card (Eds.), Handbook of Labor Economics. Elsevier, Amsterdam, pp. 3309–3416.

Decker, S., Schmitz, H., 2015. Health shocks and risk aversion. SOEP Papers 801, DIW Berlin.

Dillon, A., Friedman, J., Serneels, P., 2014. Health information, treatment, and worker productivity: Experimental evidence from malaria testing and treatment among Nigerian sugarcane cutters. Unpublished manuscript March.

Disney, R., Emmerson, C., Wakefield, M., 2006. Ill health and retirement in Britain: A panel data-based analysis. Journal of Health Economics 25, 621–649.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants and behavioral consequences. Journal of the European Economic Association 9, 522–550.

Eibich, P., Ziebarth, N., 2014. Analyzing regional variation in health care utilization using (rich) household microdata. Health Policy 114, 41–53.

Fitzgerald, T.E., Tennen, H., Affleck, G., Pransky, G.S., 1993. The relative importance of dispositional appraisal in quality of life after coronary artery bypass surgery. Journal of Behavioral Medicine 16, 25–43.

García-Gómez, P., 2011. Institutions, health shocks and labour market outcomes across Europe. Journal of Health Economics 30, 200–213.

García-Gómez, P., van Kippersluis, H., O'Donnell, O., van Doorslaer, E., 2013. Long-term and spillover effects of health shocks on employment and income. Journal of Human Resources 48, 873–909.

García-Gómez, P., Jones, A., Rice, N., 2010. Health effects on labour market exits and entries. Labour Economics 17, 62–67.

García-Gómez, P., López-Nicolás, A., 2006. Health shocks, employment and income in the Spanish labour market. Health Economics 15, 997–1009.

Goepffahrt, D., Kopetsch, T., Schmitz, H., 2015. Determinants of regional variation in health expenditures in Germany. Health Economics In press.

Gottschalk, P., 2005. Can work alter welfare recipients' beliefs? Journal of Policy Analysis and Management 24, 485–498.

Grossman, M., 1972. On the concept of health capital and the demand for health. Journal of Political Economy 80, 223–255.

Hadsell, L., 2010. Achievement goals, locus of control, and academic success in economics. American Economic Review Paper & Proceedings 100, 272–276.

Heckman, J., Stixrud, J., Urzua, S., 2006. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. Journal of Labour Economics 24, 411–482.

Heckman, J.J., Masterov, D.V., 2007. The productivity argument for investing in young children. Applied Economic Perspectives and Policy 29, 446–493.

Heineck, G., Anger, S., 2010. The returns to cognitive abilities and personality traits in Germany. Labour Economics 17, 535–546.

Heineck, G., Riphahn, R.T., 2009. Intergenerational transmission of educational attainment in germany - the last five decades. Journal of Economics and Statistics (Jahrbuecher fuer Nationaloekonomie und Statistik) 229, 36–60.

Johnson, J.A., Stoskopf, C.H., 2010. Comparative Health Systems. Global Perspectives. Jones and Bartlett Publishers, London.

Karaca-Mandic, P., Norton, E.C., Dowd, B., 2012. Interaction terms in nonlinear models. Health Services Research 47, 255–274.

Klonowicz, T., 2001. Discontended people: Reactivity and locus of control as determinants of subjective well-being. European Journal of Psychology 15, 29–47.

Lekfuangfu, W.N., Powdthavee, N., Warrinnier, N., Cornaglia, F., 2014. Locus of control and its intergenerational implications for early childhood skill formation. IZA Discussion Paper 8487, Institute for the Study of Labor (IZA).

Lindeboom, M., Kerkhofs, M., 2009. Subjective health measures, reporting errors and endogeneity in the relationship between health and work. Journal of Applied Econometrics 24, 1024–1046.

Lundborg, P., Nilsson, M., Vikstroem, J., 2015. Heterogeneity in the impact of health shocks on labour outcomes: Evidence from Swedish workers. Oxford Economic Papers 67, 715–739.

Mackenbach, J., Simon, J., Looman, C., Joung, I., 2002. Self-assessed health and mortality: Could psychological factors explain the association? International Journal of Epidemiology 31, 1162–1168.

Marshall, G., Wortman, C., Vickers, R., Kusulas, J., Hervig, L., 2014. The five-factor model of personality as a framework for personality-health research. Journal of Personality and Social Psychology 67, 278–286.

Masten, A., 2014. Ordinary magic: Resilience in development. Guilford Press, New York.

McGee, A., 2015. How the perception of control influences unemployed job search. Industrial and Labor Relations Review 68.

Piatek, R., Pinger, P., 2015. Maintaining (locus of) control? data combination for the identification and inference of factor structure models. Journal of Applied Econometrics In print.

Pillas, D., Marmot, M., Naicker, K., Goldblatt, P., Morrison, J., Pikhart, H., 2014. Social inequalities in early childhood health and development: A European-wide systematic review. Pediatric Research 76, 418–424.

Riphahn, R.T., 1999. Income and employment effects of health shocks. A test case for the German welfare state. Journal of Population Economics 12, 363–389.

Roberts, B.W., Walton, K.E., Viechtenbauer, W., 2006. Patterns of mean-level change in personality traits across the life course: A meta-analysis of longitudinal studies. Psychological Bulletin 126, 3–25.

Rotter, J., 1966. Generalized expectancies of internal versus external control of reinforcements. Psychological Monographs 80, 1–28.

