Health and Business Cycles in General Equilibrium

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PRELIMINARY AND INCOMPLETE

Abstract

We present causal evidence that bad health increases in the U.S. following contractionary demand shocks. Moreover, we show that in the aftermath of the Global Financial crisis, higher bad health predicts worse future labor market outcomes even after controlling for current labor market outcomes. In line with the micro literature, we confirm that unlike bad health, mortality falls following contractionary demand shocks, consistent with increased health inequality. To understand this interaction of health and business cycles, we propose a dynamic stochastic heterogeneous agents model with a health dimension. In the model, households can invest resources to improve their health. Consequently, health responds to business cycle shocks via income and substitution effects. To match the cross-sectional evidence on health investments, the model requires strong substitution effects so that the employed invest less in their health. To match the decline in health during economic downturns, our preliminary results thus suggest that the model requires "health shocks", which we broadly interpret as evidence of an omitted health channel. The model implies a heterogeneous response to health shocks between groups of population by productivity, financial wealth, and health status.

Introduction

During the Global Financial Crisis self-reported health markedly declined in the U.S. More broadly, self reported *bad* health has been countercyclical since the 1970s. States with

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higher proportions of the population in bad health at the height of the financial crisis still had lower hours worked several years later. Motivated by this evidence, we build a model to investigate the causes and consequences of these fluctuations in health: Do declining incomes lead to lower health investments? Or were there movements in health not directly caused by the recession that may have amplified the downturn? While perhaps implausible that outright health shocks are behind the cyclical movements in the U.S. prior to the COVID-19 pandemic, a health channel appears to be missing in business cycle models.

Specifically, we document that self-reported bad health increased by 5-10% from 2006 to 2011, the period straddling the Global Financial crisis. These results are not driven by the non-insured and are accompanied by an increase in doctor visits, ruling out institutional reasons linked to employer-provided health insurance. These results are robust across a number of surveys: the Current Population Survey (CPS, Flood et al. (2020)), the National Health Interview Survey (NHIS, Blewett et al. (2019)), and the National Longitudinal Survey of Youth 97 (NLSY, U.S. Bureau of Labor Statistics (2021)). Using the NHIS, we confirm that similar correlations hold in downturns going back to the 1970s. We also confirm that similar correlations hold during the Global Financial crisis using alternative measures such as frailty (Hosseini et al., 2019).

We document causal effects of demand shocks that are consistent with the time series correlations that we document. Using local projections, we show that bad health moves in the same direction as unemployment following both monetary policy Romer and Romer (2004), Miranda-Agrippino and Ricco (2021) and fiscal spending Ramey (2011), Drautzburg (2020) shocks. Seemingly, our motivation is in contrast to Ruhm (2000) who suggested that recessions are good for one's health, since mortality tends to be lower when the unemployment rate is higher.[1] However, the same local projection estimator that points to an increase in bad health following contractionary monetary policy shocks points to a decline in the mortality rate. This suggests that these shocks increase health inequality.

In addition, we document that in the cross-section of U.S. states, a proxy for labor markets, a one percent increase in bad health is associated with a decline in the employment by about 0.25 percentage point after five years, with initially stronger effects. States where bad health is one standard deviation higher in 2008 have, on average, total hours that are 0.3 standard deviations lower in 2014, even controlling for 2008 hours.

[1] Schwandt and von Wachter (2020) find that the immediate effects on mortality are from external causes, such as accidents, which are unrelated to individual health. They find that those who graduated in states with worse recessions, health outcomes several years later are worse. This lines up with our notion of latent health, which individuals in our model can influence via health investments in the tradition of Grossman (1972).

To study the interaction between health and business cycles, we use the insights from the data to discipline a rich heterogenous agents model. Households in the model spend income on consumption, physical investment, and health services. They decide how much of their time to spend on leisure, hours worked, and self-care, i.e., time invested in health. Households value health as an assets, because if provides three types of flow benefits: It reduces sick time (Capatina et al., 2020), increases productivity, and gives utility (Finkelstein et al., 2013). Because health responds to time and resources invested in it, health is partly endogenous in response to standard productivity and aggregate demand (preference) shocks.

Business cycle shocks affect health investments via income and substitution effects. As individuals have increased leisure in downturns and health investments require leisure, substitution effects would suggest a counterfactual increase in health investments in downturns. In contrast, income effects – or the loss of access to health insurance – would, in contrast, imply that health investments and thus future health declines during downturns. While consistent with the aggregate evidence, this reasoning is at odds with cross-sectional evidence. For example, we show analytically in a simple model of individual decision making that we need the substitution effect to dominate the income effect to fit cross-sectional moments of the data. Aggregate shocks such as in productivity shocks then cannot explain simultaneously cross-sectional facts and time-series correlations. We verify that the same mechanisms are present in a preliminary calibration of our quantitative equilibrium model.

Our objective is to use the quantitative model to quantify the overall importance of shocks emanating in the health sector on the overall economy and vice versa. We take a deliberately broad view what such "health shocks" could be and emphasize that they could reflect a health channel that responds to non-health shocks. For example, Currie and Tekin (2015) suggest that the financial stress of tge housing crisis led to worse health outcomes leading into the Global Financial Crisis. In ongoing work, we model this in a reduced form in the model as a correlation of aggregate shocks with health transition probabilities and evaluate the model with and without this channel. [2]

Related Literature

A growing body of work studies the connection between health and the macroeconomy. For example, Capatina et al. (2020) analyze how health affects earnings over the lifecycle due to human capital accumulation. De Nardi et al. (2017) analyzes the life-cycle effects

[2]While there is also causality running from health to household finances (Dobkin et al., 2018), the timing of these changes helps us identify the forces behind the health channels uncovered in our baseline model.

of health on welfare and earnings. Hosseini et al. (2019) quantify how much health contributes to earnings inequality. Relative to these papers, we simplify by abstracting from life-cycle forces to focus on cyclical fluctuations. Because we document sizable labor market effects of changes in health in the data, we need to adopt a general equilibrium perspective. This allows for feedback from the direct effects of health on labor supply and expenditures.

Our work also relates to an empirical literature that has documented various links between health and work and labor market outcomes. Several papers point to a causal link from health interventions to labor market outcomes at various time horizons: Stephens and Toohey (2022) find that treatment for cardiac problems lead to increased earnings but not participation in a controlled trial in the 1970s in the U.S. Garthwaite (2012) finds that the unexpected removal of a popular NSAID drug to treat joint pain lead to a drop in participation by 0.35pp. In the U.S. Mintz et al. (1992) find significant improvements of self-reported functional work performance in evaluating different Randomized Controlled Trials of depression treatments, with improved work performance particularly showing with delays of six months and longer. Berndt et al. (1998) also find short-term productivity gains following a pharmaceutical depression treatment in an RCT without placebo (so that unobserved heterogeneity could still be an issue). Cockburn et al. (1999) use observational data on employees in a narrow occupation of a single firm to show that those taking sedative antihistamines in the 1990s were 13% less productive. Krueger (2017) suggests that increased opioid prescriptions could account for about 40% of the decline in male labor force participation from 1999 to 2016. We view this literature as suggestive that there can, indeed, be an important health channel in the economy. At times, there are even health shocks with aggregate effects, such as the spread of opioid drugs or the removal of the NSAID drug. The consequences of health changes are, however, heterogeneous in their timing and their specific effects and our results are best interpreted as an average effect of possibly heterogeneous health changes.

Fonseca et al. (2023) study the relation between the price of healthcare and the healthcare expenditures within a heterogenous agents framework and conclude that the cross-country differences are largely related to the price of healthcare.

The paper is organized around five sections. We discuss evidence on the relation of health and economic variables in Section 2.

Then, in Section 4 we present a parsimonious model of household that allows to derive some analytical results regarding the interaction of health and labor market choices.

After that in section 5 we present a rich heterogeneous agents model that allows to capture both time series and cross-sectional moments in the data. This part is still work in progress, and we only present some preliminary results. 6 concludes.

2 Health and the business cycle: Empirics

We provide two sets of empirical facts. First, we document the cyclical behavior of health in the U.S. Second, we show that in the cross-section of U.S. states, population health today predicts future labor market outcomes.

2.1 The cyclicality of health: Time series evidence

Despite the finding in Ruhm (2000) that mortality is procyclical we document that bad health is countercyclical. For now, we focus on bad health, defined as the fraction of the population that self-reports their health status as "poor" or "fair", the two lowest rankings on a 5-tiered survey question. Subsequently, we consider alternative indicators of detrimental health.

Figure 2.1 compares the unemployment rate and the fraction of the population in bad health on a quarterly frequency from 1972 to 2019.[3] Here, we focus on log-deviations from a cubic trend. Bad health moves together with unemployment; the correlation is 0.60: Bad health is countercylical.[4] We confirm the cyclical behavior using alternative data sources and health indicators below. First, however, we show that similar correlations hold in the aftermath of well-understood demand shocks.

Overall correlations reflect all shocks affecting the economy, potentially complicating the interpretation of the countercyclical bad health. Figure 2.2 shows the response of bad health and unemployment to well-understood demand shocks:[5] the [contractionary] monetary policy shocks of Miranda-Agrippino and Ricco (2021) (top panel), and Romer and Romer (2004) (middle panel), and the surprise increases in federal defense spending constructed from Greenbook projections (Drautzburg, 2020) (bottom panel).[6] For each

[3]The data are based on the NHIS. To our knowledge, the NHIS has the longest history on annual or higher frequency data on self-reported health in the U.S. To construct this series, we splice together three sub-series that reflect from certain changes in the survey.

[4]In log-levels, the correlation is 0.59. Without detrending, bad health correlates slightly more strongly with leads of the unemployment rate than with the current or past unemployment rate.

[5]We show local projections with heteroskedasticity-robust standard errors. In the long, quarterly samples, we control for lags for lags of all three variables and the shocks, as well as a cubic trend. In the short, annual sample, we just control for lags of the left-hand-side variable and the shocks. In each case, we allow for lags of up to three years. Note that we use a trailing 4-quarter moving averages of the survey variables to account for measurement error and seasonality.

[6]These Greenbook surprises yield a similar but longer time series than the one-period ahead surprises in Ramey (2011) that are based on the SPF.

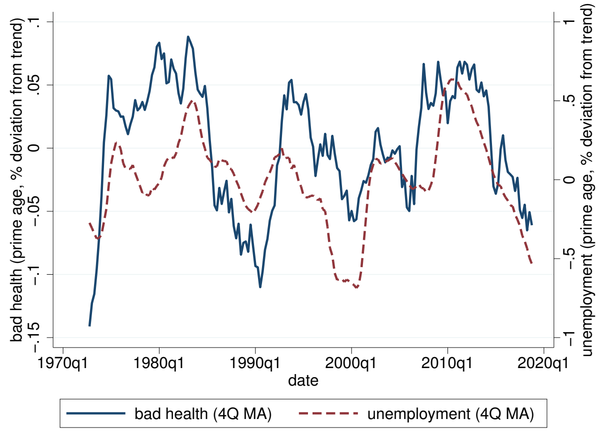


Figure 2.1: Bad health and unemployment: Deviations from trend: 1972q1–2019q4

shock, we show the response of the unemployment rate and the fraction of the population in bad health (both in percent deviations) and the response of the policy instrument. Each figures shows point estimates, as well as 68% and 90% confidence intervals. Unemployment rises after the contractionary monetary policy shocks and falls after fiscal expansions, even though the specific pattern of the responses differs across these experiments. Bad health moves in the same direction as unemployment and by about one third as much in response to each of the three shocks. For example, using annual data from the CPS and the Miranda-Agrippino and Ricco (2021) shocks, we find that the unemployment rate rises by about 0.5% to 0.7% two to four years after the shock. Bad health rises between 0.1% and 0.25% one to four years after the shock. These responses are significant at the 90% level at the three to four year horizon, and at the 68% level before that. The policy instrument is constrained by the lower bound on interest rates during this period and we find a significant increase only at the 68% level on impact.

With the same methodology, we confirm Ruhm's finding that mortality falls in downturns. Since mortality from the vital statistics is available only annually for long time periods, we use the mortality sample in the NHIS to compute death probabilities at quarterly frequency. Since death is a tail event, we compute 2-year death probabilities up to a given quarter and address seasonality and sampling noise by computing a trailing 4-quarter moving average. Figure 2.3 shows the results with quarterly CPS data from 1990q1 to 2019q4. As before, the unemployment rate rises, exhibiting a similar pattern as in the top panel of Figure 2.2. At quarterly frequency, however, the unemployment responses seems to start reverting to the mean after 16 quarters. The death probability falls immediately and remains significantly below zero throughout the first four years. If anything, the effect strengthens over time, broadly mirroring the unemployment rate dynamics. The federal funds rate increases significantly for up to three quarters after the shock.

