Investing in Health during Good and Bad Times: An Application to the China Shock*

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Abstract

Many economic shocks affect not only workers' wages and employment but also health. We study their mechanism, welfare effects, and policy implications in a dynamic quantitative model with endogenous health investment. The health production technology is flexible, allowing workers to optimally choose to forego treatment, partially treat sickness, or incur additional non-medical health investment after fully treating the sickness. Applying this model to the China shock, we estimate its causal effects on health and calibrate the model to the pre-China shock economy. Our simulations suggest that, first, the health investment mechanism is economically significant, with the model elasticity accounting for between 40-50% of the empirical estimates. Second, the workers' steady-state welfare loss is equivalent to an annual drop of 8.4% in consumption, and both endogenous health investment and health itself play important roles. Finally, while universal health insurance is effective in reducing partial or foregone treatment, it offers little protection for non-medical investment. Therefore, its overall efficacy would be nuanced.

JEL Codes: E20, I30, I10, F10
Keywords: dynamic quantitative model; heterogeneous agents; health; investment; the China shock

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1 Introduction

Economic shocks, such as mass layoffs, business cycles, and international trade, affect not only wages and employment but also health.[1] What is the *mechanism* through which these economic shocks affect health? What are the *welfare* effects of these shocks, incorporating their health effects? What *policies* may help mitigate these adverse health effects?

There are several challenges in studying these questions. The change of health is inherently a dynamic process, and it is affected by both exogenous sickness shocks and endogenous health investment. The angle of health investment is especially relevant for the U.S., because many in the U.S. may limit their healthcare utilization when they are sick due to the lack of health insurance coverage. According to the National Health Interview Survey (NHIS), 18.6% of working-age adults report not receiving medical care in 2011-2012 due to financial constraints.[2] On the other hand, there are many ways to invest in one's health beyond receiving medical care, such as consuming healthy foods and investing in exercise equipment.

In this paper, we analyze the effects of economic shocks on health, incorporating the health investment channel that explicitly accounts for both the limited sickness treatment and the non-medical, monetary investment in health. We develop a model of endogenous health dynamics and apply the model to analyze the effects of the China shock, a large increase in import penetration from China between 1990 and 2007 in the U.S. manufacturing sector. Our quantitative analysis starts by estimating the causal effects of the China shock on workers' health. We then calibrate the model to understand the economic importance of the health investment mechanism, measure the welfare losses from the China shock, and evaluate the effectiveness of providing universal health insurance.

We first develop a quantitative dynamic model, where health evolution is endogenous, similar in its foundational properties to the concept of health capital in Grossman (1972), but with distinct features. In the model, workers are endowed with a health status (good or bad) that impacts workers' utility and labor market opportunities, as well as the distribution of the sickness shock they face every period. The health production function specifies the probability of being in good health in the future, determined stochastically by current health

[1]Empirical studies include Sullivan and von Wachter (2009) for mass layoffs, Ruhm (2000) for business cycles, and Adda and Fawaz (2020) and Pierce and Schott (2020) for international trade shocks. Case and Deaton (2020) also discusses how socio-economic factors may impact health and fatalities.

[2]This was more prevalent before the major provisions of the Affordable Care Act (ACA) were implemented in 2014, which subsequently expanded insurance coverage in the U.S. population.

status, sickness shock, and the investment chosen by workers upon receiving a sickness shock. The health status governs the persistence of health. The sickness shocks are idiosyncratic, conditional on health, and they impact health production (transition to good health in the future), whose effects can be mitigated by investment. One innovation of our model is that in the flexible health production function, a sickness-dependent minimum amount is required for the health investment to yield positive returns. As a result, workers may *optimally* choose to forego treatment, partially treat their sickness, fully treat their sickness, or invest beyond the full treatment, through other non-medical, monetary investments. These properties allow our model to match a key feature of the Medical Expenditure Panel Survey (MEPS) data: the shares of individuals without medical utilization range from 7 to 10% for insured workers, but reach 28 to 34% for the uninsured, indicative of partial or foregone treatment of sicknesses.[3]

We apply this model to the China shock. Previous empirical studies have shown its adverse effects on workers' labor market outcomes (e.g., Autor et al., 2013; Autor et al., 2014) and on health (e.g.,Adda and Fawaz, 2020; Pierce and Schott, 2020).[4] Building on this body of work, we follow the identification strategy of Autor et al. (2013) to estimate the causal effects of the China shock, i.e., we instrument U.S. imports from China using the Chinese exports to other high-income countries. Distinct from this body of work, we study the probability of workers' self-reported good health using the confidential-access data from Panel Study of Income Dynamics (PSID). The commuting-zone information (from the restricted data), combined with the panel structure of the PSID allows us to control for worker fixed effects and estimate the heterogeneity of the effects of the China shock across workers. Our findings imply a statistically significant elasticity of good health probability with respect to the Import Penetration per Worker (IPW) of around -0.05. In addition, the magnitude of this elasticity is larger among the workers with good initial health.

Next, we calibrate the model to the pre-China shock economy. We embed our worker-level model of health dynamics into a sector-level model of international trade. We use the MEPS data to obtain exogenous parameters and targeted moments related to health transitions, medical expenditures, and share of workers without medical utilization by worker demo-

[3]Pashchenko and Porapakkarm (2019) also recognize that zero medical utilization is an important feature of MEPS, which is modeled as exogenous medical need shocks.

[4]In related work, McManus and Schaur (2016) show detrimental effects of import competition on health and mortality.

graphics. As discussed earlier, our model endogenously generates differential shares of zero medical utilization by insurance by health status, thanks to the health production function with minimum investment requirements, and consequently reproduces heterogeneous health outcomes across worker types. The calibrated model fits well with the targeted moments. For example, the model predicts that 27% of uninsured workers with bad health choose to forego health investment, versus 28% in the MEPS data. It also generates reasonable predictions about the value of health and workers' health investment decisions relative to the corresponding non-targeted data moments.

A unique feature of our calibrated model is that the endogenous choice of health investment in response to sickness shocks provides an additional channel for consumption smoothing. On the one hand, the workers with abundant resources find it optimal to invest beyond the treatment of sickness as a means to self-insure against the future risks of transitioning to the bad health state. On the other hand, those with limited resources often choose to sacrifice their sickness treatment for consumption, sometimes by foregoing sickness treatment. Given the model's ability to capture the heterogeneity and non-linearity in workers' health investment decisions, it serves as a suitable laboratory for studying the mechanism, welfare consequences, and policy implications for the workers facing adverse economic shocks, which, in our application, is the China shock.

We simulate the China shock following the trade literature that models it as an exogenous decrease in the domestic share of the U.S. manufacturing sector. In the simulation, we solve for the change in manufacturing wage that balances the sector-level labor demand and obtain a 5.8% drop in wage, in line with the estimates in Autor et al. (2014) of 2.3%-7.2%.[5]

We now present our quantitative findings for the *mechanism* through which the China shock affects health. Our model suggests that health deteriorates after the China shock because the loss of economic resources decreases investment in health and induces more workers to only partially treat their sicknesses. Quantitatively, the model-generated IPW elasticity of future good-health probability ranges from -0.02 to -0.03, accounting for a sizable portion of our empirical estimate of -0.05. Here, an important contributor is that the share of workers who optimally choose to forego health investment increases by 1.3 percentage points (pp), or more than one-fifth, suggesting that adjustment in health investment is an

[5] We also conduct a second simulation, where we assume instead, that the wage drop is 2.3%, the low end of the range reported in Autor et al. (2014), and solve for the change in the job destruction rate that balances labor demand. The qualitative effects from the second simulation are similar to those of the first.

economically significant channel. Putting the model-predicted elasticity into perspective, we show that the China shock led nearly half a million individuals in the U.S. manufacturing sector into bad health, resulting in approximately 100,000 more Emergency Room visits and 200,000 more inpatient hospital days per year. This health implication of the China shock (or any adverse economic shock) is a novel feature of our structural model, which cannot be captured in models that abstract away from health or those with exogenous health transitions.

In terms of *welfare*, our simulations suggest that the average worker's welfare loss from the China shock is equivalent to an annual drop in consumption of $1,721 (8.6%) when we compare the pre- and post-China shock steady states. To measure the contribution of endogenous health investment in shaping welfare, we first shut down endogenous health investment in our model. The resulting economy with exogenous health evolution over-estimates the welfare losses from the China shock, with its magnitude varying across worker types. The welfare loss is 10% higher for the average worker, but 30% higher for the unemployed worker with bad health. We then completely remove health from our model to measure the significance of health in welfare effects. In this economy, the welfare cost is lower by almost one-quarter for the average worker. These counterfactual experiments showcase the significance of both endogenous health investment and health itself in quantifying the welfare costs of an economic shock. A model that abstracts away from the former would over-estimate the welfare cost, while a model that abstracts away from the latter would under-estimate it.

Finally, we explore the potential *policy* responses by simulating a post-China economy in which all individuals are covered by health insurance. Universal health insurance substantially reduces the share of individuals who choose to forego or partially treat sicknesses, relative to the benchmark post-China economy.[6] On the other hand, universal health insurance has little effect on non-medical health investment as it is not covered by health insurance. Therefore, the overall effectiveness of universal health insurance is nuanced and hinges upon the extent to which access to health insurance can compensate for wage losses and the types of sickness shocks workers face.

[6]This result is consistent with the empirical finding that the incidence of insufficient treatment of illnesses due to resources is far more common in the U.S. than in high-income countries that provide universal health insurance (e.g. Davis and Ballreich, 2014).

Related Literature Our work fits into the literature that uses quantitative dynamic models incorporating the role of health. One line of work analyzes the role of health risks, healthcare policies, and their effects on worker behaviors and welfare, assuming that health evolves exogenously (e.g. French, 2005; French and Jones, 2011; Low and Pistaferri, 2015; Aizawa and Fang, 2020; Kim and Rhee, 2022; Jung and Tran, 2023; Chen et al., 2024; De Nardi et al., 2025; Hosseini et al., 2025). Relative to these studies, we explicitly model the workers' endogenous choice of health investment.

Our analysis thus contributes to the growing interest in studying endogenous health dynamics. Some of these works examine mortality (e.g. Hall and Jones, 2007; Fonseca et al., 2021), whereas we study non-fatal sickness and transitions between good- and bad-health statuses. There are studies focusing on health (capital) transitions (evolutions), like our study, but that model different types of health investments. Among them, Cole et al. (2019) and Mahler and Yum (2024) incorporate the role of non-pecuniary investments (e.g., exercise or lifestyle), Pashchenko and Porapakkarm (2019) uses discretionary medical investments, and Ozkan (2025) considers preventive and curative investments.[7] Compared to these studies, our health evolution is unique in several aspects. First, we focus on sickness shock-dependent monetary health investment, and distinguish between expenditures used to treat a sickness and those that are akin to general monetary investments in health, effectively allowing for two types of investment with differential returns. Second, our flexible health transition function allows workers to optimally forego or partially treat sicknesses, as well as to invest beyond the full treatment of their sicknesses. As a result, the model endogenously generates positive shares of the population without medical utilizations, consistent with empirical data. By empirically applying our model to the China shock, we show that health investments in response to sicknesses play important roles in both the mechanism and policy implications of the adverse health effects of economic shocks.

Broadly, our work also speaks to the empirical literature that studies the effects of the China shock, which we have cited and discussed above.[8] Relative to this literature, we quantify the economic significance of the mechanism in which the China shock affects health through health investment, and explore the effects of policies in mitigating such adverse

[7] Relatedly, Jang (2023) studies health insurance in a model with emergency and non-emergency medical spending and strategic defaults.

[8] There are also studies that use structural models to evaluate labor market effects of the China shock, e.g., Lyon and Waugh (2018); Caliendo et al. (2019); Carroll and Hur (2020); Ferriere et al. (2023).

health effects.

The rest of the paper is organized as follows. Section 2 presents our model of heterogeneous agents with endogenous health evolution. In Section 3, we estimate the causal effects of the China shock on health and embed our worker-level model into a sector-level model of international trade. The calibration strategy is detailed in Section 4 and its results are presented in Section 5. Our quantitative analyses, evaluating the mechanism, welfare and policy implications of the China shock, are presented in Section 6. Section 7 concludes.

2 A Model with Endogenous Health Dynamics

In this section, we develop a heterogeneous agent model with endogenous health dynamics with the following key features. First, health investment is chosen after the realization of sickness shocks. Second, the amount of health investment is not restricted to equal the magnitude of the sickness shock. That is, workers may decide to forego or partially treat their sicknesses or invest more resources beyond fully treating the sickness. Our model also specifies rich heterogeneity in worker characteristics and incorporates multiple ways in which health impacts workers' labor market outcomes, in line with empirical observations that we further detail in Section 4.

2.1 Endowments and Preferences

There are infinitely-lived workers of measure one. These workers are endowed with health status x, where $x = G$ denotes Good health and $x = B$, Bad health.[9] The workers' utility function follows that in the literature (e.g., Low and Pistaferri, 2015):

$$U\left(c;x\right)=\frac{\left[c\cdot\exp(\iota\left(x\right))\right]^{1-\rho}}{1-\rho},$$

[9] Recent works study the role of individual types in studying health and earnings dynamics. Among them, Borella et al. (2024) identifies health types among middle and old age individuals and discusses that health types are important determinants of its dynamics. De Nardi et al. (2025) incorporates fixed health types and a long history dependence to discuss welfare implications of bad health. In this paper, while we abstract from ex-ante heterogeneity, we incorporate rich heterogeneity in terms of both health statuses and sickness shocks in specifying health dynamics and studying individual behaviors with endogenous investments. Additionally, in the empirical analysis, we identify the causal effects of the China shock on worker health, after controlling for individual fixed effects.

where c denotes consumption and ρ, the relative risk-aversion parameter. The parameter $\iota(x)$ captures how health affects both the utility level and marginal utility of consumption. If $\iota(B) < \iota(G)$, being in the unhealthy state incurs utility cost, providing incentives for health investment.