Ryff, C.D., Friedman, E.M., Morozink, J.A., Tsenkova, V., 2012. Psychological resilience in adulthood and later life: Implications for health. Annual Review of Gerontology & Geriatrics 32, 73–95.

Schmitz, H., 2011. Direct evidence of risk aversion as a source of advantageous selection in health insurance. Economic Letters 113, 180–182.

Schurer, S., 2008. Discrete heterogeneity in the effects of health shocks on labour market outcomes. Melbourne Institute Working Paper 19/08.

Schurer, S., 2015. Stylized facts on the evolution of locus of control over the lifecourse. Unpublished paper, University of Sydney.

Schurer, S., 2016. Education and non-cognitive skill development in adolescence. IZA World of Labor Forthcoming.

Seligman, M., 2011. Building resilience. Harvard Business Review April.

Seligman, M.E.P., Ernst, R.M., annd Karen Reivich, J.G., Linkins, M., 2009. Positive education: positive psychology and classroom interventions. Oxford Review of Education 35, 293–311.

Smith, J.P., 1999. Healthy bodies and thick wallets. Journal of Economic Perspectives 13, 145–166.

Smith, J.P., 2005. Consequences and predictors of new health events. In D. Wise (Ed.), Analyses in the Economics of Aging. NBER, pp. 213–240.

Strudler Wallston, B., Wallston, K.A., 1978. Locus of control and health: A review of the literature. Health Education Monographs 6, 107–117.

Van Doorslaer, E., Masseria, C., 2004. Income-related inequality in the use of medical care in 21 OECD countries. Working Paper 14, OECD.

Wagner, G., Frick, J., Schupp, J., 2006. The German Socio-Economic Panel Study (SOEP) - scope, evolution and enhancements. Schmollers Jahrbuch 127, 139–169.

Watson, D., Hubbard, B., 1996. Adaptational style and dispositional structure: Coping in the context of the five-factor model. Journal of Personality 64, 737–774.

Wing Han Au, D., Crossley, T.F., Schellhorn, M., 2005. The effect of health changes and long-term health on the work activity of older Canadians. Health Economics 14, 999–1018.

Table 1: Components of locus of control recorded in 1994-1996

Variable	Mean	Std. Dev.	Min.	Max.	N	Cronbach's α if item omitted
Scale: 1 Fully applies - 4 Does not apply						
Q. 1 Have Control Over Own Life	6,068	1.880	0.710	1	4	0.722
Q. 2 Plans Are Unsuccessful	6,068	2.117	0.815	1	4	0.680
Q. 3 Behavior Determines Life	6,068	1.850	0.689	1	4	0.739
Q. 4 No One Can Escape Their Destiny	6,068	2.614	0.947	1	4	0.703
Q. 5 I Get Something Because Of Luck	6,068	2.012	0.773	1	4	0.699
Q. 6 Plans Turn To Reality	6,068	2.240	0.694	1	4	0.714
Q. 7 Something Unforseen Happens	6,068	2.280	0.835	1	4	0.656
Q. 8 The Outcome Is Always Different	6,068	2.265	0.870	1	4	0.656
Cronbach's α with eight items						0.726

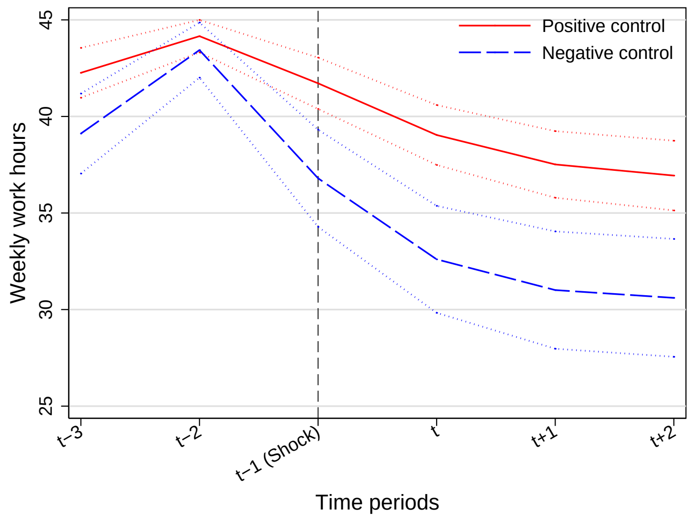
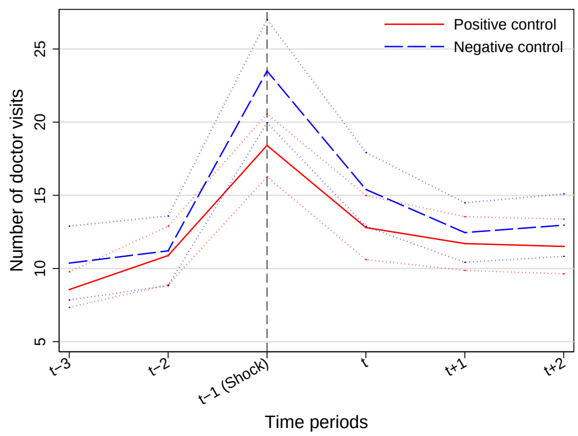
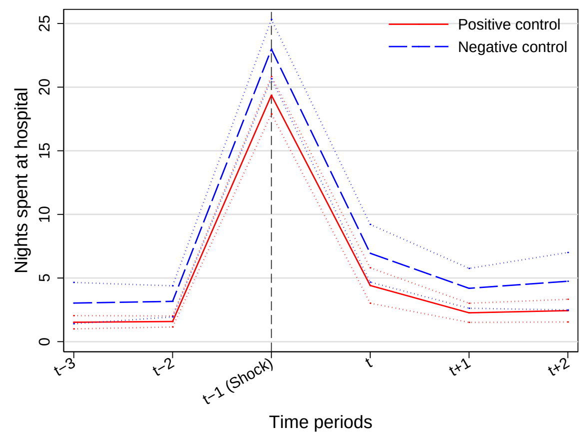