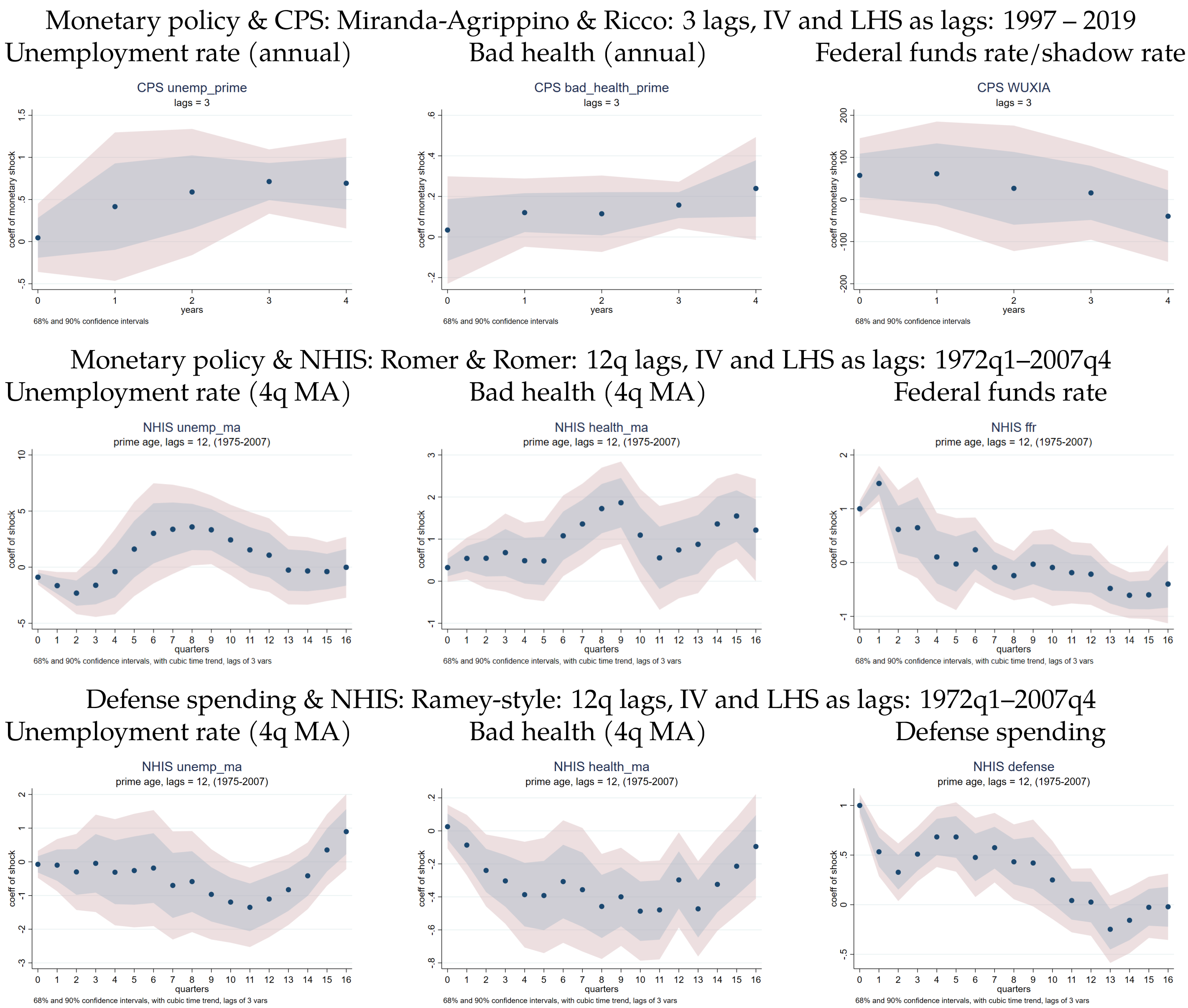


Figure 2.2: Health & unemployment responses to demand shocks: Monetary policy & defense spending.

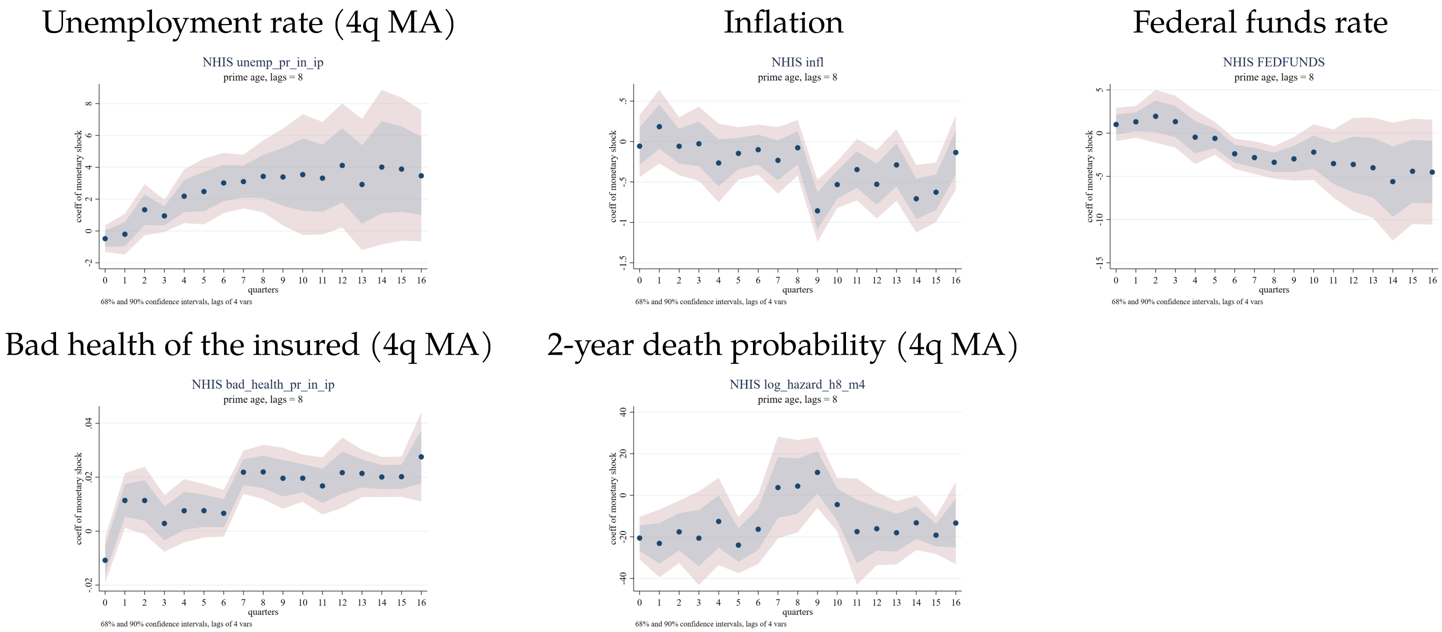
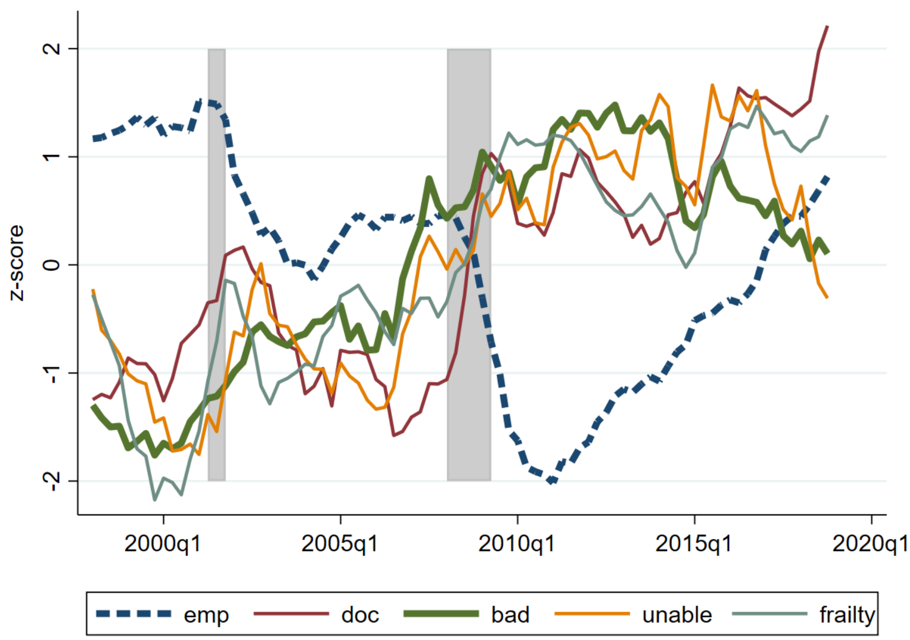


Figure 2.3: Pro-cyclical death response to monetary policy shocks

What is behind the increase in bad health during downturns? The broad, self-reported health measure could reflect physical or mental health, but possibly also just reflect changed perspective or reporting in the face of unemployment. Since the early 2000s, we have alternative measures available that allow us to rule out subjective changes in reporting without actual changes in health. The Global Financial Crisis (GFC) is thus a useful case-study. Currie and Tekin (2015) show using administrative data from four U.S. states that increased foreclosures were associated with more unscheduled hospital and emergency room visits, even when flexibly controlling for other local economic characteristics. We now show that various survey measures agree with the self-reported (bad) health measure we analyze above.

Figure 2.4 plots employment and bad health in the NHIS along with other survey measures. For ease of comparison, all time series in Figure 2.4 are expressed as z-scores, i.e., in standard deviations from their time series mean. These measures are: doctor's visits (or medical provider visits), being unable to work, and a frailty index (Hosseini et al., 2019). While noisy, the solid lines measuring undesirable health outcomes step up around the time of the 2001 recession and the GFC. The increase in bad health from 2006 to 2011 is about two standard deviations (green line). Its timing is similar to that of the fraction being unable to work, which increased by slightly more than two standard deviations (orange line). The fraction of the population with doctor visits and the frailty index similar rise from 2006 to 2011, increasing by about 2.5 and 1.5 standard deviations, respectively.

However, most of the increase in doctor visits and frailty occurs after 2007. The fact that frailty, which is based on the prevalence of specific medical conditions, rises suggests that the increase in bad health is not merely subjective. In addition, the increase in doctor visits suggests that the increase in bad health is also not caused by loss of access to health insurance.[7] Among the frailty components, depression and medical conditions, such as hypertension or asthma, rise first, while functional limitations rise with a delay of approximately one year (see Figure A.3 in the appendix).[8]



Note: We stop the NHIS time series in 2019 because of a methodological change in 2020. The CPS data come from the annual March supplement. The NHIS is a quarterly survey, and we show the 4-quarter moving average.

Figure 2.4: Robustness of the countercyclicality of bad health in the NHIS: Comparison of different indicators of adverse health for prime age individuals in the 2000s.

In the appendix, we further show that the countercyclical behavior of bad health is also present in the CPS. Moreover, after we account for life-cycle dynamics, it is also present in the NLSY cohort study within the same sets individuals over time. See Figure A.1.[9]

[7]In the appendix, we show that patterns similar to those in Figure 2.4 hold both for the insured and the uninsured (Figure A.2.

[8]In the three year period from 2007q4 to 2010q4, depression contributes about 40% to the increased frailty, followed by limitations and medical conditions, which together contribute virtually all of the remainder (see Table A.1).

[9]The fraction of prime-age (25- to 54 years old) individuals reporting to be in bad health rose by 7.5 percent from 2005 to 2010 according to the CPS and by 10% according to the NHIS. While these surveys

The fact that bad health varies with the business cycle affects individuals and their welfare. Using cross-state variation around the time of the GFC we now argue that variation in bad health also affects labor market-wide outcomes. Fluctuations in health may thus matter for understanding the size or persistence of aggregate fluctuations.

2.2 The importance of health for labor markets: Cross-state variation

Health has predictive power for current and future labor market outcomes. Even after controlling for the severity of the recession via the 2008 state employment-to-population ratio, bad health in 2008 significantly predicts the 2014 employment-to-population ratio in a state, as Figure 2.5 illustrates. The figure plots 2014 employment against bad health in 2008, both as residuals from projecting out 2008 employment. States with a 10% higher bad health in 2008 had a 0.8% lower employment (to population) in 2014.

The results are similar for other labor market outcomes. For example, Table 2.1 (a) provides analogous regressions for total hours worked for multiple years. Health in 2008 explains about 5% of the residual variation in 2014 total hours worked, after accounting for 2008 levels of hours worked. States with a one standard deviation higher bad health in 2008 on average had total hours that were 0.24 standard deviation ($= 0.28 \times (-0.05)/0.07$) lower in 2014. Similar results hold for 2012, 2013, and 2015.

Extensive margin measures are more sensitive to health than total hours. For employment and participation, Table 2.1 (b) and (c), the explanatory power is slightly higher. The partial R-squared is 0.07 for both variables and the effects of a one standard deviation shock in bad health cause movements of 0.32 and 0.39 standard deviations, respectively.

Last, the effects on hourly wages in Table 2.1 (d) are similar to the effects on total hours – both in terms of the magnitude and the sign. This is noteworthy because a simply drop in labor supply due to worse health might intuitively be associated with an increase in wages. Instead, these results suggest that either overall labor productivity drops or that there is a selection effect that lowers both wages and labor supply.

The regression results above are conservative – and extend beyond the aftermath of the

are, largely, repeated cross-sections, similar patterns hold when we analyze the cohort of the NLSY97 and analyze within-person variation. All three surveys ask exactly the same question on self-reported health. Since the NLSY97 is a cohort study of about 9,000 individuals born between 1980 and 1984, the raw data is dominated by life-cycle patterns. We report the average residual of a dummy for bad health after accounting for person fixed effects and a fourth-order polynomial in health. Figure A.1 shows that average residual bad health increased by 1.8pp between 2006 and 2011, similar to the 2pp increase in the NHIS, albeit about twice as much as the increase in bad health in the CPS over the same period. The surveys are volatile, though, and the 2005 to 2010 increase in bad health in the CPS of about 0.8pp matches that of the residual bad health in the NLSY. Using the NLSY, we also verify that these findings are not driven by varying response rates, because the results hold when we condition on individuals responding in all waves from 2005 to 2015.