The health status impacts workers in three ways. First, each period, a worker receives a sickness shock $\varepsilon(x)$ with probability $f(\varepsilon; x)$. Good health implies mild sickness shocks, i.e., $\varepsilon(G) < \varepsilon(B)$. Second, the worker may be either unemployed $l = U$ or employed $l = E$, and his transition probability to employment $1-\delta(l, x)$ is health-dependent. Good health workers have higher job continuation rate and lower job separation rate. Finally, an employed worker earns income of $w \cdot \nu(x) \cdot z$, where w is the market wage and $\nu(x)$ captures the productivity effect of health with $\nu(G) > \nu(B)$. The last term z is his idiosyncratic productivity shock, which follows an AR(1) process in logs with persistence ρ_z and standard deviation σ_z.

Lastly, workers have access to risk-free savings with an exogenous rate of return, r.

2.2 Health Production

We now specify how health evolves over time. We broadly follow the seminal study of Grossman (1972), which views health as capital that can be increased with investment. In our model, the health production function determines the probability of being in good health in the next period. The transitions are stochastically determined by the current health status, sickness shock, and health investment. While the formulation of the health process is similar to those in Cole et al. (2019) and Fonseca et al. (2021), our health production is unique in its dependence on the sickness shock ε, and in its ability to endogenously generate optimal investment choices of zero.

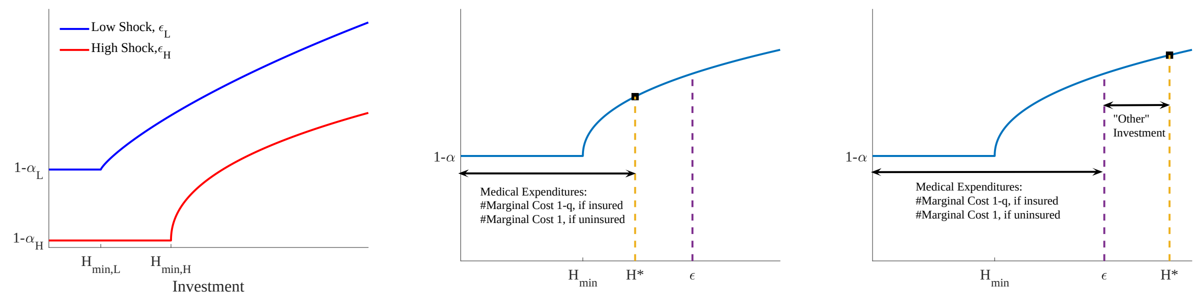
Specifically, the probability of being in good health in the next period is a function of the current health status, x, sickness shock, ε, and health investment, H, which we parameterize using the following flexible Weibull function:

$$F(H; x, \varepsilon) = \begin{cases} 1 - \alpha(x, \varepsilon) & \text{if } H \leq H_{min}(x, \varepsilon) \\ 1 - \alpha(x, \varepsilon) \exp\left[-\frac{(H - H_{min}(x,\varepsilon))^{\gamma(x)}}{\lambda(x)}\right] & \text{if } H > H_{min}(x, \varepsilon). \end{cases} \quad (1)$$

Consistent with empirical regularities we document in Section 4, all parameters of $F(\cdot)$ depend on initial health status x, capturing the heterogeneity and the persistence in future health outcomes by x.

Figure 1: Health Production and Investment

(a) Health Production Function | (b) Partial Treatment of Sickness | (c) Full Treatment & Non-Medical Investment



Note: Figures plot health production function where x-axis represents health investment H and y-axis, the probability of being in good health in the future.

Figure 1(a) illustrates the properties of the health production function. The x-axis is health investment, H, and the y-axis is the probability of transitioning to good health, $F(\cdot)$. We plot $F(H; x, \varepsilon)$ for the low (mild) and high (severe) sickness shocks of ε_L and ε_H, respectively, given initial health status x.

First, the vertical intercepts of the curves are the baseline probability of good health, $1 - \alpha(x, \varepsilon) > 0$. It says that even if $H = 0$, the probability of future good health is positive. The high sickness shock curve has a lower intercept, implying that the baseline probability of good health decreases with sickness severity.

Second, the flat portions of the curves illustrate the minimum investment, $H_{min}(x, \varepsilon)$. The return to health investment, H, is positive if and only if H exceeds $H_{min}(x, \varepsilon)$, which may be larger for a more severe sickness shock. With minimum investment, our model endogenously generates a positive share of individuals with zero medical utilization, even among those facing sickness shocks, if they find it optimal to forego treatment. Given that about a fifth of individuals in the NHIS survey report not receiving medical care due to financial constraints, this is an essential attribute for understanding the endogenous health dynamics.

Finally, any investment beyond $H_{min}(\cdot)$ yields positive returns that are diminishing. That is, for $H > H_{min}(x, \varepsilon)$, $F(\cdot)$ is increasing in H, $\partial F(\cdot)/\partial H > 0$, which approaches $+\infty$ as H approaches $H_{min}(x, \varepsilon)$ from above. Further, $F(\cdot)$ is concave with respect to H, as long as $\gamma(x) < 1$.[10]

Figures 1(b) and 1(c) illustrate the distinction between medical and non-medical health investments. In the model, we interpret health investments smaller than the sickness shock as medical expenditures used to treat that sickness, an assumption that helps us map the model to the data. In Figure 1(b), therefore, medical health investment is H^*. On the other hand, Figure 1(c) shows a case in which investment exceeds sickness shock, or $H^* > \varepsilon$. In this case, any investment beyond the sickness shock is considered non-medical health investments (e.g., gym membership or healthy food), that is, non-medical health investments are effective after the sickness has been fully treated.[11] Therefore, while both medical and non-medical investments enter H additively, they have different marginal returns because of the concavity of the health production function.[12]

In summary, the worker in our model is free to choose whatever amount of H he wants after the sickness shock, ε is realized. This optimum may be (i) $H^* = 0$ (no treatment); (ii) $H_{min}(x, \varepsilon) < H^* < \varepsilon$ (partial treatment); (iii) $H^* = \varepsilon$ (full treatment); or (iv) $H^* > \varepsilon$ (fully treat sickness and incur additional non-medical investments), but never $0 < H^* < H_{min}(x, \varepsilon)$.

2.3 Health Insurance

In our model, the worker has the exogenous probability of $\zeta(l)$ to have health insurance in each period, where l denotes employment status. The employed have a higher probability of getting health insurance (i.e. $\zeta(l = E) > \zeta(l = U) > 0$), reflecting the prevalence of Employer-Sponsored Health Insurance (ESHI) in the US, but still allowing the possibility of unemployed individuals to have (some form of) health insurance. With the premium of π, health insurance covers a $\chi(\varepsilon; x) < 1$ share of medical expenditures. However, health

[10] We do not impose restrictions on health outcomes across sickness shocks after health investment (that, for example, full-treatment outcomes are equivalent to no-sickness-shock outcomes). This approach allows us to better match the empirical data patterns, as we discuss in Section 4.

[11] We assume that non-medical investments do not enter into consumption, and so do not directly contribute to utility. This assumption represents a conservative modeling choice, because without it, workers would have even stronger incentives for non-medical health investment.

[12] Among related papers, Ozkan (2025) distinguishes preventive medicine from curative medicine, in a model with two distinct types of health capital (physical and preventive). Like Ozkan (2025), we have two types of health investments. While we do not separately parameterize the returns to these health investments, the richness of our health production function with respect to health statuses and sickness shocks captures differential effects of these investments.

insurance does not cover non-medical health investment.[13] Thus, for insured individuals, the marginal cost of health investment is $1-\chi(\varepsilon;x)$ for medical expenditures, $\min\{H,\varepsilon\}$, but 1 for the non-medical health investment beyond ε, $\max\{0,H-\varepsilon\}$.

Note that the health production technology is independent of insurance statuses. That is, health insurance affects health dynamics endogenously through the choice of health investment H in our model, distinct from the approach in papers where health transitions exogenously differ by insurance statuses (e.g., Aizawa and Fang, 2020; Chen et al., 2024).

2.4 Government

The government collects taxes on labor income $T(y)$, and uses the tax revenue to finance the unemployment benefit of b and the consumption floor of $\underline{c}$. The consumption floor, $\underline{c}$, captures various means-tested government programs, in a similar manner as in previous studies with medical expenditure risks, such as De Nardi et al. (2025). We denote the transfers made for $\underline{c}$ as tr, and assume that the individuals for whom $tr>0$ are unable to save or invest in health. The government also ensures that the health insurance sector makes zero profits through lump-sum subsidies. Note health insurance companies collect premium π and pay the insured at coinsurance rate of $\chi(\varepsilon;x)$ up to ε. We assume that premium is exogenous and that the government makes transfers to insurance companies to ensure zero profit.[14]

2.5 The Workers' Optimization Problem

We now state the optimization problem of a worker with the state $\tilde{\mathbf{s}}\equiv\{x,a,in,\varepsilon,z\}$, where x is health status, a is financial asset, in is insurance status, ε is sickness shock, and z is labor productivity shock. The worker of employment status $l\in\{E,U\}$ solves

[13] We assume, implicitly, that health insurance companies can distinguish between treatment expenditures and other non-medical investments, such as massages. As insurance companies in the U.S. review medical claims, we view this assumption as plausible in our context. In a related work, Pashchenko and Porapakkarm (2019) study an optimal contracting and implementation problem in a model where the social planner does not observe the medical need of individuals.

[14] The U.S. tax policy excludes employer-paid health insurance premiums from income and payroll taxes and allows pre-tax deductions for employee-paid premiums. Effectively, there is a tax subsidy to ESHI from the government that we may be capturing here.

$$
\begin{aligned}
V^{l}(\tilde{\mathbf{s}}) \quad = \quad & \max_{c,a',H\geq 0} U(c+tr;x) && (2)\\
& +\beta \sum_{x'\in\{B,G\}} \Pr(x')\left[\delta(l,x')\,\mathbb{E}V^{U}(\tilde{\mathbf{s}}')+(1-\delta(l,x'))\,\mathbb{E}V^{E}(\tilde{\mathbf{s}}')\right]\\
\text{s.t.} \quad & c+a'+\tilde{H}=I(l,x)+(1+r)\,a && (3)\\
& I(E,x)=w\cdot\nu(x)\cdot z-T(w\cdot\nu(x)\cdot z)\,;\quad I(U,x)=b && (4)\\
& tr=\max\{0,\underline{c}-(I(l,x)+(1+r)\,a)\} && (5)\\
& \Pr(x'=G)=F(H;x,\varepsilon)\,;\quad \Pr(x'=B)=1-F(H;x,\varepsilon) && (6)\\
& \tilde{H}=\begin{cases} H & \text{if uninsured}\\ \pi+(1-\chi(\varepsilon;x))\min\{\varepsilon,H\}+\max\{H-\varepsilon,0\} & \text{if insured.}\end{cases} && (7)
\end{aligned}
$$

A worker maximizes his utility in the current period, $U(\cdot)$, plus his discounted utility in the next period. If he is unemployed, the expectation is over insurance and sickness shock status; and if employed, he additionally takes expectation over labor productivity shock. In the current-period utility, tr guarantees consumption floor and is given in (5).

In the budget constraint (3), the worker's expenses are consumption c, tomorrow's asset a', and out-of-pocket health investment expenditures $\tilde{H}$. The worker's resources on the right-hand side of the budget constraint (3) are his net income, $I(l,x)$ and asset, $(1+r)\,a$. Equation (4) says that if the worker is employed, his net income equals wage $w\cdot\nu(x)\cdot z$ minus tax $T(\cdot)$; otherwise, the net income equals the unemployment benefit b. As discussed in Equation (1), health transition probabilities in (6) depend on health status x, sickness shock ε, and health investment H. Finally, Equation (7) summarizes our earlier discussions about medical expenditures and non-medical health investment. If the worker is uninsured, his total out-of-pocket health expenditure, $\tilde{H}$, equals his total health investment of H. For the insured, his out-of-pocket health expenditure consists of three components: the insurance premium π, the copayment of medical expenditures $(1-\chi(\varepsilon;x))\min\{\varepsilon,H\}$, and the non-medical health investment $\max\{H-\varepsilon,0\}$.

In summary, workers are heterogeneous in health status, and receive sickness and labor market shocks in each period. In this dynamic setting, workers optimally choose consumption, savings, and health investment, recognizing the benefits of good health.[15]

[15] While we abstract from modeling workers' life cycles, this abstraction allows us to calibrate a more richly parametrized health production function, the primary focus of our analysis. Specifically, for quantification, we use two health statuses and five sickness shocks per health status, generating heterogeneity in health investment and outcomes across worker characteristics. For calibration, we construct our moments after

3 Application: The China Shock

We now apply our model to the China shock, a large increase in U.S. import from China in the manufacturing sector. We first clarify why we choose the China shock as our application and then embed our worker's problem into a sector-level model of international trade to map the trade shock into our full model for counterfactual analysis.

3.1 Why the China Shock?: Empirical Motivation

Many empirical studies, including Autor et al. (2013) and Autor et al. (2014), have shown that the China shock caused adverse labor market outcomes to manufacturing workers in the U.S. Therefore, the China shock provides a good application to using our model as a laboratory for studying how changes in economic resources can impact workers' health and evaluating the role of health investment. Further, we can use the well-established empirical approach from these previous studies to estimate the causal effects of the China shock on workers' self-reported good-health status, and use our estimates for both quantitative and qualitative validations for the predictions of our model.

3.1.1 Data

In this subsection, we outline our data and the construction of main variables, and illustrate the salient features of our data.