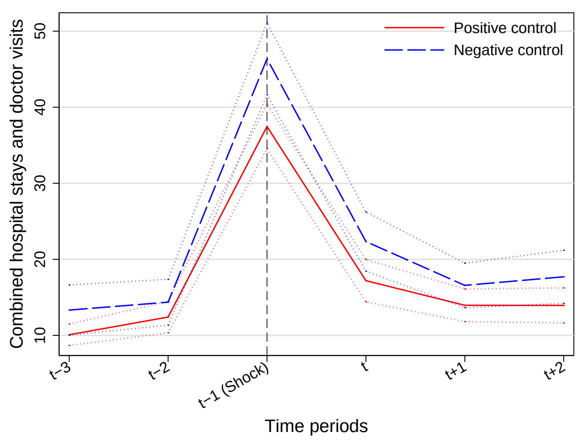
Figure 1: Mean weekly hours worked of healthy and full-time employed working-age men $(t-2)$ before and after the experience of a health shock (t-1), presented separately for men with negative and positive control beliefs. Dotted lines represent 95% confidence intervals. SOEP, 1997 to 2012 (N=649).



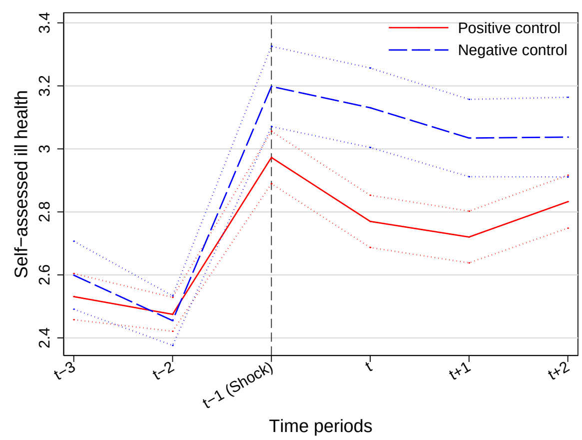
(a) Doctor visits



(b) Nights at hospital



(c) Combined doctor and hospital visits



(d) Self-assessed health

Figure 2: Change in health status and health care utilization before, during, and after experiencing a health shock ($t - 1$), by positive and negative control beliefs (N=649 individuals). Dotted lines represent 95% confidence intervals.

Table 2: Summary statistics for sample of individuals who experienced a health shock, by negative and positive control beliefs

	Positive[a]	Negative[b]	p-value[c]
Out of labor force (t)	0.042	0.077	0.059
Partime work (t) ($0 < $ Weekly work hours < 20)	0.054	0.069	0.453
Unemployment (t)	0.065	0.111	0.042
Weekly work hours (t)	39.212	35.364	0.007
Age	46.615	45.306	0.068
Years of education	12.933	10.936	0.000
Minimum schooling	0.273	0.509	0.000
Intermediate schooling	0.365	0.396	0.433
University education	0.362	0.095	0.000
Ex ante health (t=0) (1 very good, 5 bad)	2.362	2.497	0.005
Risk tolerance	0.342	0.151	0.004
Conscientiousness	0.104	0.063	0.489
Extraversion	0.037	−0.148	0.002
Agreeableness	−0.125	−0.212	0.149
Openness	0.135	−0.164	0.000
Neuroticism	−0.241	0.024	0.000
Cognitive ability	0.227	0.044	0.276
Accumulated unemployment exp. (t-2)	0.418	0.831	0.000
Weekly work hours (t-2)	44.202	43.583	0.412
Hourly wage in Euro (t-2)	16.602	12.790	0.000
Years spent at firm (t-2)	12.530	10.754	0.029
Firm size (t-2): < 20 staff	0.273	0.314	0.265
Firm size (t-2): 20199 staff	0.192	0.211	0.564
Firm size (t-2): 201999 staff	0.215	0.239	0.480
Firm size (t-2): $2000+$ staff	0.292	0.213	0.025
Self-employed	0.027	0.023	0.764
Ever smoked	0.546	0.560	0.721
Has private health insurance	0.123	0.041	0.000
Married	0.758	0.694	0.073
Foreigner	0.065	0.136	0.002
Partner is inactive	0.208	0.254	0.163
Partner has poor health	0.127	0.105	0.406
Industry: Mining (t-2)	0.019	0.031	0.343
Industry: Manufacturing (t-2)	0.292	0.339	0.205
Industry: Retail (t-2)	0.073	0.098	0.266
Industry: Transport (t-2)	0.081	0.077	0.866
Industry: Construction (t-2)	0.019	0.051	0.023
Occupation: Legislator or management (t-2)	0.069	0.072	0.893
Occupation: Professional (t-2)	0.188	0.033	0.000
Occupation: Technician (t-2)	0.235	0.116	0.000
Occupation: Service (t-2)	0.042	0.036	0.687
Missing: Education	0.000	0.018	0.008
Missing: Risk tolerance	0.088	0.149	0.017
Missing: Big Five	0.127	0.183	0.052
Missing: Cognitive ability	0.988	0.995	0.398
Missing: Occupation/Industry	0.019	0.013	0.535
Observations	389	260	

Note: a : Negative control beliefs $> 75^{th}$ percentile. b : Positive control beliefs $\leqslant 75^{th}$ percentile. c : refers to p-value of test for equality of means between individuals with positive and negative control beliefs. Omitted are year- and state-dummy variables. Sample of all individuals aged between 25 and 60 who were working fulltime and were healthy in period $t-2$, but who experienced a health shock between period $t-2$ and $t-1$.