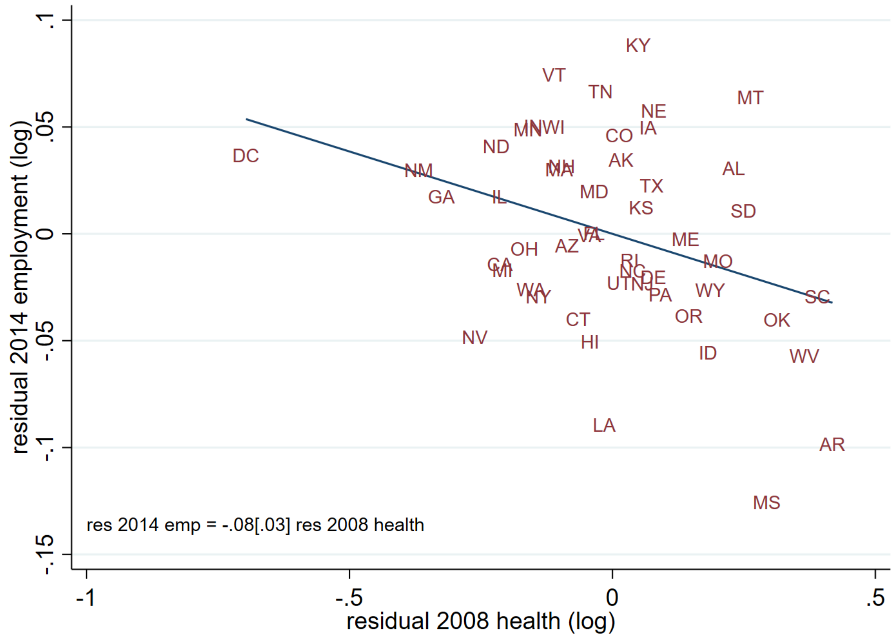


Figure 2.5: Higher bad health predicts lower future employment: Mean state health in 2008 and employment in 2014 in the CPS.

GFC. Figure 2.6 again employs local projections to show that this relationship holds more broadly during the last 25 years. Figure 2.6 (a) controls for current (and past) employment – and thus rules out current responses to lower health.[10] It implies that a state with a 1pp higher bad health today on average experiences employment that is lower by almost 0.1pp after four to five years. Figure 2.6 (b) controls only for past employment and bad health. It shows a much stronger predictive power of bad health. States with a 1 pp increase in

	(a) Total hours				(b) Empl	(c) Part	(d) hrly wage
	2012	2013	2014	2015	2014	2014	2014
LHS in 2008	0.74***	0.71***	0.64***	0.67***	0.53***	0.46**	0.40***
	(0.12)	(0.13)	(0.13)	(0.09)	(0.17)	(0.19)	(0.14)
Bad health (log) in 2008	-0.06**	-0.05*	-0.06**	-0.05*	-0.08***	-0.07**	-0.09*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Mean 2008 LHS	3.49	3.49	3.49	3.49	-0.22	-0.18	2.76
SD 2008 LHS	0.06	0.06	0.06	0.06	0.05	0.04	0.11
Mean 2008 health	-2.30	-2.30	-2.30	-2.30	-2.30	-2.30	-2.30
SD 2008 health	0.28	0.28	0.28	0.28	0.28	0.28	0.28
Mean LHS	3.42	3.43	3.43	3.46	-0.26	-0.21	2.83
SD LHS	0.07	0.07	0.07	0.06	0.06	0.05	0.11
Overall R-squared	0.68	0.62	0.56	0.61	0.53	0.53	0.26
Partial R-squared health	0.04	0.03	0.05	0.03	0.07	0.07	0.05
No. obs.	51	51	51	51	51	51	51

Table 2.1: The relationship between bad health in 2008 and future labor market outcomes across state: Total hours.

[10]Specifically, both panel (a) and panel (b) in Figure 2.6 control for state and year fixed effects as well as one lag of employment and bad health. Panel (a) additionally controls for current employment.

bad health today on average experience employment that is 0.4pp lower on impact and by about 0.25pp after 5 years. Our approach of controlling for current economic conditions when assessing the role of health therefore limits the potential role of bad health.

(a) Holding current employment constant (b) Controlling for past employment only

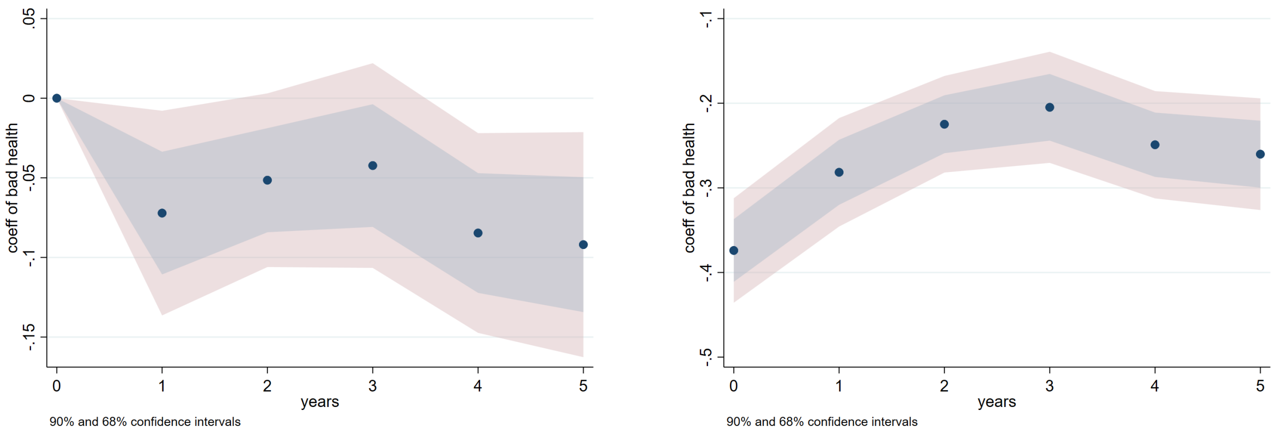


Figure 2.6: Effects of bad health on current and future employment across states: The role of controlling for current economic conditions in local projections.

We view this evidence as suggesting that differences in health outcomes are associated not only with statistically significant but also economically meaningful differences in labor market outcomes. Consequently, we need a model that can account for general equilibrium feedback.

3 Proposed mechanisms: Dominant substitution effect and health effects of economic distress

3.1 Substitution effect

Intuitively, the strength of income and substitution effects is key for determining the driving force of health fluctuations. If health is a normal good, when the income effect is strong enough, health investments will be low during downturns and health will decline. In contrast, when substitution effects dominate, downturns would be good for health – as suggested by Ruhm (2000). In that case, some other shock channel has to account for the observed behavior of health over the cycle.

To inform this debate, we turn to cross-sectional data on health investments. We observe time spent on health-care in the ATUS and in the MEPS. Using linear regression, we describe the extensive and the intensive margins of health investments. While the surveys differ in their structure – the ATUS measures behavior on a single day while the MEPS considers behavior in a calendar year – the surveys agree that employment reduces the extensive margin of health investments and mutes the correlation of bad health and health investments.

	(1) Pr{Time>0}	(2) E[Time| Time>0]	(4) E[Time]
bad hlth	0.179***	0.010	0.043***
	(10.69)	(0.22)	(11.07)
employed	-0.067***	0.024	-0.015***
	(-34.71)	(0.94)	(-8.63)
employed x bad hlth	-0.146***	-0.035	-0.032***
	(-8.28)	(-0.87)	(-4.84)
constant	0.128***	0.261***	0.032***
	(69.01)	(11.35)	(27.23)
R-squared	0.229	0.498	0.191
R-sq, within	0.044	0.002	0.015
Observations	28759	1511	27304
Years	10	10	10
States	51	40	51
FE	St×M×Y	St×M×Y	St×M×Y

Table 3.1: Health investments as a function of health and employment status: ATUS. Time is relative to disposable time

Table 3.1 shows this relationship for the ATUS. Here, thos in bad health are 18% more likely to spend time on their health when they are not employed. Employed individuals are 6.7% less likely to spend time on health on the day they are surveyed and an additional 14.6% less likely to spend time on health when they are in bad health – implying that their health investments essentially do not increase with current health status.

Table 3.2 shows that similar results hold in the MEPS, albeit at higher levels. This is intuitive, since we are now observing health behaviors over an entire year, summing across possibly lumpy health investments. To guard against mechanical effects from health care acces, here we condition on having access to health insurance. Bad health is associated with a 10% increase in health care visits, but less so for employed individuals. Employment also lowers the baseline probability of health events. Here, we also have evidence on intensive margin effects as employed individuals have fewer health events conditional on having any health events.

	Pr{Events>0}	$\mathbb{E}$[#Events|Events>0]	$\mathbb{E}$[\$exp|Events>0]	$\mathbb{E}$[\$exp]
bad health=1	0.0999***	4.627***	166.5***	202.5***
	(23.21)	(36.49)	(14.67)	(18.95)
employed=1	-0.0323***	-1.813***	-13.65*	-25.42***
	(-8.85)	(-22.36)	(-1.92)	(-4.04)
bad health=1 × employed=1	-0.0255***	-1.245***	63.60***	36.87***
	(-4.58)	(-7.94)	(4.54)	(2.80)
Constant	0.852***	8.042***	454.2***	389.8***
	(249.57)	(103.37)	(66.99)	(64.67)
R-squared	0.01	0.06	0.02	0.02
R-sq. within	0.01	0.06	0.01	0.02

Table 3.2: Health investments as a function of health and employment status, conditional on having insurance: MEPS

3.2 Health effects of economic stress

The literature suggests that negative economic events can have direct effects on health. For example, Sullivan & von Wachter (QJE, 2009) analyze the effects of mass layoffs on worker mortality in Pennsylvania. They find that the mortality hazard increases by 50% to 100% in the years following job loss. They observe that their "results are consistent with these effects causing acute stress, which may substantially raise the mortality hazard in the short term.".

Similarly, Currie and Tekin (2015) document that financial stress is associated with negative health outcomes. They estimate that zip-code level foreclosure rate increased are associated with higher urgent and unscheduled hospital visits in the run-up to the GFC. They point to stress as a chanlle, observing that: "Stress is thought to affect health both by depressing the immune system and through the direct action of "stress hormones" on factors such as blood pressure and cardiovascular health [...]. Stress can also have harmful consequences through psychological responses such as depression."

4 A simple model

Environment. Household differ in their initial health status $h \in \{0, 1\}$ and in their labor productivity a and/or their taste for leisure κ. Every household has a goods endowment of e and a time endowment of one unit. Time is spent on health transitions θx, or leisure L. Goods are spend on consumption c or health qx. The probability of being in good health is $p(x, h)$ with $p_x, p_h > 0$. Sometimes it is going to be useful to specialize to $p(x, h) = \bar{p} + p_x x + p_h h$, where $p_h + \bar{p} < 1$ and we might need to introduce an upper bound $\bar{x}$ such that $p_h + \bar{p} + p_x \bar{x} \leq 1$.

Health confers three benefits: A higher flow utility $\mu_0 + \mu_h h$, a higher productivity $(1 + \gamma h)$, and a higher probability of good health in the future.

Households value consumption and leisure as $\ln c + \kappa \ln L$ and discount the future at rate β.

Implicitly, we have that $x \geq 0$ and, possibly, $x \leq \bar{x}$. Note that x is naturally bounded by θ^{-1}, or else leisure would turn negative.

Household problem. The solution to the household problem is described by the following value function:

$$V(h) = \max_{c,x,L} \ln c + \kappa \ln L + (\mu_0 + \mu_h h) + \beta(p(x, h)(V'(1) - V'(0)) + V'(0))$$
$$\text{s.t. } c + xq \leq e + (1 - x\theta - L)aw(1 + \gamma h)$$

The model yield several analytical results that are insightful by themselves, but also provide guidance for the general equilibrium modelling .

Analysis.

It is possible to show that the following expression for consumption can be derived from the FOC for labor :

$$\begin{aligned} c &= e + (1 - \theta x - L)aw(1 + \gamma h) - xq \\ &= \frac{1}{1+\kappa}\left(\underbrace{e + aw(1 + \gamma h)}_{\equiv \tilde{e}(a,h)} - \underbrace{(\theta aw(1 + \gamma h) + q)}_{\equiv \tilde{q}(a,h)} x\right) \\ &= \frac{\tilde{e}(a, h) - \tilde{q}(a, h)x}{1 + \kappa} \equiv \tilde{c}(a, h, x) \end{aligned}$$

$\tilde{c}(a,h,x)$ is consumption after the optimal leisure choice is concentrated out: a fraction $\kappa\kappa + 1$ of total income net of medical costs is spent on leisure, the balance on consumption.