Import Penetration per Worker We measure the size of the China shock as import penetration per worker (IPW) following Autor et al. (2013):

$$\mathrm{IPW}_{cz,t} = \sum_j \frac{L_{cz,j,t}}{L_{cz,t}} \times \frac{M_{j,t}^{\mathrm{CHN}}}{L_{j,t}}. \tag{8}$$

In Equation (8), $M_{j,t}^{\mathrm{CHN}}$ and $L_{j,t}$ are, respectively, the US imports from China and employment in industry j in year t, $L_{cz,j,t}$ is the employment in commuting zone cz in industry j and year t, and $L_{cz,t}$ is the employment in commuting zone cz in year t. Intuitively, $\mathrm{IPW}_{cz,t}$

controlling for various demographics, including age, to account for confounding effects. With this abstraction, we are also able to embed the worker-level model into a sector-level model of international trade, where we endogenously solve for the wage effect of the China shock through a labor market equilibrium condition (see Sections 3.2, 4.4, and 6.1).

measures the weighted average of Chinese imports per worker, across industries, in commuting zone cz in year t, where the weights are the industries' employment shares in cz in t. In order to control for potential endogeneity in US imports, we follow Autor et al. (2013) and use the following instrument for $\text{IPW}_{cz,t}$:

$$\text{IPW}^{IV}_{cz,t} = \sum_j \frac{L_{cz,j,t-10}}{L_{cz,t-10}} \times \frac{M^{\text{OTH}}_{j,t}}{L_{j,t-10}}. \tag{9}$$

As compared with the IPW measure of (8), its instrument, (9), uses Chinese exports to eight other high-income countries and 10-year-lagged labor employments.[16] We use the China shock and its instrument data from the replication package of Autor et al. (2013).

Panel Study of Income Dynamics The rest of our data come from the PSID. We restrict our sample to those between the ages of 18 and 64 (working-age population) who work full-time (1,600 annual hours) in their initial year of entry into the PSID sample.

We use self-reported health as our measure of health status, which is common in both the structural estimation literature (e.g. Cole et al. 2019; De Nardi et al. 2025) and applied micro studies of health (e.g. Currie and Madrian, 1999). Recent studies show that self-reported health is also a good predictor of future health events, such as hospitalization (e.g. Nielsen, 2016). It also fits well with our inquiry, because the PSID data for self-reported health span the years of the China shock, 1991 through 2011.[17] In PSID, each respondent is asked to rate his health into five levels (from excellent to poor). We combine the top two levels into the single category of *good* health, and combine the other three levels into *bad* health. PSID also includes detailed demographic information such as age, gender, income, and industry affiliation. In addition, we obtain the restricted commuting-zone identifiers, to combine the worker-characteristics data with the IPW data discussed above.

Merged IPW-PSID Data The merged data set includes 508 unique commuting zones and about 33,000 worker-year observations.[18] We list the detailed summary statistics in Appendix A.1, and outline their main features. The average IPW is \$1,440 per worker and

[16] $M^{\text{OTH}}_{j,t}$ is exports from China to Australia, Denmark, Switzerland, Finland, Japan, Germany, New Zealand, and Spain.

[17] An alternative measure of health status may be the frailty index (e.g., Hosseini et al. (2022)) that uses objective health measures (e.g., indicator variables of diabetes, asthma, etc.) to construct an index. These objective measures in PSID, however, start in 2003, which makes it impossible for us to exploit the IPW variations before 2003.

[18] The number of all commuting zones is 722, implying that PSID covers around 70% of them.

the IPW distribution features a large variation with quartiles ranging from \$220 per worker to \$3,430. Most of the workers in our sample are male and about two-thirds of them are in good health. Importantly, the mean value of the good-health dummy, our measure of health status, monotonically decreases across the quartiles of IPW. In the rest of this section, we establish the causality of the effects of IPW.

3.1.2 Effects of Import Penetration on Worker Health

We exploit the rich worker-level panel data to estimate the causal effects of IPW and their heterogeneity across worker characteristics. The econometric specification is:

$$\mathrm{GH}_{i,cz,t} = \beta_i + \beta_t + \sum_k \gamma_k \cdot \mathbb{I}_{k,t_0} \cdot \mathrm{IPW}_{i,cz,t-1} + \alpha \cdot Z_{i,t} + \varepsilon_{i,cz,t}. \tag{10}$$

In Equation (10), the indicator variable $\mathrm{GH}_{i,cz,t}$ takes the value of 1 if worker i, living in commuting zone cz, has Good Health in year t. β_i and β_t are, respectively, worker- and year-fixed effects, and $Z_{i,t}$ is a vector of time-varying worker-characteristic controls (e.g., education). Given the annual frequency of the data, we include IPW in year $t-1$, to ensure that exposure to import competition had happened before the realization of the health status, $\mathrm{GH}_{i,cz,t}$. The coefficient of interest is γ_k, where $\mathbb{I}_{k,t_0} = 1$ if a worker has a certain characteristic k (e.g., works in manufacturing sector) in his initial year t_0. Thus, the coefficient γ_k allows us to measure the group-specific effects of the IPW.

The following features of the estimation of Equation (10) allow us to interpret γ_k as the causal effect of import penetration. First, both the IPW measure and the worker characteristic are lagged relative to the dependent variable. Second, we instrument $\mathrm{IPW}_{cz,t-1,k}$ using the exogenous variations in $\mathrm{IPW}^{\mathrm{IV}}_{cz,t-1,k}$ as in Equation (9). Third, the worker fixed effects, β_i, control for the idiosyncratic and time-invariant factors that could be important for workers' health, such as early life experiences and genetic differences, some of which have been emphasized in previous studies.[19] While the first two features have been used in previous studies, the use of worker-fixed effects is more novel. It implies that regression (10) asks the following: as import penetration increases in a commuting zone for exogenous reasons, relative to the sample mean, do workers in the commuting zone suffer lower probabilities of being in good health in the following year, relative to the sample mean? Because the error term might be correlated across workers within cz by year, we cluster standard errors by cz.

[19] See, e.g. Maccini and Yang (2009) and De Nardi et al. (2025).

Table 1: Import Penetration and Future Health

γ_k	Dependent variable: Probability of good health				Elasticity
	(1)	(2)	(3)	(4)	(Δ75-25%)
All	-0.019				-0.042
	(-1.60)				(-2.8 *pp*)
Manufacturing		-0.025***			-0.054
		(-2.10)			(-3.7 *pp*)
Non-Manufacturing		-0.012			-0.026
		(-1.13)			(-1.8 *pp*)
Income Q1			-0.050***		-0.110
			(-2.81)		(-7.3 *pp*)
Income Q2			-0.026		-0.056
			(-1.44)		(-3.7 *pp*)
Income Q3			-0.023*		-0.050
			(-1.84)		(-3.3 *pp*)
Income Q4			-0.012		-0.026
			(-0.98)		(-1.8 *pp*)
Initial Good				-0.031**	-0.068
				(-2.51)	(-4.6 *pp*)
Initial Bad				0.019	0.042
				(1.62)	(2.8 *pp*)
First-Stage F	12.92	52.71	15.10	58.06	
Number of Obs.			33,376		

Note: The table reports regression coefficients γ_k from Equation (10). The first-stage F-statistics are for the first endogenous variables. The standard errors are clustered by commuting zone and t-statistics are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

Table 1 reports the results from our analysis. In column (1), we pool across all workers. While the coefficient on import penetration is negative, this effect is not statistically significant. In columns (2) through (4), we divide the workers into their initial year characteristics, and report the coefficient estimates by subgroup. Column (2) shows that the effect of import penetration on manufacturing workers is negative and statistically significant, and about twice as large in magnitude as compared to the effect on non-manufacturing workers. This result is reassuring because during the China shock, import penetration primarily impacted the U.S. manufacturing sector. Our coefficient estimates in column (2) imply that the elasticity of IPW on the Good health probability is -0.054 for manufacturing workers, and that the commuting zone at the 75th percentile of the IPW distribution has 3.7 *pp* lower probability of future good health for manufacturing workers relative to the commuting zone at the 25th percentile. These findings corroborate, and add to, the findings from prior studies by Adda and Fawaz (2020) and Pierce and Schott (2020), which investigate different dependent variables (e.g. incidences of hospitalization and mortality). Column (3) of Table 1 indicates a particularly pronounced effect of import penetration on workers whose initial-year income is in the first quartile, consistent with the results from Autor et al. (2014) indicating that the China shock had a larger effect on the earnings of low-income workers. Lastly, in Column (4), we see that the IPW had more adverse health effects on workers with good initial health than on those with bad initial health. We will show, in Section 5, that this result is consistent with qualitative predictions of our model.

We have conducted additional empirical analyses to confirm robustness of our results, the details of which are in Appendix B. First, we aggregate our data into the region level and then follow the long-differencing specification of Autor et al. (2013). Our dependent variable is the long-term change in the good-health population share, and we exploit the regional variations in long-term changes in IPW exposure. This alternative approach complements the estimation of Equation (10) by capturing the overall effects of the China shock over long periods. We obtain similar results as in Table 1, with the elasticity of the good-health population share with respect to IPW ranging between -0.048 and -0.078, with the mid-point of -0.060. In addition, we estimate Equation (10) with manufacturing-by-year fixed effects to address concerns that workers in manufacturing and non-manufacturing sectors could have experienced different trends in health status during our sample period. The results are robust to the specification. Finally, using subsamples of male and manufacturing workers yield similar results.

In summary, we have shown that the increase in import penetration from the China shock caused statistically and economically significant adverse impacts on workers' health, with IPW elasticities ranging around -0.054. We embed our worker-level model into a sector-level model of international trade, and then use it as a laboratory to study the mechanism, welfare effects, and policy implications of the adverse effects of the China shock.

3.2 Closing the Model at the Sector Level

Production and Trade We close our model in Section 2 with the production and trade sides of the economy, where all markets are competitive. We assume a small-open economy and use the specific-factors model from the trade literature for the manufacturing sector.[20]

[20]Given the main inquiry of health effects in this paper, we focus on the manufacturing sector and do not model a multi-sector general equilibrium, which requires more assumptions on other sectors. Previous

We start from goods demand. The price and quantity of the final good are P and Y, respectively, and we normalize $P = 1$. The production technology of the final good is Cobb-Douglas with respect to the manufacturing good, whose price and quantity are P_m and x_m, respectively, where m indexes the manufacturing sector. Let ϕ_m denote the manufacturing sector's share in final good production and thus, $x_m = \phi_m \cdot Y/P_m$ represents the demand for the manufacturing good from the final good production. Both the final good and the manufacturing good are non-tradable, and we are agnostic about the rest of the economy, outside of the manufacturing sector.[21]

The manufacturing good, in turn, is assembled from domestic and imported inputs via the following constant elasticity of substitution (CES) technology

$$x_{mS} = \left[\omega_m^{\frac{1}{\sigma}} n_m^{\frac{\sigma-1}{\sigma}} + (1-\omega_m)^{\frac{1}{\sigma}} \left(n_m^*\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where ω_m is the weight of the domestic input, n_m and n_m^* are quantities of domestic and imported inputs, and $\sigma > 1$ is the elasticity of substitution. Let p_m denote the price of the domestic input. Meanwhile, the price of the imported input is $\tau^* p_m^*$, where $\tau^* \geq 1$ is the trade cost of manufacturing inputs. The demand for these manufacturing sector inputs are

$$n_m = \omega_m \left(p_m\right)^{-\sigma} X_{mS} P_m^{\sigma-1}, \qquad n_m^* = (1-\omega_m)\left(\tau_m^* p_m^*\right)^{-\sigma} X_{mS} P_m^{\sigma-1},$$

where $X_{mS} = P_m x_{mS}$ is the total expenditure for the manufacturing sector, and

$$P_m = \left[\omega_m \left(p_m\right)^{1-\sigma} + (1-\omega_m)\left(\tau_m^* p_m^*\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

relates the prices of the manufacturing good to the those of domestic and imported inputs.

Turning to goods supply, the domestic input is produced with labor according to the linear technology, $z_{mS} = \psi_m L_m$, where ψ_m is productivity, and L_m is the labor supply (in

empirical studies tend to find limited inter-sectoral mobility (e.g. Artuc and McLaren, 2015), particularly in response to the China shock (e.g. Autor et al., 2025). Given that the model-implied labor market effects from the China shock are similar to those in the empirical literature, this abstraction is unlikely to have large effects on our quantitative analyses. Meanwhile, this abstraction implies that our simulation is unable to show the effects of the China shock on the other sectors.

[21] Our model can be extended to incorporate a general equilibrium with multiple sectors. Such model requires more assumptions (e.g., production technology in other sectors). As we focus on the outcomes of manufacturing workers, we choose to abstract away from production in other sectors. However, as we describe in Section 4.4, we impose equilibrium conditions in the manufacturing sector, endogenizing the equilibrium wage effect in the manufacturing sector in response to the China shock.

efficiency equivalent units) of the manufacturing sector. Our use of the specific factors model implies that manufacturing labor is immobile to the rest of the economy. The price of the domestic input is thus proportional to the wage rate w_m: $p_m = w_m/\psi_m$. The domestic input is tradable. When it is exported, it faces the foreign demand of $D^*_m(p_m) \equiv D^*_m \cdot (p_m)^{-\sigma}$, where D^*_m incorporates demand shifters as foreign expenditure and export costs. Finally, because we assume that our economy is a small open economy with respect to the rest of the world, the supply of imported manufacturing inputs n^*_m, is elastic.

Market Clearing When we simulate the China shock in our quantitative model, we impose market clearing conditions in the economy. Therefore, in response to the shock in the import cost, the wage in the manufacturing sector in the post-China economy is determined endogenously. Here, we outline the key equilibrium conditions, leaving the rest and the formal equilibrium definition to Appendix C.