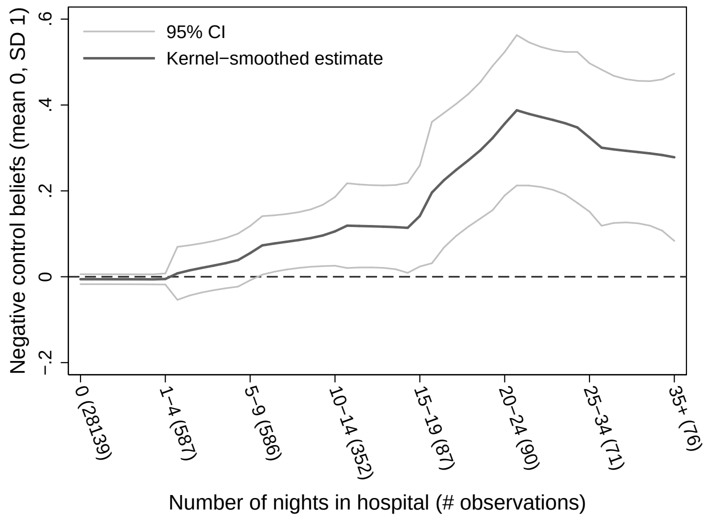


Figure 3: Relationship between negative control beliefs and increases in number of additional nights spent in hospital based on the full estimation sample (N=29988)

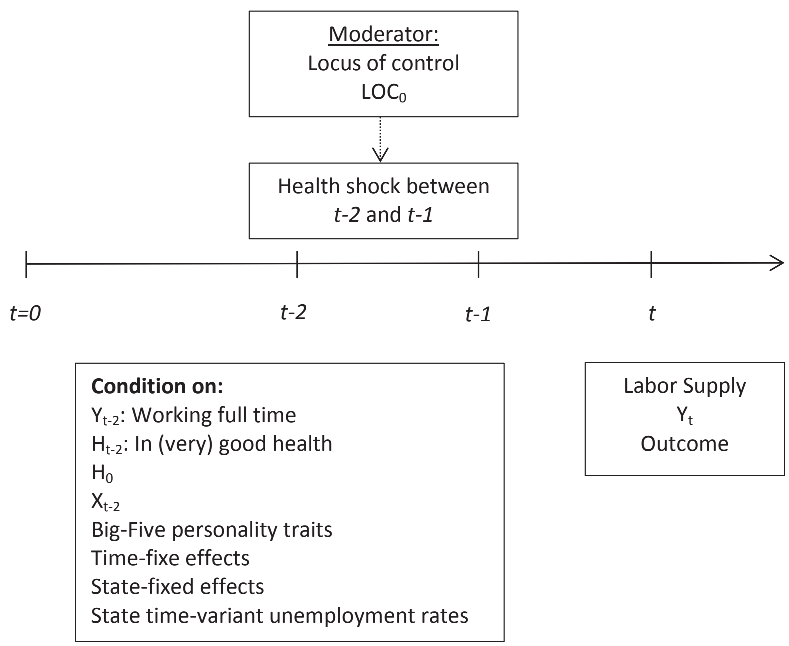
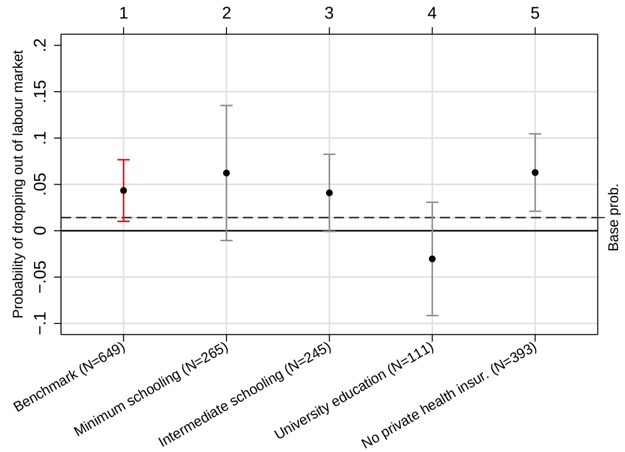


Figure 4: Identification strategy of causal interaction effect of control perceptions and health shock.

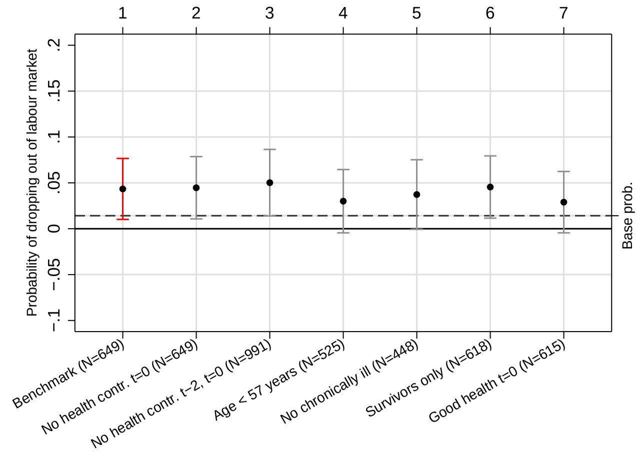
Table 3: Estimation results: Marginal probability effects of variables of interest.