For future reference, it is convenient to define the effective wage rate $\tilde{w}$ as:

$$\tilde{w}(a,h) = aw(1+\gamma h) \quad \Rightarrow \quad \tilde{w}_a, \tilde{w}_h > 0, \tilde{w}_{aa} = \tilde{w}_{hh} = 0, \tilde{w}_{ah} > 0. \tag{4.1}$$

With this definition

$$x^*(a,h) = \frac{e + \tilde{w}(a,h)}{q + \theta\tilde{w}(a,h)} - \frac{1+\kappa}{\beta p_x \Delta V}.$$

Assume that p_x is invariant in h.

$$\frac{\partial x^*}{\partial h} = \frac{(q+\theta\tilde{w}(a,h))\tilde{w}_h(a,h) - \theta\tilde{w}_h(a,h)(e+\tilde{w}(a,h))}{(q+\theta\tilde{w}(a,h))^2} \tag{4.2}$$

$$= \tilde{w}_h(a,h)\frac{q-\theta e}{(q+\theta\tilde{w}(a,h))^2} \lesseqgtr 0 \quad \Leftrightarrow \quad q \lesseqgtr \theta e. \tag{4.3}$$

So, if $q = 0$, then any increase in health only increases the relative price of health to consumption, then higher health means less health investment. By continuity, this is true when q is small. Thus, if the time cost of health investments x matters more than the monetary cost, then those with bad health invest more time in health.

Using the first order conditions for labor and health investment, we can formulate the following Lemma.

Lemma 1. Holding future productivity a' fixed, the change in leisure L, health x, and hours worked N has the same sign following an increase in productivity a or an increase in health h.

Proof. For all three outcomes, the derivatives are equal up to the factor $\frac{\tilde{w}_a}{\tilde{w}_h} > 0$. □

Key result. Collecting the above results shows that a recession caused by a fall in productivity is good for health. A recession caused by a fall in wages w would be isomorphic. This scenario is consistent with cross-sectional evidence.

Proposition 4.1. If individuals in bad health $(h = 0)$ spend more resources x on health $(q < \theta e)$, then

1. A temporary fall in productivity increases health investments and thus expected future health and expected future hours worked rise.

2. Current hours worked fall following a temporary fall in productivity.

3. In addition, in the cross-section, healthier individuals work more.

4. If also $\theta^{-1}q < aw$, then unhealthier individuals' investment in health x is lower when they work more.

Proof. (Provided in the Appendix) □

We conclude that there must be a missing health shock or a health-centered channel. A "health shock" works under the conditions of the following proposition.

Proposition 4.2. Given a path for wages, if $q < \theta e$ and if the direct effect of health dominates in equilibrium ($p_h > -(x^*(a,1) - x^*(a,0))p_x \forall a$), then an economy with lower average health $\bar{h}$ has:

1. Lower expected future health, and

2. Lower current and future hours worked.

Proof. (Provided in the Appendix) □

5 A dynamic model with heterogeneity [in progress]

To explain the observed health fluctuations and quantify the channels driving the fluctuations in health over the business cycle we develop a quantitative business cycle model with heterogeneous agents. Agents decide whether to work, how much to invest in physical capital, and, crucially, how much to invest in their health – a type of human capital in the tradition of Grossman (1972) and Grossman (2000). This allows us to analyze the interaction of labor supply and demand for health investments whose importance the simple model highlighted.

5.1 Environment

Markets are incomplete as in Capatina (2015) and De Nardi et al. (2017) and agents are subject to two types of health shocks: (1) idiosyncratic labor productivity risk as in Krusell and Smith (1998), and (2) idiosyncratic health shocks. Agents value their health because being in good health increases their flow utility while bad health reduces the time endowment because of sick time and lowers the labor productivity. The current health status also affects health transition probabilities. Health investments require both time and consumption goods.

Besides households, there is a representative firm renting capital from households and employing workers to produce a homogeneous consumption and investment good. Time is discrete.

Households There is a continuum of infinitely lived households $i \in [0,1]$ that differ across three dimensions: they can be healthy ($h_i = 1$) or unhealthy ($h_i = 0$), have productivity g_i, and own capital k_i. They get utility from consumption c_i, and disutility from working, $\ell_i \in \{0,1\}$. Healthy households enjoy a flow utility of u_h. Also, if a household is sick, $h_i = 0$, its disposable time endowment is reduced by ϕ_h. The felicity function is:

$$U(c_i, \ell_i; h_i) = \frac{\left(c_i^{\alpha}\left(1 - \phi_\ell \ell_i - \phi_h(1-h_i) - \theta_\ell x_i\right)^{1-\alpha}\right)^{1-\sigma} - 1}{1-\sigma} + u_h \tag{5.1}$$

Here, α is the relative importance of consumption c_i, σ^{-1} is the intertemporal elasticity of substitution. ϕ_ℓ is the [indivisible] time cost of working ($\ell_i = 1$) and ϕ_h is the time cost of being sick. θ_ℓ is the time cost per unit of time x_i invested in health.

Households face a sequence of static budget constraints given by:

$$wg_i(1 - (1-h_i)\theta_g)\ell_i + k_i(1 + r - \delta) = k_i' + c_i + x_i\theta_m \tag{5.2}$$

Households receive a wage w per unit of effective labor. Workers can only work full-time ($\ell \in \{0,1\}$) and their productivity has an exogenous component g_i, which follows an AR(1) process, and the partly endogenous component $(1 - (1-h_i)\theta_g)$, which depends on health h_i. The only financial asset that households can trade in is physical capital k_i. Capital depreciates at rate δ and earns a return of r. They spend their income on future capital k_i', consumption c_i, and health (medical) investments x_i with relative price θ_m.

Households discount the future at rate $\beta \in [0,1]$ so that their lifetime utility is $V_{i,t} = U_{h_i}(C_{i,t}, \ell_{i,t}) + \beta \mathbb{E}_t[V_{i,t+1}]$.

Health follows a first order Markov process. The probability of good health tomorrow is given by

$$p(h' = 1) = a(h,\ell) + \frac{b(h,\ell) - a(h,\ell)}{1 + exp(-\phi(h)(\phi_0 + \phi_1 x_i)))}$$

where $\phi(h)$ and ϕ_1 are curvature parameter, while ϕ_1 is a shifting parameter.

Firms The economy is populated by a continuum of identical competitive firms living for one period of time that rent capital from the households and employ them.

Firms maximize production $Y = AK^{\alpha}L^{1-\alpha}$ net of input costs:

$$\max_{K,L} AK^{\alpha}L^{1-\alpha} - rK - wL, \tag{5.3}$$

where capital and labor are aggregates across individuals, given by $L = \int g_i(1-(1-h_i)\theta_g)\ell_i di$ and $K = \int k_h di$.

Equilibrium and solution method Households and firms optimize taking wages w and rental rates r as given. In stationary equilibrium, the goods market clears ($Y = \int_i c_i + \theta_m x_i + \delta k_i di$), the capital rental and labor markets clear, and the cross-sectional distributions of capital holdings and health are stationary. We use the Tauchen (1986) method to approximate the AR(1) distribution of g_i. We solve the model following Krusell and Smith (1998) as described in Appendix D.

5.2 Preliminary steady state results

In the calibration exercise we use the Simulated Method of Moments (SMM) to match three groups of parameters:

- Transition probabilities between health and employment (data based on calculations from MEPS).
- Variance of income, unemployment in good and bad health.
- Regression of indicator $x > 0$ on health, employment status and their interaction.

We leave an analogous regression of x on the same variables, for all $x > 0$, untargeted.

We use 14 parameters to match the data: those parameters capture income process' dynamics and the health investment function.

Table 5.1 illustrates the model's fit at the ergodic distribution. Under this calibration the model matches closely the income variance. It overshoots unemployment levels, but unemployment in good health still remains lower than in the bad health – this result would hold also at the aggregate level, and it is crucially important for the business cycle.

Importantly, we manage to qualitatively match the regression of the intensive margin of visits to the doctor.

Name	Model	Data
Extensive margin regression		
$\{1[x_i > 0]\} = \nu + \theta_b \times 1[bad_i] + \theta_e \times 1[emp_i] + \theta_{b\times e} \times 1[bad_i] \times 1[emp_i]$		
θ_b	0.0000	0.1900
θ_e	-0.0000	-0.0100
$\theta_{b\times e}$	-0.0735	-0.0900
ν	1.0000	0.6700
Intensive margin regression [not targeted]		
$x_i = \alpha + \beta_b \times 1[bad_i] + \beta_e \times 1[emp_i] + \beta_{b\times e} \times 1[bad_i] \times 1[emp_i]$ given $z_i > 0$		
β_b	0.0259	0.1900
β_e	0.0048	-0.0700
$\beta_{b\times e}$	-0.0189	-0.0600
$\alpha(untargeted)$	0.2328	0.3500
Other targets		
income variance, log points	1.6049	0.5625
non-employment given good health	0.2646	0.0792
non-employment given bad health	0.7606	0.3623
Fraction in bad health	0.102	0.10
Fraction employed	0.684	0.90

To:	Bad hlth		Good hlth		
From	non-emp	emp	non-emp	emp	
Bad hlth non-emp	**0.562**	**0.037**	**0.297**	**0.104**	**Data**
	0.305	0.103	0.250	0.342	Model
Bad hlth emp	**0.061**	**0.248**	**0.066**	**0.625**	**Data**
	0.231	0.147	0.157	0.464	Model
Good hlth non-emp	**0.107**	**0.017**	**0.597**	**0.279**	**Data**
	0.180	0.049	0.399	0.372	Model
Good hlth emp	**0.009**	**0.036**	**0.055**	**0.901**	**Data**
	0.007	0.003	0.183	0.806	Model

Table 5.1: Calibration – data moments and model moments

5.3 Policy functions

Figure 5.1 shows households' policy functions in stationary equilibrium as a function of the (log of) idiosyncratic productivity g_i. Each panel conditions on a different level of capital holdings as an individual state variable and shows results for healthy individuals (blue lines) and unhealthy individuals (orange lines).

Investment in health is the top panel for each wealth level. Three lessons emerge. First, those in bad health tend to investment in their health than those who are healthy, as evidenced by the blue line being above the orange line. Those in bad health often max out their health investment at $x = 1$. Second, at the productivity level that induces those in bad health to become employment, they typically reduce their health investment, reflecting substitution effects. Third, as wealth rises, agents choose a weakly higher level of health investment. For example, agents with low financial wealth with a productivity around 5.5 may decide not to invest in their health when they decide to work. In contrast, richer agents with the same productivity merely reduce their health investment.

Our model calibration confirms the relevance of the economic tradeoffs isolated in the simple model: Holding fixed an individual's wealth, individuals who are in a more productive state work more, as shown by the middle chart for each wealth level. Near the employment threshold, higher productivity is associated with lower health investments and higher employment, reflecting the higher utility cost of health investments as the cost of leisure rises when individuals accept full-time work.

Moreover, healthy individuals choose employment at lower productivity levels g_i reflecting their higher effective productivity.

Last, at most levels of capital shown here the future level of capital chosen (k_i') is not too high. This reflects that individuals with high levels of capital dissave when their capital is high enough. They accumulate capital when they have low financial wealth and/or are highly productive. For each level of initial capital here, this is the case when log productivity $\log(g_i)$ 5 or 6. Individuals in good health, whose expected lifetime income is higher tend to choose a slightly higher capital stock.

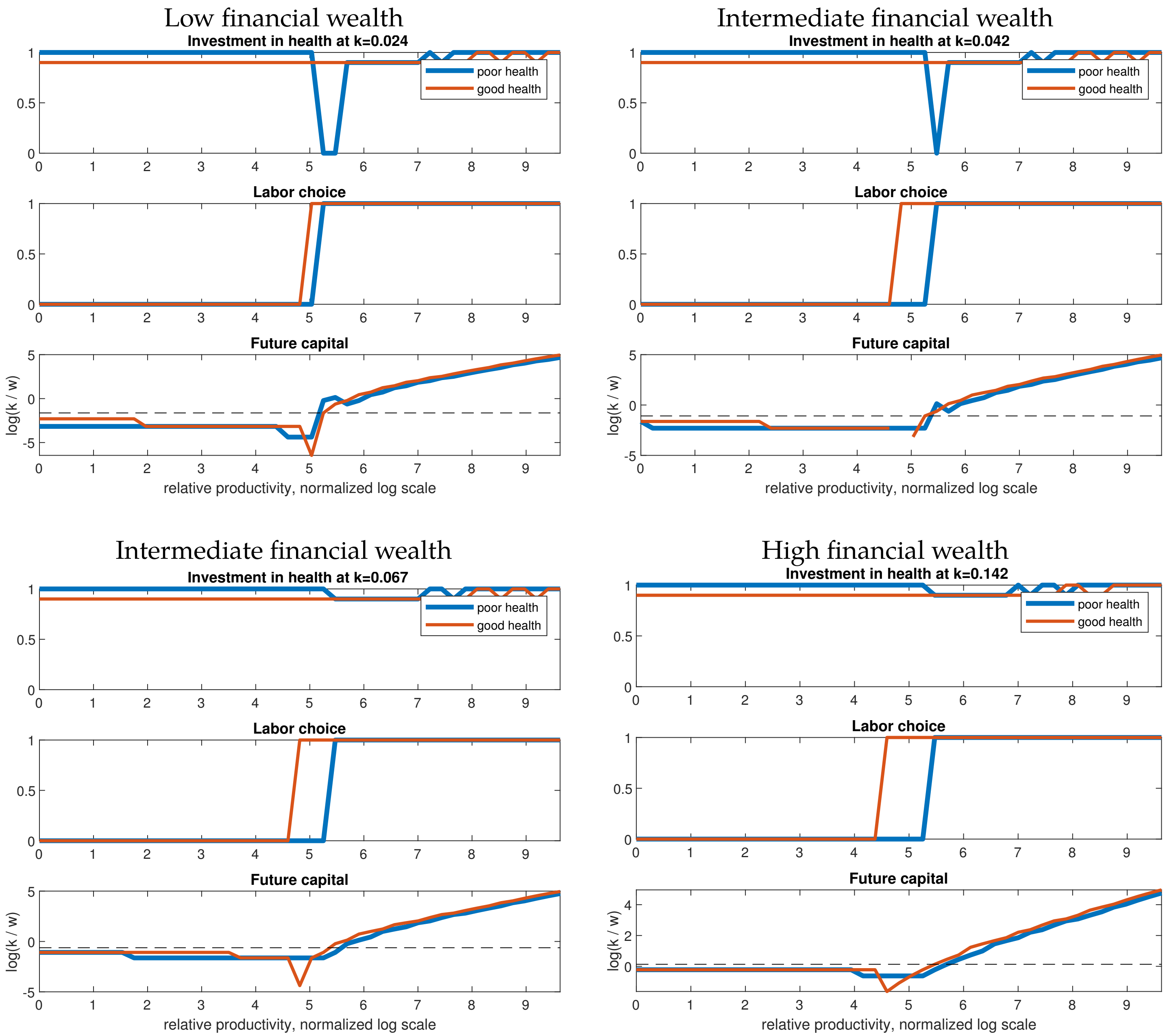


Figure 5.1: Policy functions as a function of productivity

5.4 Experiments

To analyze the effects of shocks in this model, we construct the responses to one-time unexpected technological and health shocks. Additionally, we leverage the heterogeneity among agents to obtain responses for different population groups.