Let the distribution of workers in the manufacturing sector over state space $\mathbf{s} \equiv (l, \tilde{\mathbf{s}})$ be $\mu(\mathbf{s})$. First, the aggregate labor supply, L_m, depends on workers' health (x) and productivity (z) and the stationary distribution of $\mu(\mathbf{s})$:

$$L_m = \sum_{\mathbf{s}} \nu(x) \cdot z \cdot \mathbb{I}_{l=E} \cdot \mu(\mathbf{s}). \tag{11}$$

On the other hand, the market clearing conditions for the manufactured good and for the domestic inputs imply that when the labor market clears,

$$w_m L_m = \pi^D_m \phi_m Y + D^*_m p_m^{1-\sigma}, \quad \pi^D_m = \frac{\omega_m (p_m)^{1-\sigma}}{\omega_m (p_m)^{1-\sigma} + (1-\omega_m)(\tau^*_m p^*_m)^{1-\sigma}}, \tag{12}$$

where π^D_m is the domestic share of the manufacturing sector. On the right-hand side of Equation (12), $\pi^D_m \phi_m Y$ represents the labor demand from domestic production, and $D^*_m p_m^{1-\sigma}$ represents the labor demand from exports. Equation (12) says that the aggregate labor demand and labor supply, L_m, jointly determine the wage, w_m, for the manufacturing sector.

Thus, our sector-level model ensures that the wage and labor supply are consistent with the labor demand, through Equation (12). These two pieces of our model allow us to quantify the China shock using the standard practice in the trade literature, and to endogenously determine workers' wage, w_m, in the post-China economy, which we discuss in Section 4.4.

4 Calibration

In this section, we map our model to the data to quantify the effects of the China shock on workers' health and welfare. In addition to PSID, we use the Medical Expenditure Panel Survey (MEPS), Current Population Survey (CPS), STructual ANalysis Database (STAN), and World Development Indicators (WDI), to set parameter values and generate target moments. We first discuss the key empirical facts concerning medical expenditures and health transitions that are used to guide exogenously set parameters and data moments. Then, we describe predetermined parameters, and present calibration procedures for the worker-side and the sector-level parameters.

4.1 Key Empirical Facts

As we showed in Section 2, a key element of our model is the workers' optimal choice of medical expenditures. Individual-level data on medical expenditures are available from MEPS, which we use to establish the stylized facts in two areas: firstly, medical expenditures and medical utilizations, and secondly, transition probabilities to good health, by worker characteristics.[22] These stylized facts provide the starting point of our calibration process.

In Table 2, we document average medical expenditures and the shares of individuals with zero medical utilization by health and insurance statuses. For the latter, we use the Household Component Event files of the Medical Conditions data to identify those who never

Table 2: Medical Expenditures and Medical Utilizations

		Insured	Uninsured
Average Medical Expenditures	Bad	\$3,297	\$1,755
(positive only)	Good	\$2,246	\$1,294
Share of Individuals	Bad	0.07	0.28
without medical utilizations	Good	0.10	0.34

Note: For medical expenditures, we document group-level average expenditures among those who have positive spending, after controlling for age, sex, race, education, Census region, marital status, and survey panel dummies. An individual is considered to have utilized medical service if one had prescribed medicine, dental visit, outpatient event, home health provider event, office-based medical provider visit, emergency room visit, or other medical expenses.

[22]For parameters governing health production, we calculate moments using all workers in the sample without restricting the sample to those in the manufacturing sector (which we do for wage moments) for a larger sample size. The underlying assumption is that all individuals face the same health production technology regardless of the sector they are employed in.

reported medical events or utilizations, such as outpatient visits and prescribed medicine.[23]

Next, to better understand the relationship between medical expenditures, insurance status, and health transitions, we run the following regression:

$$\text{Health}_{i,t+1} = \beta_0 + \beta_1 \cdot \text{Health}_{i,t} + \sum_{k=1}^{10} \beta_{2,k} \cdot D^{med}_{i,t,k} + \Gamma \cdot X_{i,t} + \varepsilon.$$

The variable $\text{Health}_{i,t(t+1)}$ takes a value of one if the individual is in Good health, and 0 otherwise in year t $(t+1)$. We then construct deciles of medical expenditures among insured individuals with positive expenditures, and assign each individual i a dummy variable $D^{med}_{i,t,k}$ where k indicates either a zero expenditure or the decile of medical expenditure (total of 11 groups) in year t. The individual-level controls $X_{i,t}$ include not only demographics (e.g., quadratic in age, education, race, census region, gender, and marital status) and panel fixed effects, but also the number of reported medical conditions, employment, and insurance status. Figure 2 plots the predicted values of $\text{Health}_{i,t(t+1)}$ against the medical-expenditure deciles. Figure 2(a) is for individuals with bad initial health, and Figure 2(b), for those with good initial health. Both subplots distinguish the insured (circles) from the uninsured (crosses).

The salient features in Table 2 and Figure 2 are as follows. First, Figure 2 shows that the future good-health probabilities are monotonically decreasing in current medical expenditure deciles for all groups, after controlling for various medical conditions. It implies that a large expenditure this period reflects the severity of the sickness shock a worker experienced.

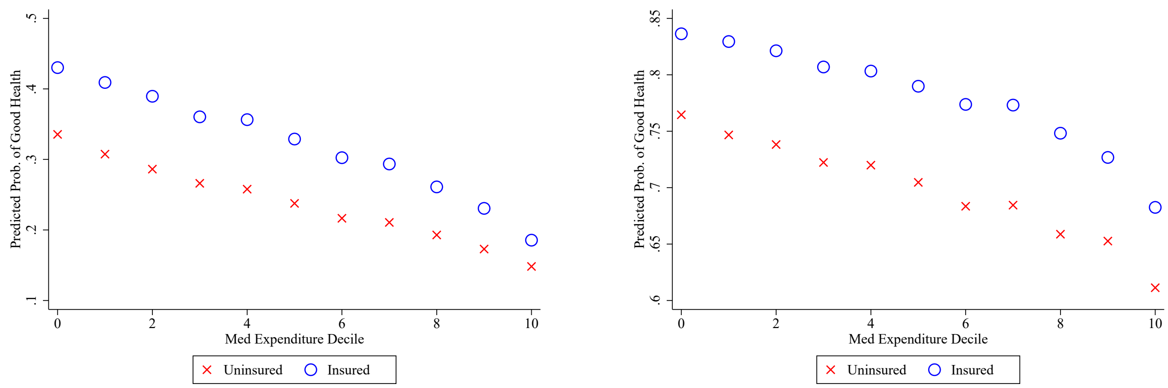
Second, initial health status matters. From Table 2, we note that individuals with good health incur lower medical expenditures and are less likely to utilize medical services compared to those with bad health. From Figure 2(a), we note that for individuals with bad initial health, the predicted future good-health probabilities range from 0.15 to 0.42, while in Figure 2(b), they range from 0.60 and 0.84 for those with good initial health. These patterns suggest that individuals with good health experience milder sickness shocks and have higher probabilities of future good health.

Finally, insurance status also matters. From Table 2, we see that 7%-10% of insured individuals report zero medical utilization, while 28%-34% of uninsured individuals do, and the mean medical expenditure (conditional on positive) of the insured is almost twice as

[23]Event level data is a better measure than zero medical expenditure shares, because some individuals might receive medical treatment free of charge, e.g., in emergency rooms or through charity care.

Figure 2: Medical Expenditures, Insurance, and Future Health

(a) Bad Initial Health (b) Good Initial Health



large as that of the uninsured. Meanwhile, Figure 2 shows that the uninsured have lower probability of being in good health in the future than the insured in every single medical-expenditure decile, regardless of initial health status. These suggest that the variations across insurance status in Table 2 may not be because the uninsured are healthier, but potentially because they are not able to receive sufficient medical care due to their lack of resources and access.

We summarize these patterns as the following empirical facts and utilize them to calibrate worker-level parameters.

Empirical Fact 1. Initial Health, expenditures, and future health

- *(a) Individuals with good health have lower medical expenditures and are less likely to utilize medical services than those with bad health* (Table 2).
- *(b) Conditional on characteristics, individuals with good initial health have higher probabilities of being in good health than those with bad initial health* (Figure 2).

Empirical Fact 2. Insurance, expenditures, and future health

- *(a) Insured individuals incur higher medical expenditures and are more likely to utilize medical services than uninsured individuals* (Table 2).
- *(b) Conditional on medical expenditures and characteristics, insured individuals have higher probabilities of being in good health than uninsured individuals* (Figure 2).

4.2 Predetermined Parameters

Given the empirical facts, we now discuss predetermined parameters with a model period of a year. All predetermined parameters are summarized in Tables 3 and 4.

Preferences and Labor Market The coefficient of relative risk aversion ρ, discount factor β, and interest rate r are set to 1.5, 0.95, and 0.02, respectively, which are standard values in the literature.

Then, we use the PSID data in pre-China years (1991–1996) to obtain the average income of workers in the manufacturing sector. One of the important components in our quantitative analysis is the health gradient of income. Due to selection into employment, using the observed incomes across health status may be biased. To correct for the bias, we follow Low and Pistaferri (2015) and conduct a two-step wage estimation using the amount of "potential" government transfers as an instrument variable to obtain $\nu(B)$, after normalizing $\nu(G)$ to one.[24] Given this procedure, the average labor income of a worker with Good health is \$50,211 and the health gradient of income, $\nu(B) = 0.81$. The productivity shock process has the persistence and standard deviation parameters of 0.95 and 0.15, and we discretize the process following Tauchen (1986). The job continuation and job finding rates by health status are from the Annual Social and Economic Supplement of the CPS in years 1996-1999.[25] The job continuation and finding rates are 0.6pp and 0.14pp higher among good health individuals than their counterparts.

We set the unemployment benefit to 20% of average wage income across health statuses, which amount to \$9,086. Additionally, the consumption floor is \$3,000, similar to one estimated in De Nardi et al. (2025), and the income tax rate is 20%.

Table 3: Predetermined Parameters

Parameter	Description	Values	Parameter	Description	Values
Household and Labor Market			Government Policies		
ρ	Risk aversion	1.5	b	UI benefit	\$9,086
β	Discount factor	0.9	$\underline{c}$	Cons. floor	\$3,000
r	Interest rate	0.02	τ	Income tax rate	20%
w_m	Pre-China wage	\$50,211	Production		
$\nu(B)$	Health effect on wage	0.81	ω_m	Home bias	0.5
(ρ_z, σ_z)	Inc. shock: pers.; st.dev.	0.95; 0.15	$\sigma - 1$	Trade elasticity	3
$1 - \delta(E, x)$	Job continuation: B; G	0.87; 0.93	ϕ_m	Manuf. share	0.17
$1 - \delta(U, x)$	Job finding rate: B; G	0.18; 0.32	$\pi^D_{m,pre;post}$	Domestic share	0.85; 0.71

[24]The "potential" government transfers refer to the amount of benefits from welfare programs (e.g., SNAP, TANF) that a representative individual worker would have received in his residential state. The details regarding the first-stage and the second-stage estimation results are relegated to Appendix D.1.

[25]The CPS allows us to track workers' employment statuses for a larger sample of individuals than PSID.

Sickness Shocks and Health Insurance Qualitatively, as shown in Figure 2, high medical expenditures in MEPS imply severe sickness shocks, ε, in our model. Quantitatively, however, there are two additional issues related to data availability. First, although in the model, ε is distinct from medical expenditures, $\min \{H, \varepsilon\}$, we only observe medical expenditures in the data.[26] Second, although we observe whether an individual utilized medical services or not (lower panel of Table 2), it does not perfectly coincide with whether an individual experienced a sickness shock this period. To address these issues, we assume that individuals who are insured and employed (those most likely to have sufficient resources) choose full treatment of sicknesses, and that the uninsured face the same distribution of sickness shocks as the insured.[27] These assumptions are consistent with *Empirical Fact 2.*

Given these assumptions, we can use the medical expenditures for the insured and employed from MEPS to parameterize the sickness shock process in our model, $\{\varepsilon(x), f(\varepsilon; x)\}$. As reported in Table 4 below, we discretize $\varepsilon(x)$ into five events. We refer ε_0 to the event of being sickness free (i.e. $\varepsilon_0 = 0$), and its frequency is given by the shares of the insured and employed with no medical events as reported in the lower panel of Table 2 above. Then we construct the values and frequencies of the remaining four sickness events, ε_1 through ε_4, by health status using within-quartile averages of medical expenditures conditional on positive values. Table 4 shows that individuals with bad initial health have more severe sickness shocks ($\varepsilon(B) > \varepsilon(G)$) and a lower probability of not getting sick ($f(\varepsilon_0; B) < f(\varepsilon_0; G)$), as consistent with *Empirical Fact 1.*

The parameters for health insurance are straightforward to obtain from MEPS and are reported in Table 4. We note that first, the expenditure-dependent coinsurance rates, $1 - \chi(\varepsilon; x)$, help us parsimoniously capture such components of insurance plans as deductibles and out-of-pocket maximum. Second, the coinsurance rate decreases with the severity of the sickness, implying that health insurance is more useful for severe sickness shocks than for mild ones. Lastly, although we do not directly model insurance for low-income people, such as Medicaid, the unemployed in our model have a positive probability of having health insurance.[28] These features help our model predictions match the pattern in the upper panel of Table 2 that the mean medical expenditure is higher for the insured, and generate,

[26] Although MEPS asks respondents about their medical diagnosis akin to sickness shocks in our model, it is difficult, if not impossible, to translate the diagnosis into a numerical value.

[27] Implicitly, we abstract away from adverse selection in insurance status.

[28] The consumption floor in our model proxies for other social insurance policies for low-income individuals.