	(1) Work hours	(2) Inactive	(3) Part-time	(4) Unempl.
Health shock (0,1)	−3.856	0.0162	−0.0069	0.0106
	(0.7337)	(0.0055)	(0.0088)	(0.0044)
Negative control beliefs (Std)	−0.6912	0.0113	0.0002	0.0009
	(0.1516)	(0.0041)	(0.0080)	(0.0038)
Interaction health shock × neg. control beliefs	−4.5516	0.0434	0.0004	0.0034
	(2.0280)	(0.0169)	(0.0224)	(0.0197)
Base level or probability[a]	39.2	0.042	0.054	0.065
AIC: with interaction	210110.1	3962.6	12723.0	7500.1
AIC: without interaction	210119.4	3965.3	12721.0	7498.1
McFadden R^2: with interaction	0.015	0.0823	0.0553	0.1841
McFadden R^2:without interaction	0.015	0.0816	0.0555	0.1843
NT	27237	28223	27681	28223
N	3730	3793	3762	3793
T max	16	16	16	16

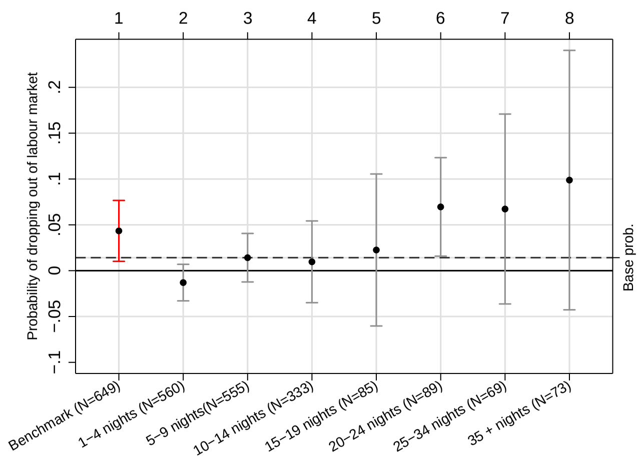
Note: Table 3 reports marginal effects of variables of interest on either the probability to a change labor force status (Probit models) or on weekly hours worked (Tobit model, censored from below at 0). Interaction effects are calculated according to Karaca-Mandic et al. (2012) in STATA. Standard errors in parentheses are calculated with the delta method in STATA. Full estimation results are presented in Table A.4 in the Online Appendix. Number of individuals who experienced a health shock defined as an increase in the nights spent at hospital from period $t-2$ to $t-1$ of 10 or more is 649. The total number of individuals who experienced a health shock and who changed labor force status in period t are 41 (inactivity), 40 (part-time) and 60 (unemployment). [a]: Base level or probability refers to time period t for individuals with positive control beliefs who also experienced a health shock.



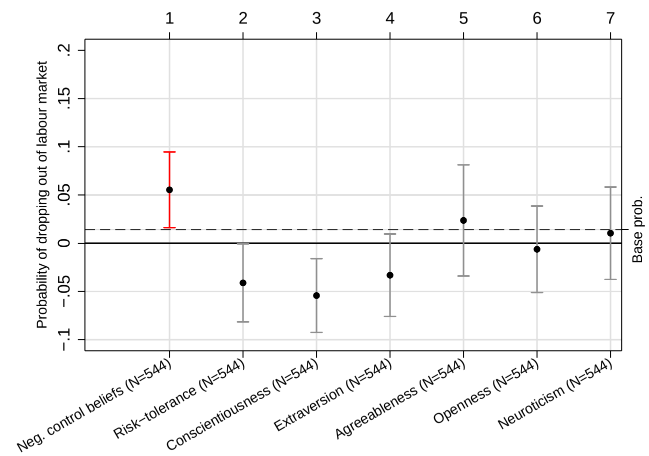
(a) Mechanism 2



(b) Mechanism 3



(c) Mechanism 4



(d) Mechanism 5

Figure 5: Reported are marginal interaction effects of the health shock with negative control beliefs (mechanisms 2-4) or alternative non-cognitive skills (mechanism 5) on the probability of dropping out of the labor market. The marginal effect represents the differences in the predicted probability for health-shocked individuals between the bottom and top 10th percentile of the skill distribution. Capped lines report 95% confidence intervals.