5.4.1 TFP shock

In Figure 5.2 we show the response of the economy to an aggregate TFP shock. Employment falls, while health rises and health investment falls. Thus, health is countercyclical with respect to employment, and health investment is pro-cyclical.

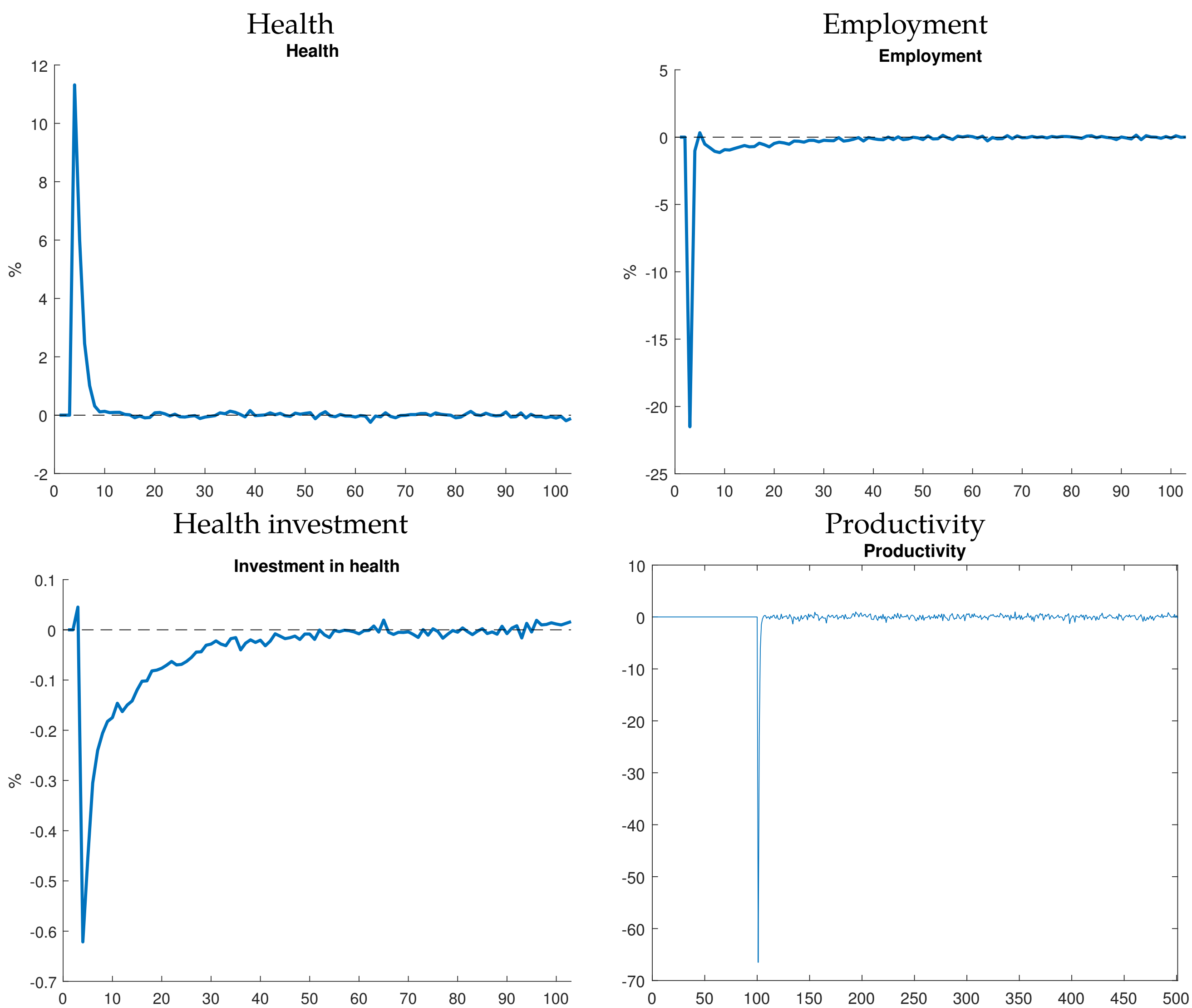


Figure 5.2: Responses of population-wide aggregates to a short-lived TFP shock

This pattern is at odds with our empirical estimates, which should pro-cyclical health and health investment that is a-cyclical or countercyclical. Consequently, there must be another shock that is in line with the empirical patterns. We now show that a health shock exhibits patterns in line with the data, in line of the need to include a health shock or a health channel in the model.

Even though the productivity shock cannot explain the business cycle patterns that we have uncovered by itself, it still has interesting implications. When we group response by initial health and employment status in Figures 5.3 to Figure 5.6, we find that health and employment exhibit similar patters across groups. In contrast, health investment declines persistently and by a large amount for those in poor health who are initially employed (after a small, initial spike). In contrast with this decline in health investment, this group increases its capital holdings, while all other groups dissave. The productivity boost thus causes this group to initially save when they are enjoy a short-lived productivity boom and then to decumulate health and capital gains.

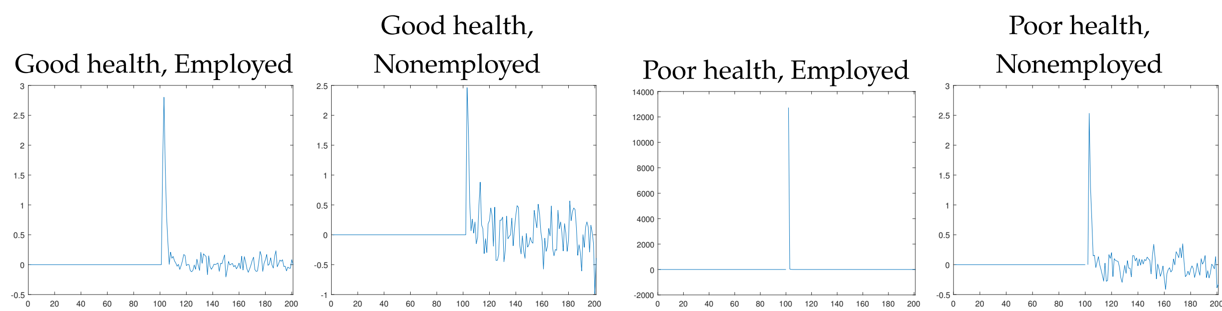


Figure 5.3: Response of Health to a TFP shock

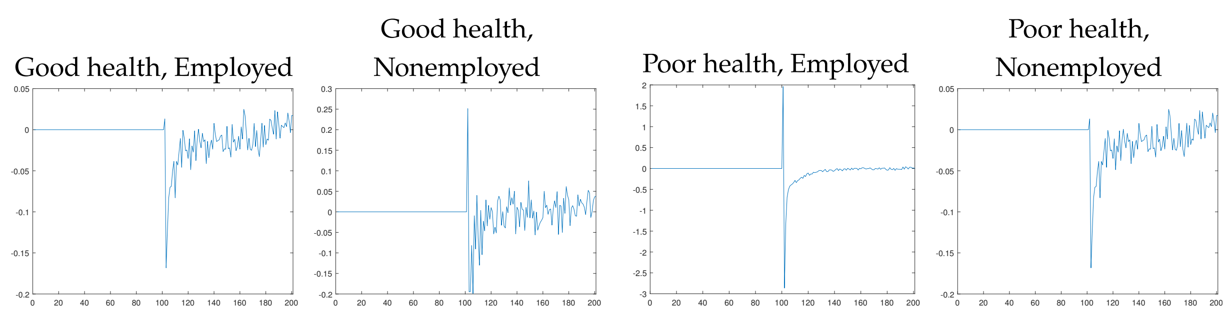


Figure 5.4: Response of Health investment to a TFP shock

Good health, Employed | Good health, Nonemployed | Poor health, Employed | Poor health, Nonemployed

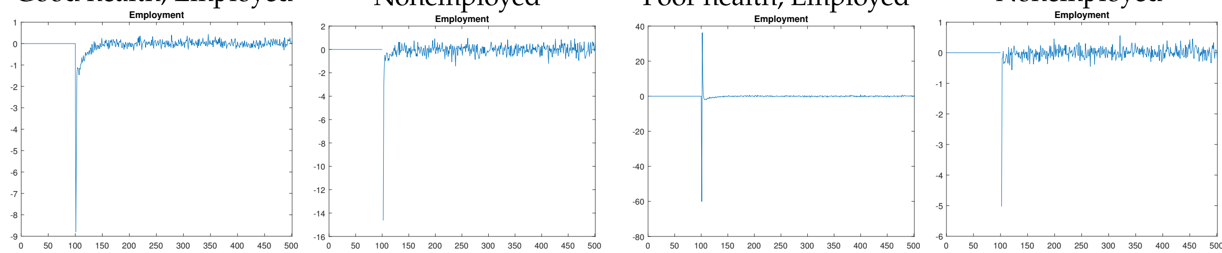


Figure 5.5: Response of Employment to a TFP shock

Good health, Employed | Good health, Nonemployed | Poor health, Employed | Poor health, Nonemployed

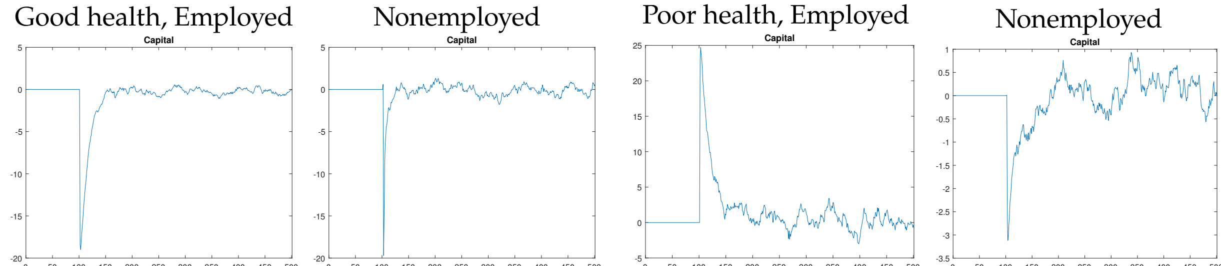


Figure 5.6: Response of capital to a persistent TFP shock

5.4.2 10% become sick Health shock

Here, we introduce a shock to the health distribution, calibrated so that the fraction of the population in bad health rises by 10%. Figure 5.7 shows the responses of health, employment, health investment, and capital averaged across the population.