Table 4: Predetermined Parameters Regarding Sickness Shocks and Health Insurance

Parameter	Description		Values				
			ε_0	ε_1	ε_2	ε_3	ε_4
$\varepsilon(x)$	Sickness shocks	Bad	\$0	\$370	\$1,454	\$3,599	\$9,446
		Good	\$0	\$220	\$769	\$1,877	\$6,453
$f(\varepsilon; x)$	Probability	Bad	0.07	0.23	0.23	0.23	0.23
		Good	0.10	0.23	0.23	0.23	0.23
$1-\chi(\varepsilon; x)$	Coinsurance rate	Bad	-	0.38	0.33	0.28	0.20
		Good	-	0.39	0.39	0.34	0.23
$\zeta(l)$	Insurance prob.	Emp.			0.82		
		Unemp.			0.63		
π	Insurance premium				\$1,889		

Note: All statistics are from the MEPS data (1996-2014). The values of sickness shocks $\varepsilon(x)$ are constructed from the predicted values of medical expenditures among the insured population after controlling for age, sex, race, education, Census region, marital status, and survey panel dummies. We use fourth quantiles conditional on positive spending for values ε_1–ε_4 by health status. The probabilities of not experiencing a sickness shock $f(\varepsilon_0; x)$ are those of the insured individuals from MEPS-HC data as described in Table 2. The coinsurance rate is calculated from MEPS using out-of-pocket expenditures and total medical expenditures, and the insurance premium is defined as a weighted average of sickness shocks, using $f(\varepsilon; x)$ as weights.

endogenously, the heterogeneous effects of the China shock across workers (see Section 6).

Production We normalize the manufacturing sector productivity ψ_m to one, set the sectoral home bias, ω_m, to 0.5, and the trade elasticity, $\sigma - 1$, to 3, following Simonovska and Waugh (2014). The manufacturing share ϕ_m is set to 0.17, following the mean of manufacturing value added as a share of U.S. GDP for 1990-1992 in WDI; and the domestic share π_m^D in the pre-China economy is $= 0.85$, from its average for 1990-1992 from STAN. For simulating the post-China-shock economy in Section 6, we follow the sufficient-statistics approach in the trade literature, and model the China shock as an exogenous drop in π_m^D to 0.71, the average value for the post-China-shock years of 2010-2012. This approach allows us to be agnostic about the specific sources of this shock, because the shock reduces labor demand for the manufacturing sector by the same degree, whether it is caused by a drop in p_m^* (which may result from an increase in foreign productivity), a drop in import cost τ_m^*, or combinations of the two.

4.3 Calibration of Worker-Level Parameters

On the household side, the remaining parameters are those governing the health production $F(H; x, \varepsilon)$ and preferences $\{\iota(x)\}$. To discipline parameters to match data moments, we parameterize $H_{min}(x,\varepsilon) = s(x) \cdot \varepsilon$, with $s(x) \leq 1$, that is, within health status x, the level of minimum health investment increases as ε increases, but its share relative to ε is constant. Further, we normalize $\iota(G) = 0$, leaving us with 17 parameters to be calibrated: $\alpha(x,\varepsilon)$, $s(x)$, $\gamma(x)$, $\lambda(x)$, and $\iota(B)$. Meanwhile, our data targets are group-specific averages of (i) the sickness shock-dependent probabilities of future good health (analogous to Figure 2 but with five sickness shocks, 20 moments); (ii) the share of the population with zero medical utilizations (Table 2, 4 moments); and (iii) the average medical expenditures (Table 2, 4 moments). We jointly calibrate the 17 model parameters to target 28 data moments.

In order to develop the intuition for how the parameters are identified, we first describe the most salient effects of these parameters on targeted model moments. First, from Figure 1(a), we see that an increase in $\alpha(x,\varepsilon)$ lowers the baseline probability of future good health, and so $\alpha(x,\varepsilon)$ are identified from the variation of the good health probabilities across sickness sock ε and health status x. Second, both $\lambda(x)$ and $\gamma(x)$ impact the marginal benefits of investment, but differentially. An increase in $\lambda(x)$ compresses effective health spending, $H - H_{min}(x,\varepsilon)$, and drags down the concave portion of $F(\cdot)$. On the other hand, for $\gamma(x) < 1$, an increase in $\gamma(x)$ changes the curvature of the concave portion of $F(\cdot)$ by rotating this portion counter-clockwise around the point $(H_{min}(x,\varepsilon) + \lambda(x), 1 - \alpha(x,\varepsilon)/e)$. Thus, $\lambda(x)$ and $\gamma(x)$ are identified from the variation in the mean medical expenditures and probabilities of future good health across current health status. Lastly, an increase in the minimum share, $s(x)$, directly impacts the share of workers who choose zero utilization. It also decreases the probability of future good health for large sickness shocks, but has more limited effects on those of small sickness shocks. On the preference side, $\iota(B) < 0$ affects the utility loss of being in bad health. An increase in $\iota(B)$, or a decrease in its magnitude, increases the zero shares for the uninsured. As a result, $s(x)$ and $\iota(B)$ are identified from the population shares of zero medical utilizations across health statuses.

4.4 Calibration of Sector-Level Parameters

We now relate the worker-side decisions to the market clearing condition in the manufacturing sector, Equation (12), and clarify how we introduce the China shock into our model.

Pre-China Economy In the pre-China-shock economy, where we take w_m as exogenous (Table 3), the labor supply, L_m, is pinned down by the workers' optimal choices and their distribution, as expressed in Equation (11). Our remaining task is to ensure that the right-hand side of Equation (12) stays in balance. As listed in Table 3, ϕ_m and π_m^D are set to 0.17 and 0.85 exogenously. This means that we are left with two unknowns, the export-demand shifter D_m^*, and the total output in the economy Y, in Equation (12).

We thus use the model-implied ratio of manufacturing export to Gross National Expenditure (GNE),

$$\frac{\text{Manufacturing Export}}{GNE} = \frac{D_m^* \cdot {p_m}^{1-\sigma}}{Y} \tag{13}$$

as an additional target. From STAN, we obtain that this ratio is 0.057 (the average for 1990-1992). We then use equations (12) and (13) to calibrate values of D_m^* and Y that are consistent with the solutions from the household side.

Post-China Economy As summarized in Table 3, the domestic share of manufacturing goods decreases to 0.71. Given that we remain agnostic about the non-manufacturing part of the economy, our model is unable to predict how the China shock affects total output, Y. However, as the trade literature estimates limited output gains from trade relative to autarky, a much larger change than the China shock we model (e.g. Costinot and Rodriguez-Clare, 2014), we assume that there is no change in Y, as an approximation, and that D_m^* remains unchanged.[29]

Under these assumptions, there are two endogenously determined outcomes in Equation (12), the wage rate w_m and the total labor supply L_m. We use two approaches to simulate the effects of the China shock, keeping the parameter values for the health production and worker utility functions at the pre-China-shock levels. In the first approach, we assume that the job continuation rates remain unchanged. Equation (12) allows us to solve for the post-China-shock wage that clears the labor market in Equation (11), using the labor supply, L_m, from workers' problems and that $p_m = w_m$. In the second approach, we allow both w_m and job continuation rates to change. In order to contrast with the first approach, we set the wage decline to be 2.3%, the lower end of the estimates from Autor et al. (2014), and search for the change in $1 - \delta(E, x)$ that balances equation (12).

[29]This literature examines the change in real GDP, which is closely related to Y, the real GNE.

5 Calibration Results

In this section, we focus on our calibration results of worker-side parameters. We report and discuss the calibrated parameter values and model fit, show model validation, and clarify the key model features.

5.1 Parameter Values and Model Fit

Table 5 reports the values of our calibrated parameters. In order to illustrate their intuition, we plot the health production function, $F(\cdot)$, as implied by these parameters by sickness shock by initial health in Figure 3.

First, the ten baseline probability parameters, $1-\alpha(x,\varepsilon)$, determine the vertical intercept of the health production function, $F(\cdot)$. We see that the baseline probability of future good health is high when current health is good. We also see that the vertical intercept shifts down from ε_0 through ε_4 in both Figures 3(a) and (b), that is, the baseline probability of future good health is low when sickness is severe.

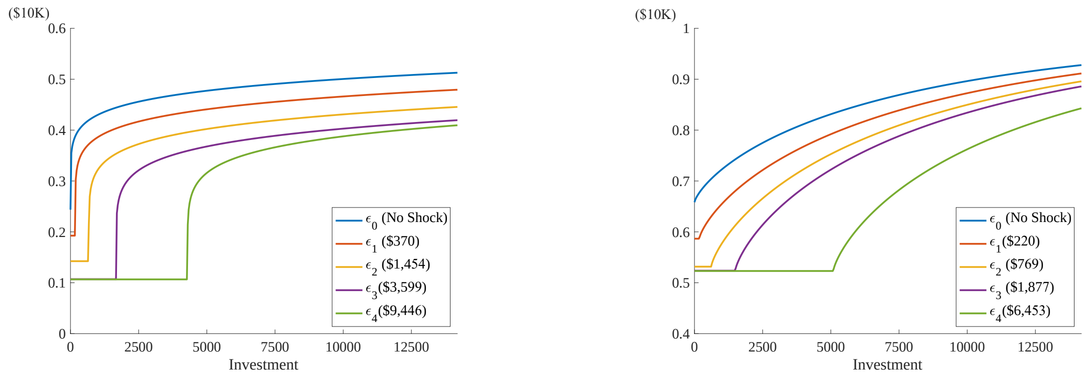
Second, the remaining six parameters of the health production function determine its shape, which differs substantially across initial health status. This happens for two reasons. One, the production function is more concave for bad initial health, because $\gamma(B)$ is smaller and $\lambda(B)$ is larger than their counterparts for good health. Two, the ratio of minimum health investment to ε for bad health, $s(B)$, is smaller than that for good health, $s(G)$, making the kink point of $F(\cdot)$ under bad initial health farther away from ε. The calibrated production function implies that for bad health individuals, it is important to alleviate the sickness through medical expenditures, whereas for good health individuals, there is more

Table 5: Parameters Calibrated in the Model

Parameter	Description		Values				
Health production							
			ε_0	ε_1	ε_2	ε_3	ε_4
$1-\alpha(x,\varepsilon)$	Baseline probability	Bad	0.244	0.193	0.142	0.107	0.107
		Good	0.658	0.587	0.532	0.524	0.523
$\lambda(x)$	Scale: Bad; Good		2.411; 0.839				
$\gamma(x)$	Concavity: Bad; Good		0.167; 0.757				
$s(x)$	Min. inv. share: Bad; Good		0.467; 0.797				
Worker Utility							
$\iota(x)$	Marginal utility: Bad; Good		-0.931; 0 (normalization)				

Figure 3: Calibrated Health Production

(a) Bad Initial Health (b) Good Initial Health



scope for forgoing treatment or incurring additional non-medical investment.

Lastly, $\iota(B)$ implies that bad health is associated with a utility loss of about 60% of consumption, which is within the range of those in Low and Pistaferri (2015).[30] We further confirm the validity of $\iota(B)$ in Section 5.2 by comparing the model-implied value of a statistical injury with empirical estimates from the literature.

Table 6 shows that our model generates reasonable fits on the target moments reported in Table 2. The model predicted shares of zero medical utilization align well with the MEPS data. For example, it is 0.27, versus 0.28 in the data, for the uninsured workers with bad initial health.[31] On medical expenditure side, the model-predicted patterns of expenditures across worker characteristics are qualitatively consistent with those of the data: conditional on insurance (health) statuses, uninsured (good health) workers' average expenditures are lower than those of insured (bad health) workers. Figure 4 plots the future good health probabilities by initial health status, by insurance status, by sickness shock. We see that the model predictions ($\circ$) track the data targets ($\times$) fairly well.[32]

[30] Low and Pistaferri (2015) estimates disutility effects from health and employment. Their estimates imply between 36% and 66% loss in utility depending on the employment and health statuses.

[31] It is the sum of the probability of not being sick (i.e. $\varepsilon_0 = 0$) and the share of endogenously chosen zero treatment ($H^* = 0 < \varepsilon$).

[32] Given the workers' choices and coinsurance rates, the actuarially fair health insurance premium in the equilibrium is $2,260, close to the exogenously set premium of $1,889 (Table 4) from the MEPS data. In counterfactual analyses, we use transfers to ensure budget neutrality of the government, incorporating the gap between the health insurance premium and endogenously determined medical expenditures.

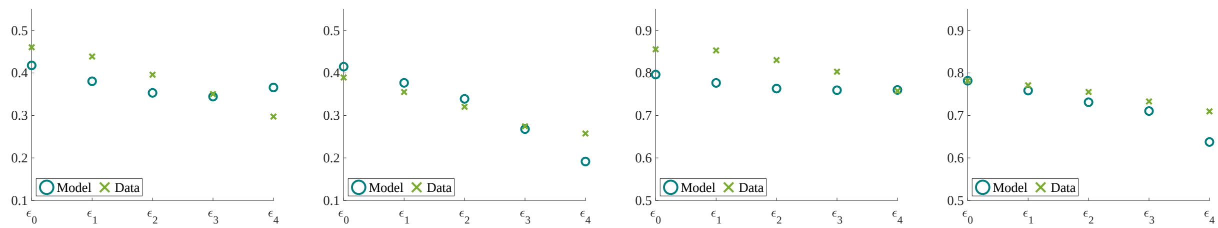
Table 6: Model Fit on Targeted Moments

		Insured		Uninsured	
		Model	Data	Model	Data
Average Medical Expenditures	Bad	\$3,134	\$3,297	\$1,802	\$1,755
(positive only)	Good	\$2,155	\$2,246	\$1,545	\$1,294
Share of Individuals	Bad	0.07	0.07	0.27	0.28
without medical utilizations	Good	0.12	0.10	0.34	0.34

Figure 4: Model Fit on Good Health Probability

Bad Initial Health — (a) Insured, (b) Uninsured

Good Initial Health — (c) Insured, (d) Uninsured



5.2 Validation of the Model

Having established the model's good fit with targeted moments, we now test the empirical validity of the calibrated model by comparing its predictions on the value of health and workers' health investment decisions with the corresponding untargeted data moments.