ONLINE APPENDIX

Table A.1: Illustration of three-year interval generation for analysis

	t-2	t-1	t					
		t-2	t-1	t				
1	1997	1998	1999					
2		1998	1999	2000				
3				…	……			
⋮					⋮	⋮		
13					2009	2010	2011	
14						2010	2011	2012

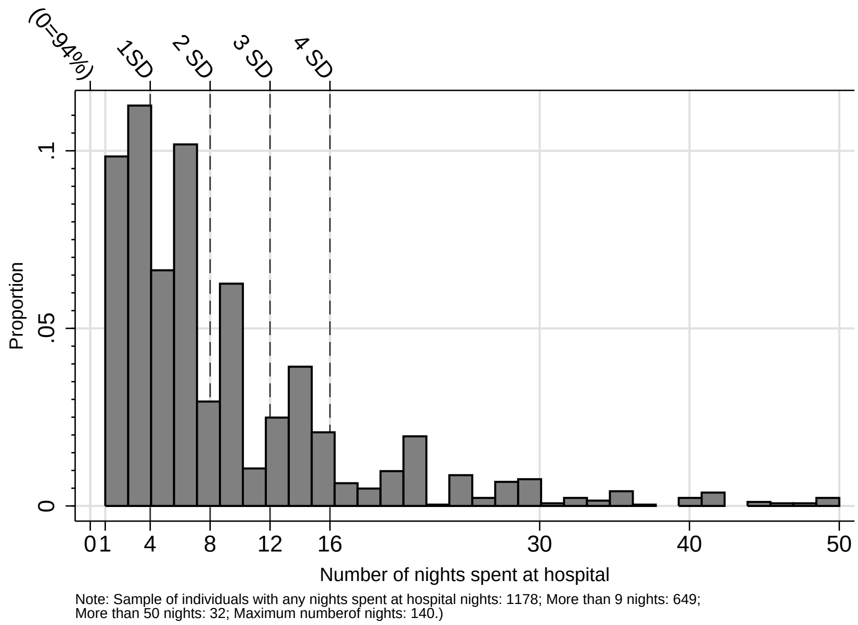


Figure A.1: Description of number of nights spent in hospital in estimation sample

Table A.2: Probability of dropping out of the sample in period $t + 1$: Presented are marginal probability effects based on coefficients from a Probit model

	Probability dropout from Sample in $t + 1$
Ex ante health (Std)	-0.000953^{**}
	(0.000384)
Ex ante control beliefs (Std)	0.000666^{*}
	(0.000363)
Health shock	0.0124^{***}
	(0.00325)
Ages 30-34	0.0000751
	(0.00191)
Ages 35-39	-0.00298^{*}
	(0.00173)
Ages 40-44	-0.00443^{***}
	(0.00167)
Ages 45-49	−0.00191
	(0.00181)
Ages 50-54	−0.00246
	(0.00183)
Ages 55-60	−0.00195
	(0.00182)
Unemployment experience	0.000405^{***}
	(0.000143)
Currently out of labor force	0.00776^{***}
	(0.00132)
Base probability	0.0054
Observations (NT)	40815

Note: The dependent variable is a binary indicator of not being interviewed in t+1 due to refusal, moving abroad, dying, or the inability of interview team to establish contact with the individual or household.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Relationship between illness categories, health shock and negative control beliefs

	(1) Cancer	(2) Asthma	(3) Cardio	(4) Depression	(5) Diabetes	(6) Stroke	(7) Megrim	(8) High BP	(9) Oth Illn.	(10) No illn.
Health shock	0.033***	0.020	0.067***	0.106***	0.066***	0.009	0.005	0.117***	0.156***	−0.392***
	(0.009)	(0.018)	(0.015)	(0.016)	(0.017)	(0.008)	(0.016)	(0.036)	(0.030)	(0.059)
Base group: age 36-39	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Age 40-44	0.003	−0.002	−0.000	0.001	0.006	−0.002	0.029**	0.078***	0.017	−0.128***
	(0.008)	(0.018)	(0.007)	(0.014)	(0.012)	(0.006)	(0.015)	(0.020)	(0.028)	(0.039)
Age 45-49	0.009	−0.002	0.024***	0.041***	0.023*	0.002	0.011	0.153***	0.036	−0.179***
	(0.008)	(0.017)	(0.009)	(0.015)	(0.012)	(0.006)	(0.012)	(0.020)	(0.027)	(0.037)
Age 45-49	0.012	0.004	0.028***	0.032**	0.026**	0.005	0.005	0.158***	0.032	−0.190***
	(0.008)	(0.017)	(0.009)	(0.014)	(0.012)	(0.006)	(0.011)	(0.019)	(0.026)	(0.036)
Age 50-54	0.015*	−0.010	0.072***	0.033**	0.049***	0.009	−0.008	0.247***	0.035	−0.312***
	(0.008)	(0.017)	(0.012)	(0.014)	(0.014)	(0.007)	(0.010)	(0.021)	(0.027)	(0.037)
Age 55-60	0.017**	−0.009	0.096***	0.050***	0.108***	0.017**	−0.007	0.330***	0.082***	−0.416***
	(0.008)	(0.017)	(0.013)	(0.015)	(0.016)	(0.008)	(0.011)	(0.023)	(0.028)	(0.036)
Base group: Pos. control beliefs	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2nd quartile	−0.002	−0.007	−0.007	0.017	−0.010	0.002	0.023***	0.018	0.011	−0.027
	(0.008)	(0.011)	(0.010)	(0.012)	(0.012)	(0.004)	(0.007)	(0.021)	(0.019)	(0.026)
3rd quartile	0.000	−0.006	0.007	0.022*	−0.001	0.014**	0.016**	0.030	0.019	−0.060**
	(0.008)	(0.011)	(0.011)	(0.012)	(0.013)	(0.006)	(0.007)	(0.022)	(0.020)	(0.026)
4th quartile	−0.009	−0.017	0.015	0.001	0.000	0.009	0.009	−0.003	0.006	−0.031
	(0.007)	(0.011)	(0.012)	(0.011)	(0.013)	(0.006)	(0.007)	(0.023)	(0.020)	(0.027)
Neg. control beliefs	−0.018***	0.005	0.034**	0.022	0.006	0.005	0.026***	−0.019	0.004	−0.003
	(0.006)	(0.013)	(0.015)	(0.014)	(0.015)	(0.006)	(0.009)	(0.024)	(0.021)	(0.029)
Base probability	0.018	0.040	0.051	0.056	0.059	0.011	0.023	0.217	0.153	0.486
Observations	3081	3081	3081	3081	3081	3081	3081	3081	3081	3081