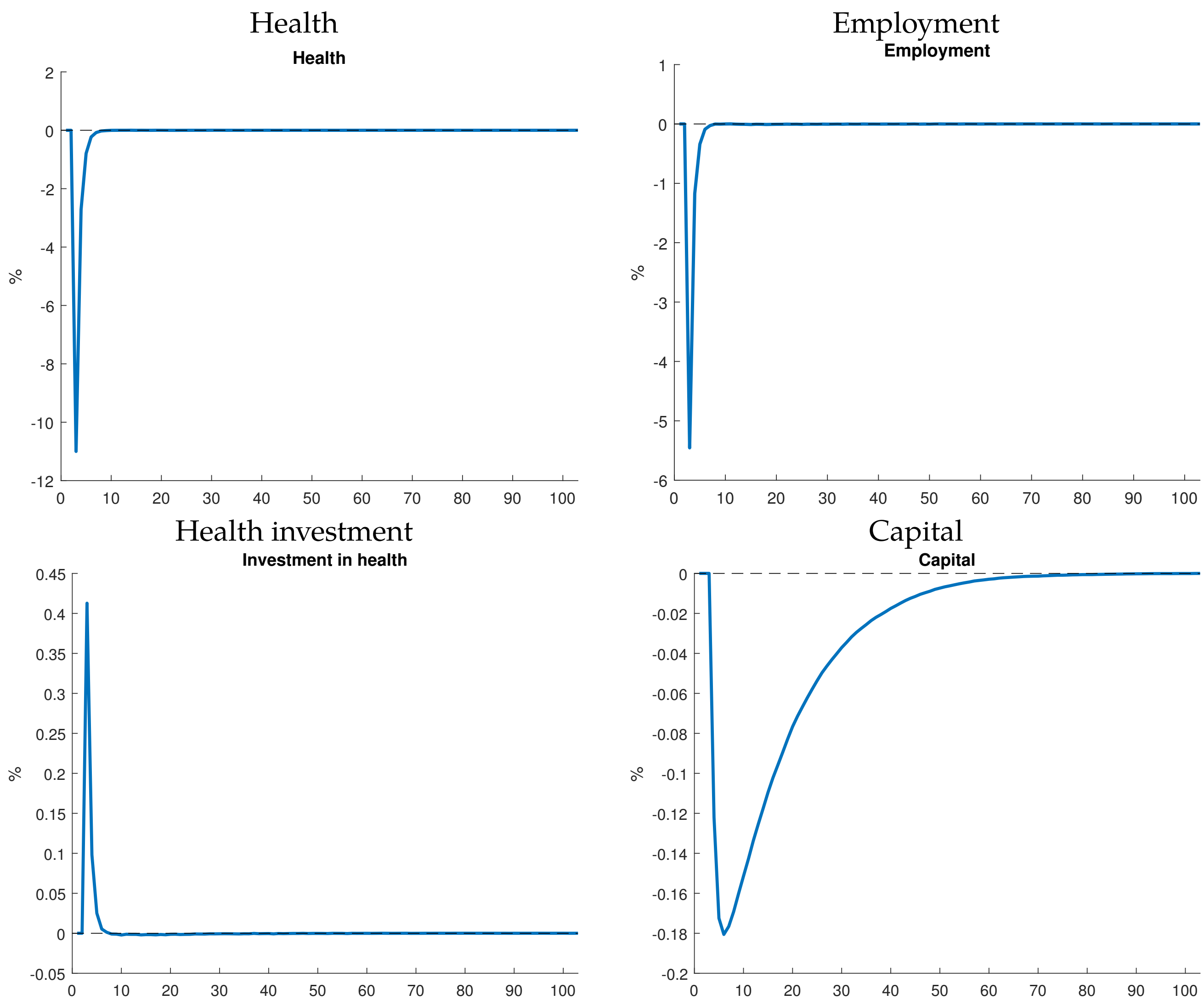


Figure 5.7: Responses of population-wide aggregates to a one-time health shock

Health is procyclical – the fall in health is associated by a fall of employment that is about half as large. Health investment is countercyclical, rising as health and employment fall. These patterns are consistent with the empirically estimated impulse-responses.

Note that the responses of employment are economically large – employment declines by a similar magnitude as bad health. In the full model, we would therefore expect wages per efficiency unit to rise. More generally, we can expect this large shock to have general equilibrium effects.

When we incorporate general equilibrium effects, we would expect to see a rise in the wage per efficiency unit and the return of capital. These price effects would partly mitigate the effects shown here and also cause responses by the individuals not directly affected by the shocks. This may also prompt declines in health investments and, subsequently, health by those not shocked.

We now turn to responses by group, where we define groups based on initial employment and health status in the baseline. The responses are relative to the baseline without the shock.

Figure 5.8 shows the responses of the fraction of each group being in good health. Here, and in the following figures, the two panels on the left show the response of those who are initially in good health, while the two plots on the right show those initially in bad health. The The first and third plot show the groups that are initially (before being shocked) employed. Given the discrete nature of health in our model, only those who were initially in good health experience lower health when shock. The response is short lived.

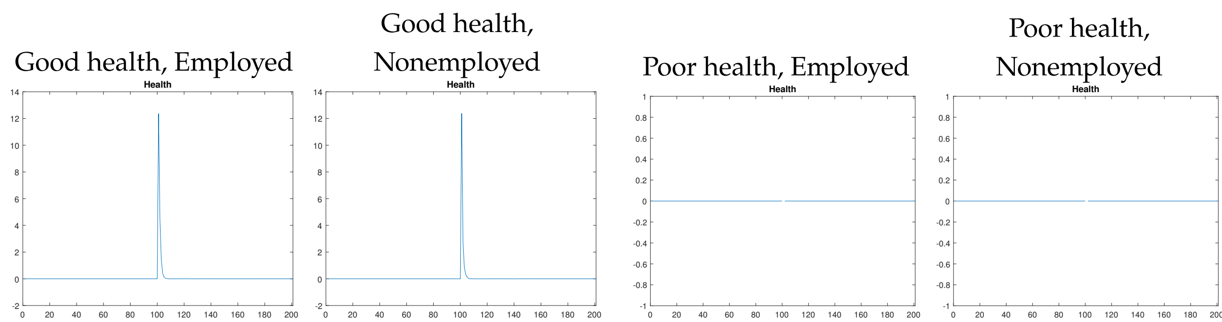


Figure 5.8: Response of Health to a Health shock

Figure 5.9 shows how health investments change by group. We find that only those who were initially non-employed and whose health worsened increase their health investment – qualitatively in line with our descriptive regression evidence that those in bad health increase their health investments less when employed.

Figure 5.10 shows the responses of employment by (baseline) group. After the negative health shock, fewer stay employed and transition to employment in the next period. For those in good health and employment the magnitude is large 8%, relative to the drop in health of 12%. This effect is about ten times smaller for the initially non-employed. This is due to the unobserved heterogeneity – those non-employed are, all else equal, of lower

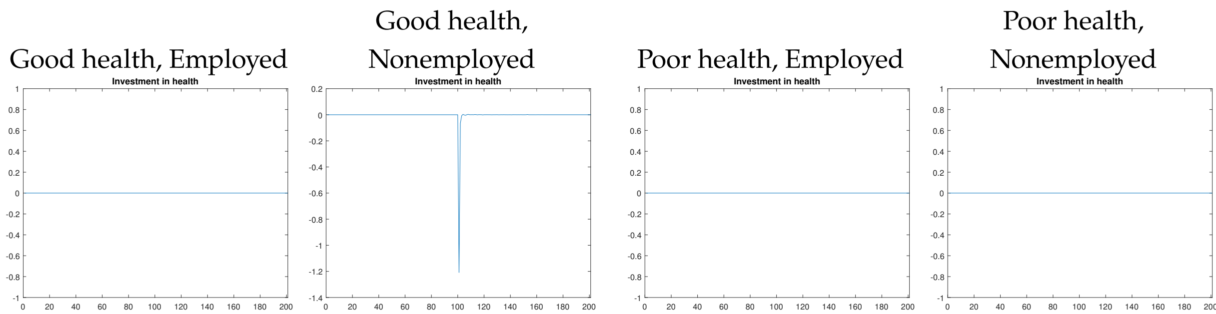


Figure 5.9: Response of Health investment to a Health shock

productivity. Since health affects their earnings potential proportionally to productivity, the (dis)incentive effects of worse health are less relevant for this group.

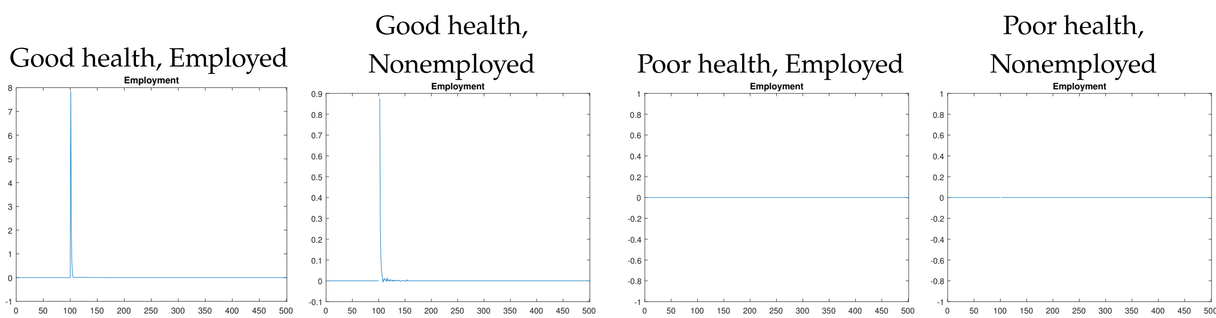


Figure 5.10: Response of Employment to a Health shock

Figure 5.11 shows that those affected by bad health dip into their savings – smoothing out the consequences of the shock.

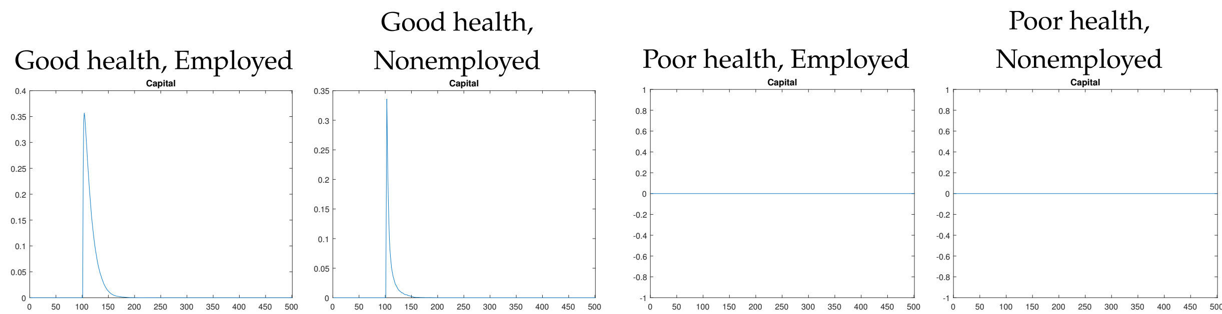


Figure 5.11: Response of Capital to a Health shock

5.5 Ongoing work and model extensions

In ongoing work we continue to assess which quantitative features are necessary to better match calibration targets, before computing the effects of business cycle shocks using transitions between steady states based using the first-order equivalence of this approach. To the extent that such transitions require an additional (reduced-form) direct health effect of negative shocks this would represent evidence in favor of a health channel of business cycles.

For now, we focus on ex ante heterogeneity of agents. In practice, there are important differences in labor market outcomes across demographic groups such as educational groups (e.g., Capatina (2015)): Less educated workers tend to experience more volatile employment and worse health outcomes, see Figure B.1 in the appendix. Capturing this ex ante heterogeneity may thus be important to accurately quantify the channels behind health fluctuations.

Similarly, we currently abstract from health insurance because we document that the same qualitative facts hold when we focus on the insured population only. However, it is plausible that differences in insurance status could amplify health effects of business cycle shocks as negative shocks could increases costs of accessing health care.

6 Conclusion

The health of the U.S. prime age population is procyclical, both unconditional and in response to demand shocks. Using a simple model of household decision making we demonstrate that such relation is likely to result from health-related shocks or from the transmission mechanism that propagates the standard business cycle shocks through a health channel. This highlights the importance of adding the health component to standard business cycle models.

We are currently developing a heterogeneous agents model that incorporates this insight into a framework that allows to track the relation of health and business cycle fluctuations.