Value of Health We first aim to confirm whether the value of the calibrated parameter $\iota(B)$, the utility loss from bad health, is plausible. Motivated by Hall and Jones (2007), who use the estimates of value of a statistical life (VSL) to calibrate the flow utility parameter in their model, we compare our model's prediction of value of a statistical injury (VSI) to the empirical estimates. We combine the CPS data with the BLS data on non-fatal injuries, and find that a 1% increase in the industry injury risk is associated with a 0.37% reduction in the workers' probability of self-reported good health, conditional on worker characteristics. The empirical estimate of VSI obtained from our data is around 3.3 times the average wage, or \$153,000, which is comparable to those in the literature; e.g., Biddle and Zarkin (1988) report VSI of 3.7 times the average wage and the corresponding estimate in Hersch and Viscusi (1990) ranges between 3.3 and 5.4. Meanwhile, our model-predicted VSI is 3.8 times the mean wage, or \$176,000, given the conditional correlation between self-reported health and injury risk discussed above. This prediction is similar to our estimate and within the range of the literature's estimates.[33]

Income Elasticity of Health Investment We compare the model-predicted income elasticity of health investment with the estimates from previous empirical studies. To do so, we use our model to simulate a temporary increase in income and evaluate their effects on health investment. The average elasticity in our model is 0.47, in line with the range of estimates from previous studies (e.g. Acemoglu et al., 2013) of 0.3 to 1.1.[34] Thus, the workers' quantitative responsiveness of health investment in response to income changes in the model is in line with empirical studies.

Prevalence of Foregone or Partial Sickness Treatment A novel feature of our model is that workers may endogenously choose to partially treat or forego their treatment of sicknesses. As another measure of such behavior, we utilize survey questions from the NHIS data in 2011-2012 that ask whether the respondent missed or reduced medical care or medicine doses due to cost.[35] We obtain that 18.5% of the working-age adults (18-64) in the U.S. reports having had such experiences. In comparison, our model's predicted share of such individuals (those with $\varepsilon > 0$ and $H^* < \varepsilon$) is 18.9% in the pre-China economy, close to the empirical share from the NHIS.

Magnitude of Non-Medical Monetary Investment The model also predicts that workers may endogenously choose to incur additional investments in health beyond sickness treatment, in the amount of $\max\{H^* - \varepsilon, 0\}$. From the data, it is difficult to disentangle non-medical expenditures that help improve health (e.g., healthy foods) from ordinary consumption expenditures. As a result, we compute the total non-medical consumption of $c + \max\{0, H^* - \varepsilon\}$ in the model, which would be measured as the total consumption expenditures net of medical expenditures in the data. Using the recent surveys of the PSID (1999-2013) that include consumption data, we show that among the employed, the ratio

[33] See also Viscusi and Aldy (2003) for estimates. The detailed description is contained in Appendix D.3.

[34] Acemoglu et al. (2013) obtains the range of 0.3-1.1 for the income elasticity of hospital expenditure at the U.S. Economic Subregion level, by instrumenting local income by global oil price and ESR-level importance of oil in the economy. Other papers that estimate the elasticity are Moscone and Tosetti (2010),Baltagi and Moscone (2010), and Baltagi et al. (2017) and their estimates vary between 0.35 and 0.9.

[35] These questions are not available for earlier years, and we stop in 2012 because the ACA went into effect in 2014. We use questions that ask whether, due to affordability, the person restricted medical care (PNMED12M), prescription medicine (AHCAFYR1), a specialist visit (AHCAFYR5), follow-up care (AHCAFYR6), skipped medication (ARXPR1), or took less medicine (ARXPR2).

of non-medical consumption to income is 70% for those with bad health and 60% for those with good health.[36] In the model, these ratios are 83% and 73%, respectively for bad and good health individuals, both in line with the data in terms of levels and the differences across health statuses. That is, our model generates a reasonable non-medical consumption to income ratio, even though this ratio is not directly targeted.

Overall, our model replicates several untargeted moments relating to the value of health and health investment. We provide additional validation for the post-China economy in Section 6, but before doing so, we discuss the key features of our model.

5.3 Key Model Features

Our main model mechanisms revolve around the optimal health investment, H^*, which consists of both medical expenditures, $\min\{H^*, \varepsilon\}$, and non-medical expenditures beyond the treatment of sickness, $\max\{H^* - \varepsilon, 0\}$. We illustrate the key model features using Figures 5(a) through 5(d), which summarize health investment choices for employed workers by health and insurance statuses.[37] In the plot, we demonstrate, for each sickness shock, the size of the sickness shock ε, the average medical expenditures $\min\{H^*, \varepsilon\}$, and the average health investment H^*. The unit of the vertical axis is \$10K.

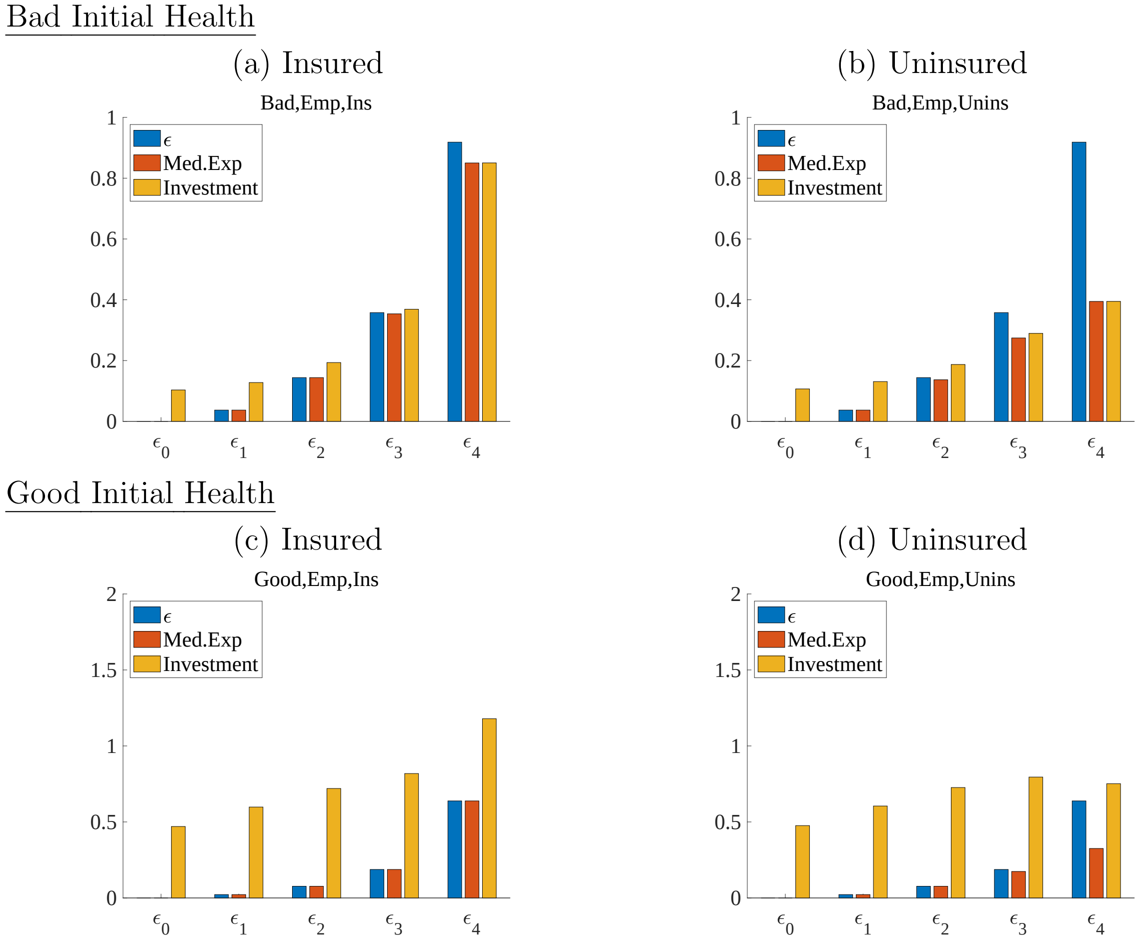
Non-Medical Health Investment as a Channel for Self-Insurance In our model, bad health individuals experience a direct utility loss ($\iota(B)$), lower probabilities of employment ($1 - \delta(l, B)$), and lower wages ($\nu(B)$). As a result, workers have incentives to self-insure against the future risk of landing in a bad-health state. Individuals with good initial health do so by investing in health beyond the full treatment of sicknesses, which is a novel feature of our model relative to the literature. As illustrated in Figures 5(c) and 5(d), the average health investment exceeds the size of the sickness shock ($H^* - \varepsilon > 0$) regardless of sickness severity and regardless of insurance status.

The quantitative magnitude of the the additional investment depends on their marginal benefits. As seen in Figure 3, the marginal benefit of health investment for good-health individuals remains substantial even when the investment is large. As a result, the average

[36]As the PSID data records consumption at the household level, we use equivalent scale (0.7 for an additional adult and 0.5 for an additional child) to adjust for family size. Our sample includes those who are employed with positive labor income and we drop those with ratios in top and bottom 1% of the distribution.

[37]We relegate the discussion of unemployed workers to Appendix D.2 as they are qualitatively similar.

Figure 5: Health Investment of Employed Workers



amount of non-medical investment in Figures 5(c) and 5(d) is typically large, exceeding \$5K, except for the uninsured workers with the most severe sickness of ε_4. For individuals with bad health, the shocks of severe sickness are especially large (Table 4). As a result, the bad-health workers are incentivized to invest when they are not sick or when they have mild sickness, as illustrated in Figures 5(a) and (b). However, the amount of the average non-medical investment is much smaller than for good-health workers, because the marginal benefits to investment decrease sharply in the health production function for bad-health workers.

Partial Treatment and the Role of Health Insurance Another novel feature of our model is that workers may choose to forego or partially treat sickness, sacrificing treatment for consumption, especially when the cost is high. In our model, the cost of treatment is closely related to health insurance status and minimum investment.

First, health insurance has no direct effect on health in our model. Instead, it lowers the marginal cost of medical expenditures, allowing covered workers to leverage more resources for treatment. Figures 5(a) and 5(b) illustrate this channel by showing the bad-health workers' optimal choices of medical spending. The insured (Figure 5(a)) tends to fully treat their sicknesses (average medical expenditure is very similar to the sickness shock), while the uninsured (Figure 5(b)) only partially treat their sicknesses ($H^* < \varepsilon$). The amount of the shortfall in treatment is modest, but becomes large for the most severe sickness ε_4, approaching $6K.

In addition, the health production function in our model incorporates that a minimum investment is required before the benefits of health investment materialize. For the good-health individuals, the minimum health investment is large relative to sickness (Table 5), and so many of them choose not to invest in health at all (Table 6). Figure 5(d) illustrates this channel for the uninsured workers when they face the severe sickness of ε_4. We see that the average medical expenditure is lower than ε, because many choose zero treatment ($H^* = 0$), due to the lack of resources and high minimum investment. This optimal choice of foregoing sickness treatment, a feature of our health production, is an important contributor to the model-predicted effects of the China shock on health that we discuss below.

6 Quantitative Analysis

We now use the calibrated model as a laboratory to quantify the effects of the China shock on workers' health through the optimal health investment mechanism, to compute the effects of the China shock on workers' welfare, taking this mechanism into account, and to evaluate the effectiveness of potential policy responses.

6.1 The Post-China Economy

As discussed in Section 4.4, we simulate two versions of the China shock. In the first, wage adjusts to clear the labor market in response to the China shock, and in the second, both wage and job destruction rates adjust. Table 7 describes the main aggregate outcomes of the post-China economies in the manufacturing sector.

The first panel of Table 7 recaps the wage, employment rate, and export-GNE ratio of the pre-China economy. The second panel shows that in our first simulation, the model predicts a 5.78% drop in the wage rate of manufacturing workers. This is because the increase in import competition from the China shock reduces demand for manufacturing labor, as can be seen from Equation (12). The magnitude of the wage decline falls within the range of the estimates from Autor et al. (2014), 2.3% to 7.2%, even though we have endogenously solved for the wage change through the labor-market equilibrium condition of (12). We also see that the export-GNE ratio for the U.S. manufacturing sector increases from 0.057 to 0.068. as the lower manufacturing wage reduces the production cost of the domestic input. The value of the post-China export-GNE ratio is comparable to the mean value for the years of 2010-2012 in the data, 0.077.

The last panel of Table 7 shows the results of our second simulation. We fix the wage drop at 2.3%, the lower end of the estimates in Autor et al. (2014), and find that an increase of 1.12*pp* in the job destruction rate balances the labor market clearing condition of (12). Relative to the pre-China economy, the manufacturing sector employment rate drops by 2.8*pp*. With the manufacturing sector employment share of 15%, this implies that the ratio of manufacturing employment to population declines by 0.42*pp*, accounting for a substantial portion of the effect of the China shock, 0.88*pp*, as reported by Autor et al. (2013).

Overall, the macroeconomic predictions of our model for the effects of the China shock are consistent with both data and estimates from previous studies. These results provide further validation of our model on post-China economy simulations and therefore, its suitability as a laboratory for analyzing its effects.

6.2 Mechanism: The China Shock and Health Investment

We now discuss the health effects of the China shock as predicted by our model. We start with the aggregate effects and uncover the heterogeneity in its effects across worker characteristics.