Note: Each column represents the marginal probability effects reporting the respective health condition obtained from a separate probit model where the health condition is the outcome variable. Health conditions are available for individuals aged 35 and over in years 2009 and 2011.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Full estimation results: Benchmark model

	(1) Inactive Probit	(2) Work hours Tobit	(3) Part-time Probit	(4) Unempl. Probit
Average health 1994-1996 (Std) (1 very good, 5 bad)	0.050**	0.275*	0.007	0.007
	(0.024)	(0.144)	(0.023)	(0.018)
Negative control beliefs (Std)	0.044*	-0.651***	-0.029	0.042**
	(0.026)	(0.152)	(0.023)	(0.020)
Health shock	0.493***	-3.857***	-0.064	0.279***
	(0.103)	(0.734)	(0.086)	(0.088)
Health shock × Negative control beliefs (Std)	0.181**	-1.737**	-0.001	-0.000
	(0.090)	(0.774)	(0.076)	(0.079)
Base group: Age 25-29	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Age 30-34	-0.043	1.443**	-0.051	0.067
	(0.111)	(0.560)	(0.077)	(0.082)
Age 35-39	-0.159	1.184**	-0.110	0.112
	(0.118)	(0.599)	(0.089)	(0.087)
Age 40-44	-0.148	1.054*	-0.028	0.184**
	(0.120)	(0.629)	(0.092)	(0.089)
Age 45-49	0.032	1.193*	-0.036	0.231**
	(0.120)	(0.669)	(0.095)	(0.092)
Age 50 to 54	0.113	1.240*	0.022	0.220**
	(0.132)	(0.707)	(0.100)	(0.099)
Age 55-60	0.527***	-1.950**	0.114	0.724***
	(0.124)	(0.785)	(0.105)	(0.094)
Years of education (Std)	0.013	1.096***	-0.029	-0.201***
	(0.042)	(0.224)	(0.035)	(0.036)
Risk tolerance (Std)	-0.047*	0.558***	-0.040	-0.010
	(0.027)	(0.152)	(0.027)	(0.021)
Conscientiousness (Std)	-0.045**	0.847***	-0.124***	-0.035*
	(0.023)	(0.161)	(0.024)	(0.021)
Extraversion (Std)	0.052*	0.594***	-0.015	-0.015
	(0.028)	(0.157)	(0.029)	(0.023)
Agreeableness (Std)	-0.002	-0.440***	0.050*	0.028
	(0.028)	(0.150)	(0.029)	(0.020)
Openness to experience (Std)	0.046*	-0.152	0.047	-0.022
	(0.028)	(0.160)	(0.030)	(0.022)
Neuroticism (Std)	0.060**	-0.195	-0.009	0.064***
	(0.025)	(0.150)	(0.026)	(0.020)
Cognitive ability (Std)	-0.051	-0.195	0.033	0.106**
	(0.045)	(0.187)	(0.029)	(0.044)
Accumulated unemployment experience (t-2)	0.039***	-1.482***	0.063***	0.098***
	(0.014)	(0.163)	(0.015)	(0.011)
Hourly wage ln (t-2)	-0.022	-0.082	-0.060	-0.174***
	(0.066)	(0.387)	(0.055)	(0.046)
Years spent at current firm (t-2)	-0.036***	0.201***	0.009	-0.060***
	(0.008)	(0.046)	(0.007)	(0.007)
Years spent at current firm (t-2)^2	0.001***	-0.008***	-0.000	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
Firm size 2-20 employees (t-2)	0.120*	1.552***	-0.047	0.071
	(0.063)	(0.394)	(0.055)	(0.046)
Firm size: 200-2000 employees (t-2)	-0.105	-0.321	0.050	-0.045
	(0.069)	(0.316)	(0.061)	(0.053)