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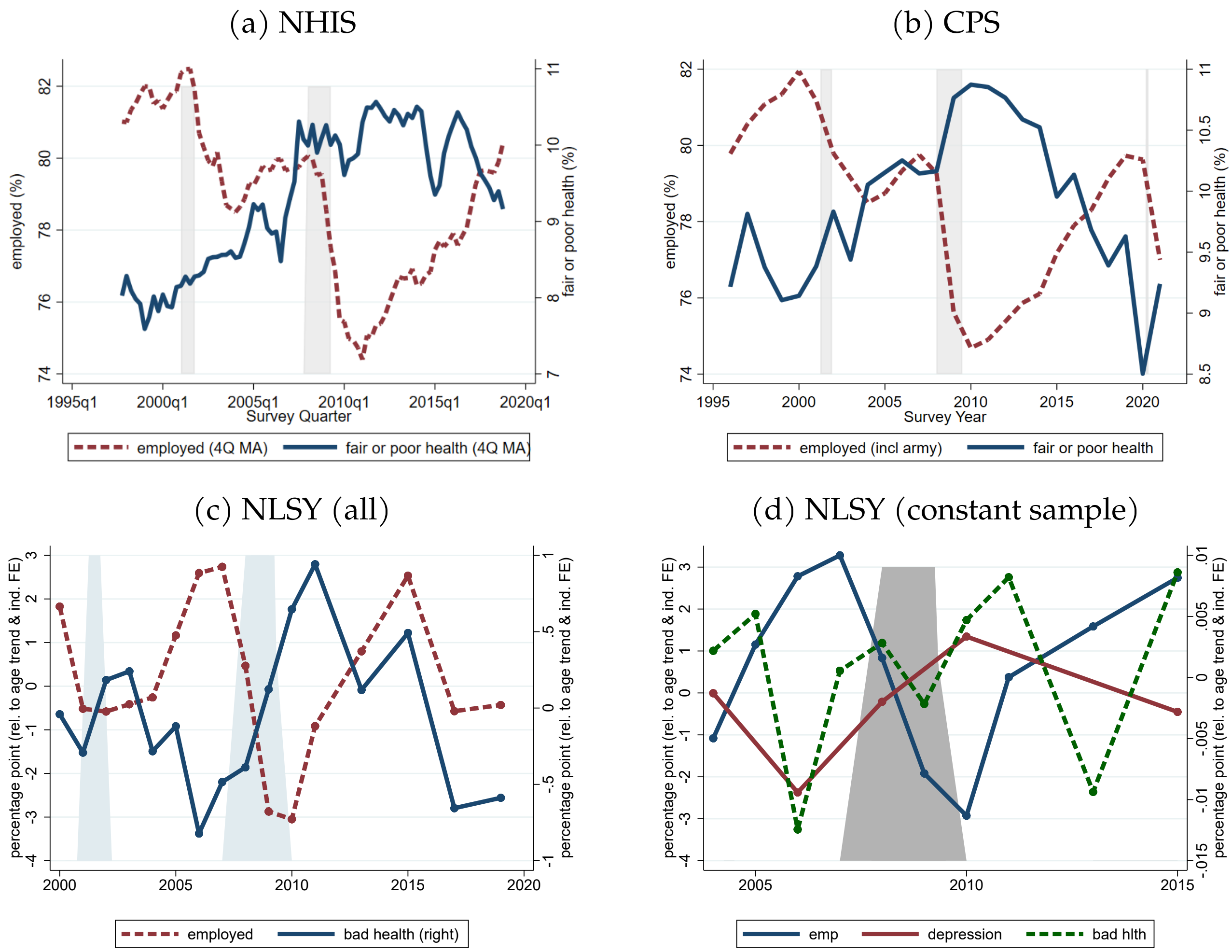
Appendices

A Additional Empirical Findings



Note: We stop the NHIS time series in 2019 because of a methodological change in 2020. The CPS data come from the annual March supplement. The NHIS is a quarterly survey, and we show the 4-quarter moving average. The NLSY sampling frequency changes from annual to biannual after 2011; the depression screener question is asked biannually at first and then quinquennially.

Figure A.1: The counter-cyclical behavior of bad health: Self-reported bad health and employment NHIS and CPS (prime-aged individuals), and the NLSY

	Levels		Difference		Detrended	
	2007Q4	2010Q4	change	contribution(%)	change	contribution(%)
conditions						
angipecev	0.007	0.010	0.003	1.095	0.004	1.307
emphysemev	0.007	0.009	0.002	0.730	0.002	0.654
cancerev	0.036	0.046	0.010	3.650	0.009	2.941
diabeticev	0.051	0.061	0.010	3.650	0.007	2.288
cheartdiev	0.015	0.014	-0.001	-0.365	-0.002	-0.654
heartattev	0.012	0.012	0.000	0.000	0.000	0.000
strokev	0.009	0.015	0.006	2.190	0.006	1.961
asthmaev	0.106	0.129	0.023	8.394	0.018	5.882
hypertenev	0.184	0.217	0.033	12.044	0.022	7.190
ulcerev	0.057	0.051	-0.006	-2.190	0.001	0.327
total	0.484	0.565	0.081	29.562	0.068	22.222
limitations						
lawalk	0.027	0.025	-0.001	-0.365	-0.002	-0.654
flstoop	0.161	0.179	0.018	6.569	0.025	8.170
flgrasp	0.050	0.055	0.005	1.825	0.009	2.941
flreach	0.061	0.058	-0.003	-1.095	-0.002	-0.654
flclimb	0.076	0.075	-0.001	-0.365	-0.003	-0.980
flwalk3bl	0.097	0.103	0.005	1.825	0.005	1.634
flcarry	0.063	0.077	0.014	5.109	0.018	5.882
flgoout	0.056	0.065	0.009	3.285	0.010	3.268
flpushlar	0.084	0.098	0.014	5.109	0.027	8.824
flrelax	0.031	0.036	0.005	1.825	0.007	2.288
flsocial	0.048	0.055	0.007	2.555	0.009	2.941
ladl	0.009	0.012	0.004	1.460	0.003	0.980
laiadl	0.024	0.025	0.002	0.730	0.000	0.000
laother	0.009	0.007	-0.002	-0.730	0.000	0.000
lamemry	0.022	0.024	0.002	0.730	0.002	0.654
total	0.817	0.895	0.077	28.102	0.106	34.641
depression						
total	0.469	0.573	0.105	38.321	0.142	46.405
overweight						
total	0.269	0.281	0.011	4.015	-0.010	-3.268

Table A.1: Detailed breakdown of changes in frailty by component: 2007q4 to 2010q4

Figure A.2: Invariance with respect to insurance status

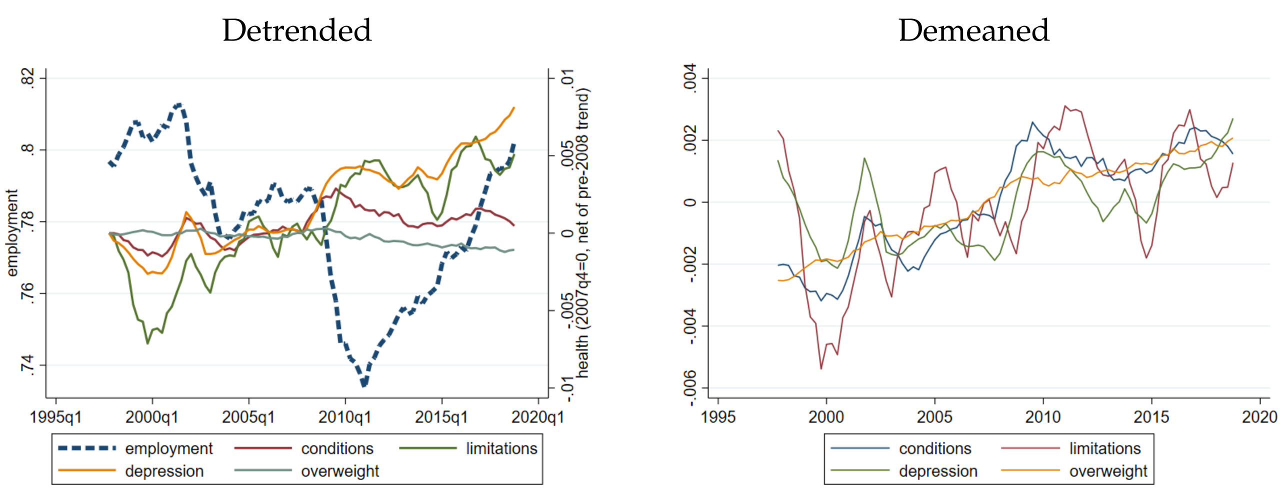


Figure A.3: Decomposition of frailty index

B Heterogeneity

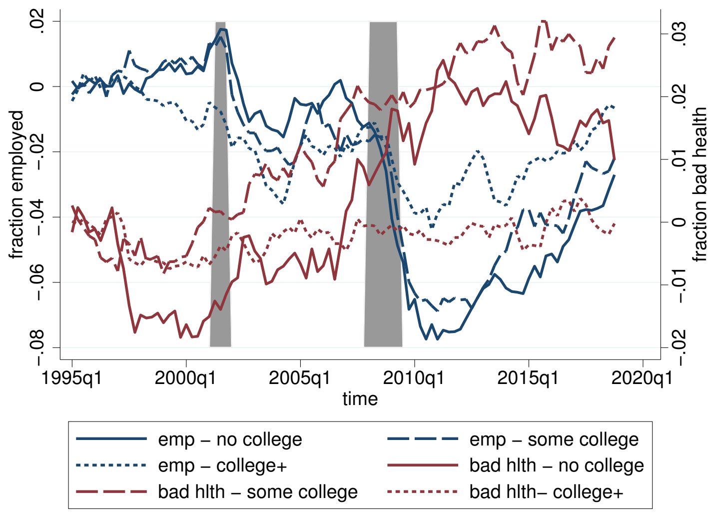
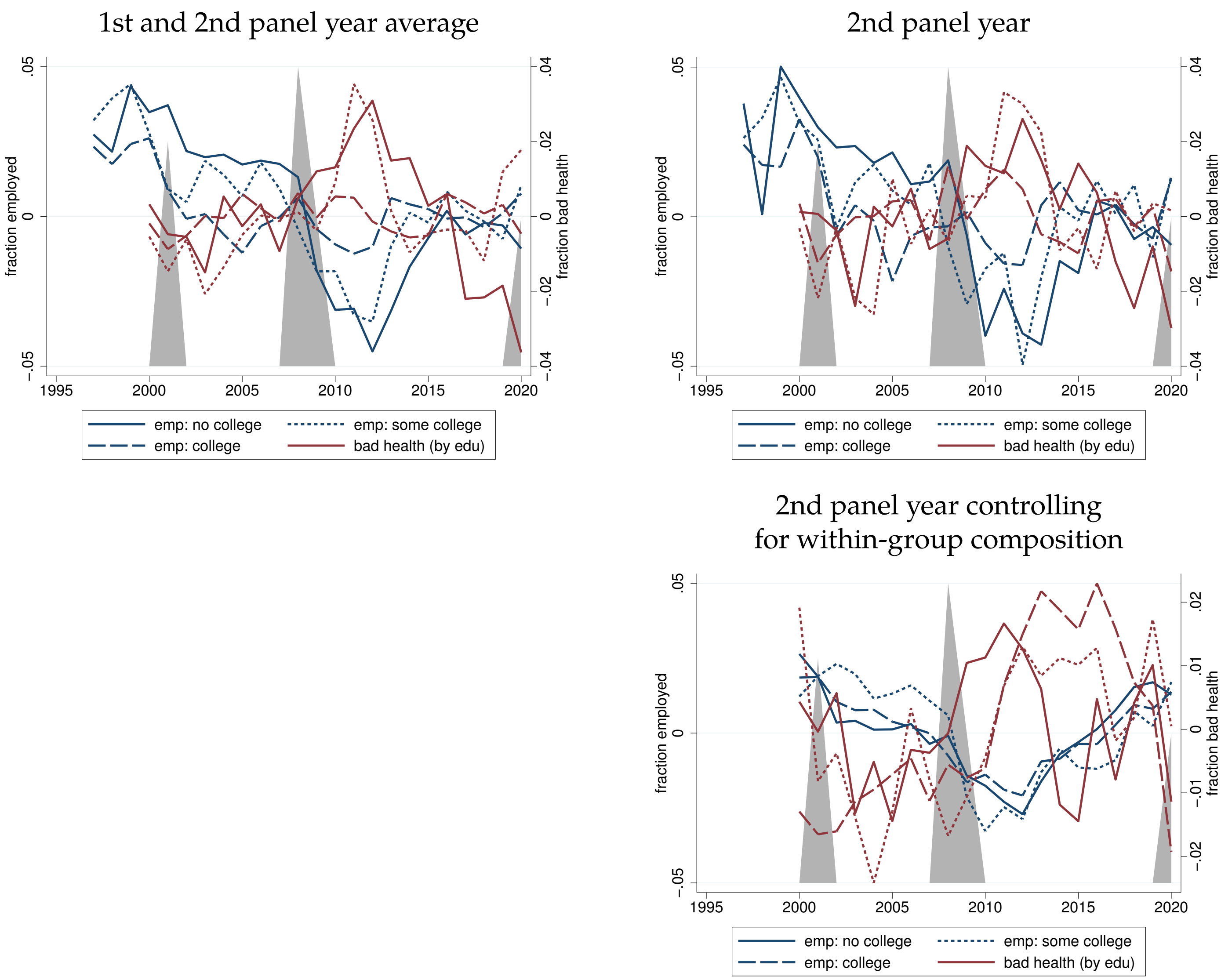


Figure B.1: Different amplitude of bad health and employment fluctuations by educational attainment: NHIS



Note: The differences in the amplitude of fluctuations across educational groups disappears once individual effects are eliminated by summing within-individual changes from the 1st to the 2nd panel year [and projecting out demographics (sex by age by education)].

Figure B.2: Heterogeneity of bad health and employment dynamics by educational attainment: MEPS.