Table 7: Manufacturing Sector Outcomes in the Post-China Economy

	Wage	Employment	Export-GNE
Pre-China economy	\$50,211	72.5%	0.057
Post-China I: Wage ⇓	\$47,308	72.2%	0.068
Change from Pre-China	-5.78%	-0.30*pp*	+19.65%
Post-China II: Wage ⇓ & Job destruction ⇑	\$49,056	69.8%	0.061
Change from Pre-China	-2.30%	-2.76*pp*	+7.28%

6.2.1 Aggregate Effects

Table 8 summarizes the aggregate effects of the China shock. The second column summarizes the key metrics about health and health investment in the pre-China economy, and the next two columns show how these metrics change in the simulated post-China economies.

The top panel of Table 8 focuses on changes in the shares of workers with good health. We see that, in the first post-China simulation, the good health share decreases by 1.2*pp*. This means that the model-predicted elasticity of good-health share with respect to import penetration per worker (IPW) is -0.0203. In Section 3.1, we have shown that the empirical estimate of this elasticity is -0.054. That is, the mechanism of optimal health investment can account for around 38% of the estimated empirical elasticity. In the second post-China simulation, the model-predicted elasticity is larger in magnitude, at -0.0282, accounting for 52.2% of the empirical estimate. These results imply that the optimal health investment mechanism is economically significant in explaining the health effect of the China shock, and that it might be important for understanding the health effects of other negative economic shocks. In comparison, the models that abstract away from health or treat health transition as exogenous would be unable to shed light on the health effect of the China shock (or other economic shocks in general).

The second panel of Table 8 clarifies the economic intuition of the results in the first panel, by showing the workers' choices regarding the optimal health investment in the pre-China economy, and how these choices change in the post-China simulations. We see that the amount of total investment, H^* drops significantly, by 6.8% and 9.5%, because both medical expenditures and non-medical investment decrease substantially.[38] The decrease of

Table 8: The Effects of the China Shock on Health and Health Investment

		Δ from Pre-China Economy	
	Pre-China	Post-China I	Post-China II
Good health share	58.9%	-1.2*pp*	-1.7*pp*
Implied elasticity		-0.0203	-0.0282
(% of empirical elasticity, -0.054)		(37.6%)	(52.2%)
Total health investment, H^*	\$5,140	-6.8%	-9.5%
Medical expenditure, $\min\{H^*, \varepsilon\}$	\$2,359	-11.6%	-11.8%
Partial treatment share	12.7%	-0.0*pp*	+0.9*pp*
No treatment share	6.2%	+1.3*pp*	+0.9*pp*
Non-medical investment, $\max\{H^* - \varepsilon, 0\}$	\$3,024	-10.6%	-14.9%

[38] Although the wage drop is mild in the second post-China simulation, the increase in the probability of

medical expenditures, in turn, is closely related to the increase in the share of workers who choose a partial treatment of sickness ($H^* < \varepsilon$). In particular, more sick workers choose to forego all treatment ($H^* = 0$), increasing its share by 1.3*pp* and 0.9*pp*. Intuitively, due to the minimum health investment, more workers who are on the fence between H^* of zero and a slightly higher value than H_{min} in the pre-China economy are pushed into choosing $H^* = 0$ when the China shock hits. As a result, these workers' medical expenditures change substantially, from higher than H_{min} to 0, contributing to the decrease in overall medical expenditures. Additionally, non-medical investment decreases considerably after the China shock.

We can use these estimates to quantify the aggregate health effects implied from our model. In the first post-China economy, the share of workers with good health decreases from 58.9% to 57.7%. This translates into nearly half a million, or 460,000 individuals, being pushed into bad health, assuming that the manufacturing sector accounts for 15% of the U.S. population (251.6 million) in 1990-1992. According to MEPS, individuals with bad health have more frequent visits to the emergency room (ER) than their good health counterparts—0.44 per person per year versus 0.21—and also longer hospital stays—0.67 inpatient days per person per year, versus 0.26. As a result, our model predicts that, in response to the China shock, the U.S. manufacturing workers experience 103,000 more ER visits and spend 189,000 more inpatient days in hospitals *per year*, causing economically significant aggregate health impacts.

6.2.2 Individual Heterogeneity

The aggregate effect analysis above masks substantial heterogeneity in individuals' responses to the China shock. Given the qualitatively similar patterns in the two post-China simulations, we focus on the first simulation in the remaining analyses.

In Table 9, we show the change in good-health probabilities between the pre- and the post-China economy by worker characteristics.[39] The left panel of Table 9 shows that the health effects of the China shock are more pronounced for workers with good initial health

unemployment implies that the loss of overall economic resources is substantial.

[39]With π_m^D of 0.71 and 0.85 in pre- and post-China economies, the elasticity is the percent change in good health share divided by 93. The aggregate health effects in Table 9 reflect the intensive-margin effect from group-specific elasticities, $\Delta \Pr(G; \boldsymbol{s})$, and the extensive-margin effect from compositional changes, $\Delta \mu(\boldsymbol{s})$. Therefore, the values in the rows with "All" are sometimes larger in magnitude than those in the other group-specific rows.

than for those with bad initial health, both overall and within employment status. For example, employed workers with good initial health suffer a drop of 1.33% in good health transition probabilities, but those with bad initial health suffer a drop of only one-third as much, about 0.46%. Intuitively, these model predictions are because, as seen in Figure 5, the workers with good initial health often choose to incur non-medical investment in health as self-insurance, and they have a larger margin of response to the China shock. These predictions suggest that the decrease in the mean non-medical investment in Table 8 is largely driven by workers with good initial health. This feature is also qualitatively consistent with our empirical finding from Table 1, where the coefficient estimate for the effect of the China shock is large in magnitude and statistically significant for workers with good initial health, but small in magnitude and statistically insignificant for those with bad initial health.

The right panel of Table 9 shows that the health effects of the China shock are more pronounced for those who experience severe sickness, and conditional on sickness, those who are uninsured. For example, while those with the severe sickness of ε_4 see their good-health probability decrease by 2.22% on average, those who are sickness-free (ε_0) experience a mild decline of 1.48%. Among the former group, the decrease in good-health probability is larger for the uninsured than the insured, 2.94% versus 2.04%. This is because the agents in our model may incur additional investment in health beyond treating their sickness, and such tendency decreases in response to the China shock. Thus, even the sickness-free workers (ε_0) face a lower probability of good health. In addition, the drop in non-medical investment is higher for those with severe sicknesses and for those without health insurance.

Table 9: Heterogeneity in Health Effects of the China Shock

% Change in Transition to Good Health (from Pre-China)							
By Initial Health and Employment				By Sickness Shock and Insurance			
Health	All	Unemployed	Employed	Sickness	All	Uninsured	Insured
All	-2.03	-2.04	-1.92	All	-2.03	-2.30	-1.95
Bad	-0.47	-0.49	-0.46	ε_0	-1.48	-1.46	-1.48
Good	-1.47	-1.93	-1.33	ε_1	-1.87	-2.22	-1.78
				ε_2	-2.11	-2.07	-2.22
				ε_3	-2.15	-2.45	-2.06
				ε_4	-2.22	-2.94	-2.04

6.3 Welfare: The China Shock and Welfare Cost

Having established the health effects of the China shock, we discuss the steady-state welfare effects. We first present the benchmark welfare cost, where we compare the pre-China economy with the first post-China simulation. Then, we present the welfare costs from two counterfactuals, the exogenous health economy and the no-health economy, to understand and quantify the role of health investment and health in forming the welfare costs.

In the second column of Table 10, we summarize the benchmark welfare cost of the China shock as a compensating consumption equivalent, the amount of consumption such that the worker's lifetime utility in the post-China economy is the same as that in the pre-China economy. The steady-state welfare loss amounts to 8.4% of average annual consumption in the pre-China economy, or $1,721. There is also heterogeneity by worker characteristics. As the China shock directly impacts the wages of employed workers, the welfare loss is higher for the employed, at $1,989 of annual consumption, whereas for the unemployed, the welfare loss is $966. Within employment status, the welfare loss is similar across health statuses.

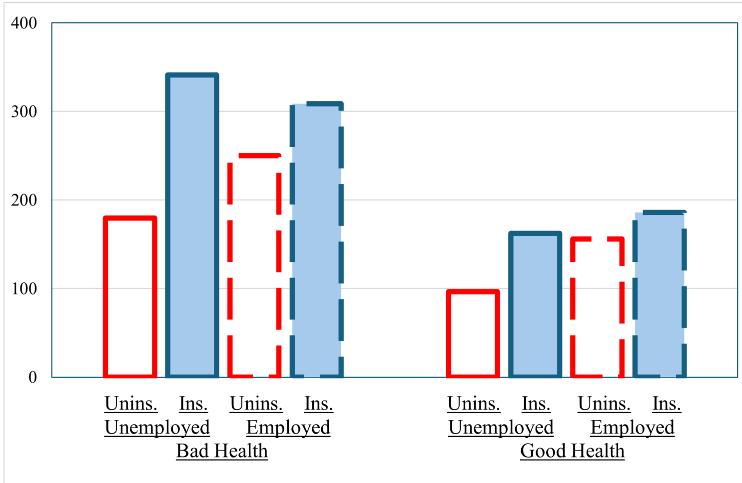
The benchmark welfare cost captures both health and health investment featured in our model. Health matters because the state of bad health carries both direct utility losses and economic consequences such as lower probability of employment and lower earnings when employed. Meanwhile, health investment serves as an additional channel for consumption smoothing; e.g. sick workers who are already in bad health may have an incentive to sacrifice sickness treatment for consumption.

To further understand the roles of these two model features in shaping the welfare effects, we first consider the counterfactual economy in which the workers are not allowed to choose their health investment. We refer to this counterfactual as the "exogenous health

Table 10: Welfare Cost of the China Shock

		Counterfactual Economy, Change from BM Cost	
	Benchmark Economy	Exogenous Health Economy USD (% of BM Cost)	No Health Economy USD (% of BM Cost)
Aggregate	$1,721	+$173 (10%)	-$452 (24%)
Unemployed	$966	+$196 (20%)	-$205 (18%)
Bad health	$919	+$281 (30%)	-
Good health	$974	+$138 (14%)	-
Employed	$1,989	+$157 (8%)	-$512 (24%)
Bad health	$1,818	+$298 (16%)	-
Good health	$1,978	+$181 (9%)	-

Figure 6: The "Value" of Health Investment Channel (USD) by Worker Characteristics



economy." To be specific, we assume that all workers experiencing a sickness shock of ε are forced to spend ε. That is, sickness shocks are equivalent to income shocks in the form of medical expenses. This assumption implies that the exogenous health economy is consistent with models with exogenous health evolution. We further assume that the workers' health transition probabilities are equal to the model-predicted values in the pre-China economy.

The welfare effects from the exogenous health economy are summarized in the third column of Table 10, expressed as changes from the benchmark welfare effects in the previous column. In the aggregate, the welfare cost of the China shock is equivalent to an annual loss in consumption of \$1,895, which is \$173 higher than the benchmark welfare cost. That is, because we have deprived the workers of a consumption-smoothing channel when facing a negative economic shock, the welfare losses are higher, and this difference is about 10% of the benchmark welfare cost. Table 10 also shows that the *additional* welfare loss in the exogenous health economy varies substantially across workers. For example, it is \$281, or 30% of the benchmark welfare loss, for the unemployed with bad health, over twice as high as the additional loss of \$138, or 14%, for the unemployed with good health. These additional welfare losses gauge how much the workers in our benchmark model value the consumption-smoothing channel via endogenous health investment.

Figure 6 further highlights the heterogeneity in this value of health investment by plotting the additional welfare costs in dollar values by health, employment, and insurance statuses. It shows that the additional welfare losses are positive for all worker groups, implying that for all the workers in our benchmark model, endogenous health investment provides an important buffer in the face of an adverse shock, even for employed and insured individuals. Figure 6 also shows that the value of endogenous health investment is especially high for workers with bad health, as they have relatively fewer resources. As a result, abstracting away from endogenous health investment would likely overstate the welfare losses, especially for workers with bad health or with scarce resources. Overall, the results for the counterfactual of the exogenous health economy suggest that modeling endogenous health investment is significant for measuring the welfare effects of the China shock, and may also be useful for studying negative economic shocks in general.

We now move on to clarify how the second model feature, health itself, contributes to the welfare losses from the China shock. To do so, we consider the counterfactual economy in which health does not have any roles, the "no health economy." To be specific, we set the labor income and job transition rates to be averages across health status, and set the utility loss from bad health and probability of sickness shocks to zero.

The results for the no health economy are presented in the fourth column of Table 10. In the aggregate, the welfare cost of the China shock would be \$1,270, substantially lower than the benchmark cost of \$1,721, by 24%. For the unemployed workers, the no-health economy underestimates the welfare loss by \$205, or 18% of the benchmark loss, and for the employed workers, the underestimation is \$512, or 24%. The welfare losses are lower in the no-health economy because the model does not capture the direct utility loss and the adverse labor market outcomes associated with bad health. Therefore, abstracting away from health is likely to substantially underestimate the welfare losses from the China shock and potentially from other economic shocks as well.

6.4 Policy: Universal Health Insurance

In this section, we highlight the policy implications of our model. Specifically, we simulate a post-China economy in which all individuals are covered by health insurance with premium and coinsurance rates specified in Table 4.[40] This is a pertinent counterfactual to consider, as the increase in import penetration from China was most pronounced between 1990 and 2007, before the implementation of the major provisions of the ACA that subsequently expanded insurance coverage. We report the results in the last column of Table 11, as changes relative

[40]We also impose budget neutrality, i.e., individuals receive lump-sum transfers so that the government's aggregate expenditure in the counterfactual economy is equal to that in the benchmark post-China economy.

to the pre-China economy. The rest of Table 11 recap the results from Table 8, to place the results of the counterfactual into context.