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	(1) Inactive Probit	(2) Work hours Tobit	(3) Part-time Probit	(4) Unempl. Probit
Firm size: over 2000 employees (t-2)	0.079	-1.086***	0.103	-0.119**
	(0.067)	(0.333)	(0.065)	(0.058)
Self-employed (t-2)	0.067	5.690***	0.481***	-0.424***
	(0.123)	(0.907)	(0.123)	(0.129)
Has ever been a smoker	0.131***	0.052	-0.032	0.117***
	(0.049)	(0.279)	(0.047)	(0.040)
Has private health insurance	-0.179**	3.076***	-0.159**	-0.985***
	(0.087)	(0.409)	(0.076)	(0.179)
Married	-0.148***	1.786***	-0.067	-0.287***
	(0.057)	(0.329)	(0.054)	(0.045)
Immigrant after 1984	0.039	-1.421***	0.218***	0.184***
	(0.079)	(0.465)	(0.073)	(0.064)
Partner is unemployed or inactive	0.141**	-0.860***	-0.045	0.225***
	(0.055)	(0.294)	(0.051)	(0.043)
Partner's health status is poor	0.053	-0.190	0.052	0.006
	(0.068)	(0.373)	(0.058)	(0.057)
Regional annual unemployment rate (Std)	0.077	-1.363***	-0.003	0.113
	(0.114)	(0.485)	(0.081)	(0.080)
Schleswig-Holstein	0.072	-0.895	-0.354*	-0.032
	(0.192)	(0.957)	(0.184)	(0.149)
Hamburg	-0.091	0.108	-0.346	0.092
	(0.248)	(1.303)	(0.258)	(0.193)
Lower-Saxony	0.236***	0.219	0.056	-0.158*
	(0.091)	(0.529)	(0.084)	(0.084)
Hessia	0.172	0.279	-0.178	-0.036
	(0.120)	(0.616)	(0.110)	(0.113)
Rhineland-Palatinate	0.095	-0.247	-0.133	0.081
	(0.131)	(0.704)	(0.121)	(0.109)
Baden-Wuerttemberg	0.110	-0.235	0.014	-0.182
	(0.146)	(0.668)	(0.111)	(0.118)
Bavaria	0.194	-0.888	-0.156	0.036
	(0.139)	(0.646)	(0.115)	(0.108)
Saarland	0.362	-0.705	-0.007	0.072
	(0.239)	(1.265)	(0.301)	(0.184)
Berlin	0.052	0.279	0.072	0.114
	(0.239)	(1.244)	(0.177)	(0.171)
Brandenburg	-0.021	0.611	-0.097	0.170
	(0.190)	(1.036)	(0.151)	(0.137)
Mecklenburg-Vorpommern	-0.141	0.689	-0.356	0.164
	(0.232)	(1.191)	(0.218)	(0.170)
Saxony	-0.020	0.617	-0.270**	0.111
	(0.166)	(0.807)	(0.136)	(0.117)
Saxony-Anhalt	-0.164	2.346*	-0.476**	0.082
	(0.261)	(1.250)	(0.191)	(0.169)
Thuringia	-0.043	1.488	-0.352*	0.175
	(0.154)	(0.937)	(0.195)	(0.110)
Year 1999	-0.015	0.826**	0.024	-0.201***
	(0.076)	(0.331)	(0.041)	(0.059)
Year 2000	-0.031	0.783**	-0.015	-0.224***
	(0.086)	(0.376)	(0.050)	(0.067)
Year 2001	-0.033	0.456	-0.072	-0.167**

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	(1) Inactive Probit	(2) Work hours Tobit	(3) Part-time Probit	(4) Unempl. Probit
	(0.089)	(0.386)	(0.053)	(0.066)
Year 2002	0.055	0.499	-0.069	-0.234***
	(0.081)	(0.367)	(0.052)	(0.070)
Year 2003	-0.159	0.545	0.017	-0.018
	(0.098)	(0.393)	(0.053)	(0.068)
Year 2004	-0.175*	0.686*	-0.025	-0.060
	(0.103)	(0.400)	(0.057)	(0.074)
Year 2005	-0.171	1.037**	-0.074	-0.098
	(0.111)	(0.428)	(0.062)	(0.081)
Year 2006	-0.284**	1.492***	0.025	-0.155*
	(0.129)	(0.434)	(0.063)	(0.087)
Year 2007	-0.168	1.783***	-0.060	-0.462***
	(0.131)	(0.471)	(0.079)	(0.119)
Year 2008	-0.352**	1.204**	-0.116	-0.316***
	(0.170)	(0.562)	(0.093)	(0.122)
Year 2009	-0.235*	1.062**	0.004	-0.201*
	(0.137)	(0.530)	(0.082)	(0.109)
Year 2010	-0.148	0.592	-0.044	-0.170
	(0.150)	(0.578)	(0.093)	(0.117)
Year 2011	-0.162	1.443**	-0.073	-0.627***
	(0.177)	(0.638)	(0.104)	(0.178)
Year 2012	-0.311	1.408**	-0.130	-0.456***
	(0.198)	(0.694)	(0.113)	(0.173)
Worked in mining sector (t-2)	0.230*	2.801**	-0.212	-0.019
	(0.118)	(1.121)	(0.163)	(0.105)
Worked in manufacturing industry (t-2)	-0.161***	0.587**	0.286***	-0.125***
	(0.060)	(0.290)	(0.044)	(0.046)
Worked in retail sector (t-2)	-0.017	2.239***	-0.015	-0.089
	(0.080)	(0.480)	(0.078)	(0.061)
Worked in transportation sector (t-2)	-0.091	4.462***	-0.342***	-0.308***
	(0.104)	(0.681)	(0.098)	(0.088)
Worked in construction sector (t-2)	0.124	0.160	-0.213	-0.250**
	(0.133)	(0.662)	(0.170)	(0.127)
Occupation: Legislator or management (t-2)	-0.240**	5.009***	-0.325***	-0.064
	(0.107)	(0.561)	(0.086)	(0.084)
Occupation: Professional (t-2)	-0.164*	1.021**	-0.027	0.007
	(0.098)	(0.450)	(0.075)	(0.080)
Occupation: Technical (t-2)	-0.113	0.866**	0.037	-0.156**
	(0.076)	(0.353)	(0.068)	(0.065)
Occupation: Service (t-2)	0.014	1.378**	0.000	-0.212**
	(0.105)	(0.653)	(0.113)	(0.102)
Constant	-1.353***	38.556***	-1.715***	-1.995***
	(0.370)	(2.011)	(0.319)	(0.463)
Sigma		12.973***		
		(0.169)		
Observations (NT)	28223	27237	27681	28223