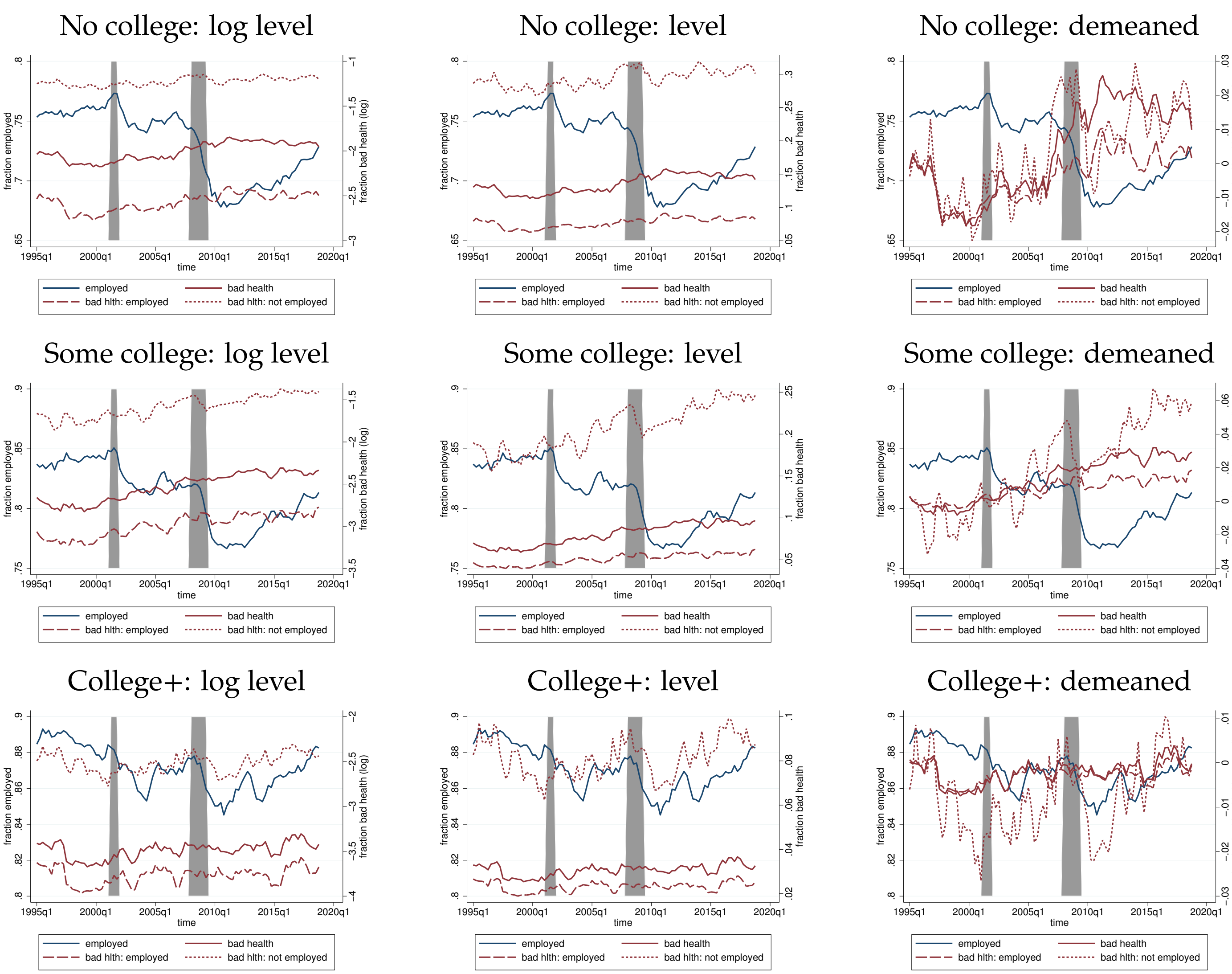


Figure B.3: Heterogeneity of bad health dynamics by educational attainment: Within-group breakdown

B.1 Cyclicality of health inputs

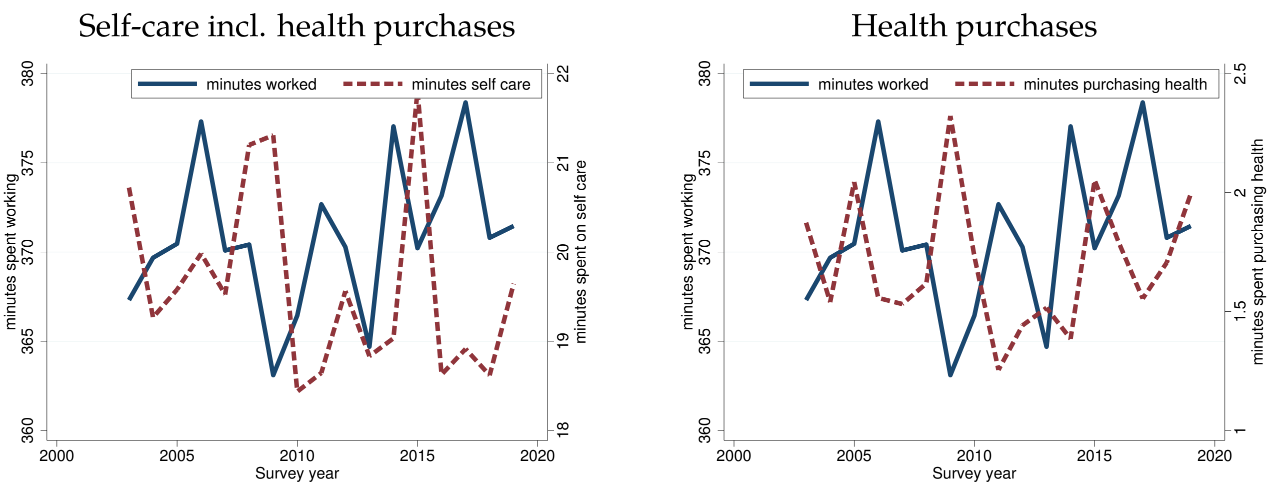


Figure B.4: Cyclicality of time spent on health-care vs time spent working: prime-aged individuals, ATUS

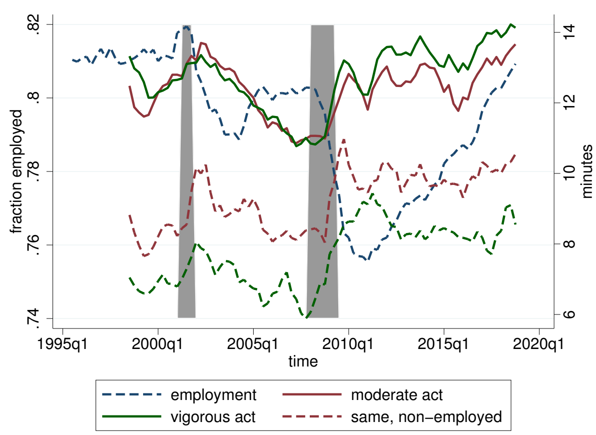


Figure B.5: Cyclicality of time spent exercising: prime-aged individuals, NHIS

C Simple model: additional derivations

Labor

$$
\begin{aligned}
N = 1 - L - \theta x &= 1 - \frac{\kappa}{\kappa+1}\left(1 + \frac{e}{\tilde{w}(a,h)} - x\left(\theta + \frac{q}{\tilde{w}(a,h)}\right)\right) - x\theta \\
&= 1 - \frac{\kappa}{\kappa+1}\left(1 + \frac{e}{\tilde{w}(a,h)}\right) - x\left(\frac{\theta}{1+\kappa} - \frac{\kappa}{1+\kappa}\frac{q}{\tilde{w}(a,h)}\right),
\end{aligned}
$$

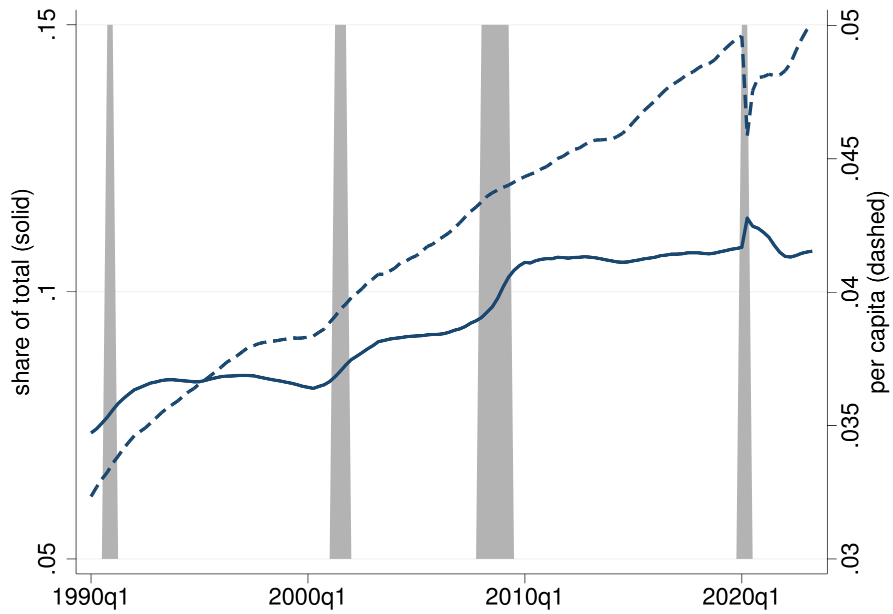


Figure B.6: Cyclicality of the health-care employment share

$$= -\frac{\kappa}{\kappa+1}\frac{e-xq}{\tilde{w}(a,h)} + \frac{1-\theta x}{1+\kappa} \tag{C.1}$$

It follows that:

$$\begin{aligned}
\frac{dN}{da}\Big|_{da'=0} &= \frac{\kappa}{\kappa+1}\frac{e-xq}{\tilde{w}(a,h)}\frac{\tilde{w}_a}{\tilde{w}(a,h)} + \left(\frac{\theta}{1+\kappa} - \frac{\kappa}{1+\kappa}\frac{q}{\tilde{w}(a,h)}\right)\left(-\frac{dx}{da}\Big|_{da'=0}\right), \\
&= \frac{\kappa}{\kappa+1}\frac{e-xq}{\tilde{w}(a,h)}\frac{\tilde{w}_a}{\tilde{w}(a,h)} + \left(\frac{\theta}{1+\kappa} - \frac{\kappa}{1+\kappa}\frac{q}{\tilde{w}(a,h)}\right)\frac{\theta e - q}{\tilde{q}^2}\tilde{w}_a, \\
&= \frac{\kappa}{\kappa+1}\frac{\tilde{w}_a}{\tilde{w}(a,h)}\left(\frac{e-xq}{\tilde{w}(a,h)} - q\frac{\theta e - q}{\tilde{q}^2}\right) + \frac{\theta}{1+\kappa}\frac{\theta e - q}{\tilde{q}^2}\tilde{w}_a, \\
&= \frac{\kappa}{\kappa+1}\frac{\tilde{w}_a}{\tilde{w}(a,h)^2\tilde{q}^2}\big((e-xq)\tilde{q}^2 - q\tilde{w}(a,h)(\theta e - q)\big) + \frac{\theta}{1+\kappa}\frac{\theta e - q}{\tilde{q}^2}\tilde{w}_a, \\
&= \frac{\kappa}{\kappa+1}\frac{\tilde{w}_a}{\tilde{w}(a,h)^2\tilde{q}^2}\big((e-xq)(q^2 + 2q\theta\tilde{w}(a,h) + \theta^2\tilde{w}(a,h)^2) - eq\theta\tilde{w}(a,h) + q^2\tilde{w}(a,h)\big) + \frac{\theta}{1+\kappa}\frac{\theta e - q}{\tilde{q}^2}\tilde{w}_a, \\
&= \frac{\kappa}{\kappa+1}\frac{\tilde{w}_a}{\tilde{w}(a,h)^2\tilde{q}^2}\big((e-xq)(q^2 + q\theta\tilde{w}(a,h) + \theta^2\tilde{w}(a,h)^2) + (e-xq)q\theta\tilde{w}(a,h) \\
&\qquad -(e-xq)q\theta\tilde{w}(a,h) - xq \times q\theta\tilde{w}(a,h) + q^2\tilde{w}(a,h)\big) + \frac{\theta}{1+\kappa}\frac{\theta e - q}{\tilde{q}^2}\tilde{w}_a, \\
&= \frac{\kappa}{\kappa+1}\frac{\tilde{w}_a}{\tilde{w}(a,h)^2\tilde{q}^2}\left(\underbrace{(e-xq)}_{>e-\theta^{-1}q}(q^2 + q\theta\tilde{w}(a,h) + \theta^2\tilde{w}(a,h)^2) + \underbrace{(1-x\theta)}_{>0}q^2\theta\tilde{w}(\circ)\right) + \frac{\theta}{1+\kappa}\frac{\theta e - q}{\tilde{q}^2}\tilde{w}_a,
\end{aligned} \tag{C.2}$$

D The full model: details

Method We solve the model using the following algorithm based on the Krusell and Smith (1998).

Step 0. Initialize perceived aggregate transition functions $\hat{K}', \hat{L}', \hat{H}'$.

Step 1. Solve HH problem: find

$$x_s(k,h,A,L,K,H), \ell(k,h,A,L,K,H), k'(k,h,A,L,K,H)$$

given prices

$$W(A,L,K,H), r(A,L,K,H)$$

and perceived processes

$$K' = \hat{K}(A,L,K), H' = \hat{H}(A,L,K,H),$$
$$L' = \hat{L}(A,K,H,L)$$

Step 2. Simulate dynamics of economy with 10000 households.

1. Simulate initial h, k for period 0.
2. Guess the aggregate L^0.
3. Find $\ell(k,h,A,L^0,K,H)$ for each household and aggregate them to $\tilde{L}^0$.
4. Adjust the initial guess L^1 and repeat until convergence $||L^{ii} - \tilde{L}^{ii}|| < \epsilon$ for some ii, ϵ is the tolerance level
5. Using policy functions and transition equations, calculate k' and simulate h'.
6. Repeat for T periods and store $\{K, L_t, H_t, A_t\}_{t=0}^{T}$
7. Estimate aggregate transition functions for K', L'_t, H'.

Step 3. Repeat Step 1 and Step 2 until convergence of aggregate transition functions.

To find the ergodic distribution we set $L' = L$, $K' = K$,$H' = H$ and search for such L, K, H that are consistent with households' choices.