In the aggregate, the population share of good-health workers would increase by 1.1*pp* with universal health insurance (UHI), in contrast to the 1.2*pp* drop under the benchmark post-China economy, i.e., UHI would fully remedy the adverse health effect of the China shock. The economic intuition of this result is as follows. First, medical expenditure would only drop by 0.2% under UHI, in sharp contrast to the 11.6% drop under the benchmark. This reversal, in turn, is closely related to the large decrease in the share of workers choosing no treatment, because for the workers who switch out of no treatment, medical expenditures increase sharply, from 0 to above the minimum investment of H_{min}. This effect through medical expenditures enhances the efficacy of UHI. On the other hand, the drop in the average non-medical investment is similar to that in the benchmark at around 10%, as health insurance does not cover non-medical investments in our model. This feature limits the efficacy of UHI. In the aggregate, with a relatively modest 5.8% decrease in the wage, the first effect dominates, making UHI an effective policy for mediating adverse health effects. This finding suggests that the overall efficacy of UHI is nuanced and hinges upon the effects of wage losses on investments and the extent to which health insurance can compensate for such losses. To further clarify this, we further examine how the efficacy of UHI varies across commuting zones experiencing different exposures to the China shock.

We start by multiplying the percentiles of the distribution of the change in import penetration per worker, ΔIPW (e.g. \$4,500 per worker, or 4.5 units, at the 75th percentile) by the estimate of 2.14% per unit of ΔIPW (Table 9 of Autor et al., 2013), to obtain the percentiles of the distribution of empirically estimated wage changes (e.g. $4.5 \times 2.14\% = 9.7\%$ at the 75th percentile). We list these percentiles and wage changes in the first two columns of Table 12. We interpret each percentile as a single commuting zone and simulate the ef-

Table 11: Effects of Universal Health Insurance

		Post-China, Δ from Pre-China Economy	
	Pre-China	Benchmark Economy	Universal Insurance
Good health share	58.9%	-1.2*pp*	+1.1*pp*
Total health investment	\$5,140	-6.8%	-1.2%
Medical expenditure	\$2,359	-11.6%	-0.2%
Partial treatment share	12.7%	-0.0*pp*	-0.51*pp*
No treatment share	6.2%	+1.3*pp*	-4.0*pp*
Non-medical investment	\$3,024	-10.6%	-10.0%

Table 12: Effects of Universal Health Insurance by IPW Exposure

		% Population with Good Health (pp change from Pre-China)	
ΔIPW Percentile	Wage Drop (%)	Benchmark Insurance	Universal Insurance
5^{th}	0.2	58.9 (-0.00)	60.2 (+1.26)
10^{th}	0.4	58.8 (-0.05)	60.1 (+1.21)
25^{th}	2	58.6 (-0.35)	59.8 (+0.90)
50^{th}	5.5	57.8 (-1.13)	59.2 (+0.24)
Mean (53^{rd})	7.3	57.4 (-1.53)	58.8 (-0.11)
75^{th}	9.7	56.9 (-2.00)	58.3 (-0.60)
90^{th}	15.8	55.6 (-3.31)	57.1 (-1.85)
95^{th}	21.7	54.3 (-4.58)	55.9 (-3.07)

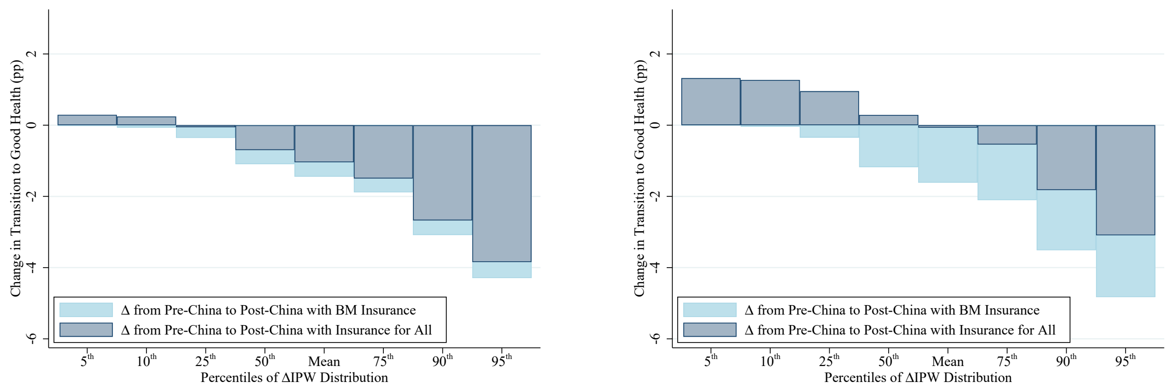
fect of the China shock by feeding in the commuting zone specific wage drops exogenously. We report the results of these simulations in the third column of Table 12 and perform the same counterfactual UHI analysis and present the results of these counterfactuals in the last column.

From Table 12, we see that the commuting zones with high exposure to the China shock experience a large deterioration in health. For example, although the median commuting zone experiences a drop of 1.1pp in the population share of good health, the 95^{th} percentile commuting zone has a sharp decline of 4.6pp, more than 8%. We also see that while UHI helps mitigate these negative health effects, the efficacy of the mitigation varies substantially across commuting zones. For a commuting zone with a small wage decline (e.g. those below the median), UHI delivers higher population shares with good health than the pre-China economy, more than fully reversing the adverse health effect of the China shock. In contrast, for the commuting zone at the 95^{th} percentile, even with UHI, the good health share would still drop by 3.1pp. This means that UHI would only remedy around 33% ((4.6-3.1)/4.6) of the health deterioration from the China shock. The intuition of these results is similar to that for Table 11. Relative to the benchmark post-China economy, UHI has little effect on the change in non-medical investment, but increases medical expenditure substantially. When the wage decline is small, the increase in medical expenditure dominates. With large wage declines, however, the drop in non-medical investment dominates, limiting the overall efficacy of UHI.

In Figure 7, we investigate how the efficacy of UHI would vary by sickness shock. Figure 7(a) plots the change in the good health probability relative to the pre-China economy under benchmark insurance and under UHI by percentiles of ΔIPW among those with the

Figure 7: Effects of Universal Health Insurance by IPW Exposure and Sickness

(a) Moderate Sickness Shocks (ε_2) (b) Severe Sickness Shocks (ε_4)



moderate sickness of ε_2, and Figure 7(b) plots this change for the severe sickness of ε_4.[41] In both plots, the gap between the two bars measures the effectiveness of UHI. We see from Figure 7(a), that among those mildly sick, the gap between the bars is small across the ΔIPW distribution, in contrast to those with severe sicknesses in Figure 7(b). In other words, Figure 7 shows that for severely (mildly) sick individuals, UHI is (not) very effective in mitigating the adverse health effects of the China shock.

7 Conclusion

In this paper, we develop a model with endogenous health dynamics to study the mechanism, welfare consequences, and policy implications of the impacts of economic shocks on health. A key innovation of our model is that workers may optimally choose to forego or only partially treat a sickness, or to incur non-medical investment in health beyond the full treatment of sickness itself. We use the China shock as our empirical application and estimate its causal effect on workers' probabilities of being in good health using micro-level panel data. Our estimates show that the elasticity of future good health probability with respect to IPW is around -0.05. We then embed our worker-level model of health transition dynamics into a sector-level model of international trade.

The calibrated model simulation shows that the health investment mechanism is quantitatively important, capturing about 40% of our empirical elasticity estimates. It generates an economically significant aggregate health effect, pushing nearly half a million manufacturing

[41]The graphs for ε_0 and ε_1 are similar to Figure 7(a), and the graph for ε_3 is similar to Figure 7(b).

workers into bad health. Our simulations suggest that the average worker's welfare loss from the China shock is equivalent to a drop in annual consumption of $1,721. Importantly, the welfare losses would be over-estimated in an economy with exogenous health dynamics, and under-estimated in an economy that abstracts away from health. Our evaluations show the significance of capturing both endogenous health investment and health itself in measuring the welfare costs from negative economic shocks.

In terms of policy implications, we find that universal health insurance, if implemented after the China shock, would provide a useful remedy for the adverse health effects, primarily through the substantial improvements in the treatment of sicknesses. However, since health insurance does not cover non-medical expenditures in health, the efficacy of universal health insurance would be fairly limited for workers with large exposure to the China shock who suffer large wage losses, with the silver lining that it would still be highly effective for the individuals with the most severe sicknesses. Our results speak to the recent discussions about whether some form of universal health insurance would be beneficial for the U.S. (e.g. Baicker et al., 2023; Einav and Finkelstein, 2023; Chen et al., 2024). These analyses may also be relevant for the second China shock on the horizon, as the impacts of China's excess industrial capacity may be felt around the globe, including in many middle-income countries with evolving healthcare systems.[42]

[42] Quoting Janet Yellen, the U.S. Treasury Secretary, "China's industrial policy may seem remote as we sit here in this room, but if we do not respond strategically and in a united way, the viability of businesses in both our countries and around the world could be at risk." (Lawder, 2024)

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Online Appendix to "Investing in Health during Good and Bad Times: An Application to the China Shock"

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October 21, 2025

A Data

A.1 Panel Study of Income Dynamics

We use the publicly available PSID data (in years 1991-2011) combined with the restricted commuting-zone identifiers and the IPW data for empirical analysis in Section 3. Further, we obtain income in the manufacturing sector in the pre-China shock economy and its health gradient for calibration using the PSID data in years 1991-1996. The details of the process for calibrating the income and its health gradient are summarized in Section D.1 below.

The sample is restricted to those between the ages of 18 and 64 who work more than 1,600 hours (full-time) in their initial year of entry into the PSID. For the measure of health status, we use self-reported health status, which assigns a value between 1 and 5 with 1 being in excellent health. We define a worker to be in good health if he reports to be in the top two levels of health and in bad health, otherwise. The number of observations for the empirical analysis is 33,376.

In Table A.1, we report the summary statistics from our merged data set. The averages of the sample are reported with standard deviations in parentheses. Labor income is expressed in 2015 dollars.

A.2 Medical Expenditure Panel Study (MEPS)

We use the Household Component of the MEPS data to construct target moments related to medical expenditures and health status transitions. MEPS began in 1996 and conducts several rounds of interviews over two years, making it a suitable data set for analyzing

Table A.1: Descriptive Statistics

Variable	All	by IPW Quartile Q1	Q2	Q3	Q4
IPW ($,000/Worker)	1.44	0.22	0.54	1.17	3.43
	(1.68)	(0.09)	(0.12)	(0.28)	(2.05)
Age	41.43	39.96	40.76	41.62	42.99
	(10.97)	(10.31)	(10.69)	(10.95)	(11.51)
Male	0.78	0.78	0.78	0.79	0.78
	(0.41)	(0.41)	(0.41)	(0.41)	(0.42)
College	0.56	0.53	0.56	0.56	0.60
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Labor income (log)	10.73	10.69	10.78	10.72	10.71
	(0.86)	(0.80)	(0.87)	(0.87)	(0.88)
Health status (5 levels)	3.82	3.89	3.87	3.83	3.72
	(0.92)	(0.90)	(0.90)	(0.92)	(0.95)
Good-Health Share	0.65	0.68	0.67	0.65	0.61
	(0.48)	(0.47)	(0.47)	(0.48)	(0.49)
Manufacturing	0.20	0.18	0.22	0.19	0.21
	(0.40)	(0.38)	(0.41)	(0.40)	(0.40)

Note: Authors' calculations from the merged IPW and PSID data (1991-2011) using longitudinal individual weights.

health transitions in our framework. Additionally, MEPS reports medical expenditures at the individual level, in contrast to the PSID with family-level expenditures.

We use panels 1 through 13 which cover data between 1996 and 2009. Our sample is restricted to non-military, non-institutionalized civilians aged between 18 and 64 with a total number of observations of 107,781. We use total medical expenditures (in 2015 U.S. dollars) among the insured and employed individuals in our sample to construct the medical expenditure deciles for establishing the empirical relationship in Figure 2. For target moments in Table 2 and predetermined sickness shock values reported in Table 4, we use predicted values of medical expenditures, conditional on positive expenditures, after controlling for demographic characteristics that include age, sex, race, education (five categories), Census region, marital status, and survey panel dummies. After establishing the sickness value grids, we calculate the coinsurance rates using the ratios between total expenditures and out-of-pocket expenditures within the sickness shock bins.

As for the share of individuals without medical utilizations, we use the Household Component Event files in MEPS. The recorded medical events include eight categories: prescribed medicines, dental visits, hospital inpatient stays, emergency room visits, outpatient visits, home health provider visits, office-based medical provider visits, or other medical expenses.

We define an individual to not have utilized medical services if he does not have any of the events during the calendar year. These shares are reported in Table 2.

B Empirical Analysis: China Shock and Health

B.1 Effects of Import Penetration: Region-Level Analyses

To complement the individual-level analysis of IPW and the health of workers, we conduct a region-level analysis by utilizing cross-sectional variations. Although our measure of IPW is at the commuting zone level, some commuting zones in the data only have small numbers of observations. As this may cause the dependent variable to be noisy, we aggregate commuting zones into regions by their IPW exposure. Specifically, our estimation equation, following Autor et al. (2013), is

$$\Delta \text{GHSH}_{r,t} = \beta + \beta_t + \gamma \cdot \mathit{\Delta}\text{IPW}_{r,t} + \varepsilon_{r,t}, \tag{A.1}$$

where the dependent variable, $\Delta\text{GHSH}_{r,t}$, is the change in the share of individuals with good health in region r within period t; β_t is the period fixed effect; and $\mathit{\Delta}\text{IPW}_{r,t}$ is the change in the IPW in region r in period t. Because we instrument the change in import penetration per worker, $\mathit{\Delta}\text{IPW}_{r,t}$, using the change in its instrument specified in Equation (9), we interpret the coefficient estimate of γ as the causal effect of the China shock on the population share of good health.

In column (1) of Table A.2, we report results using two time periods, 1991-1999 and 2001-2007, and 10 bins of IPW exposure per period. The F-statistic of the first-stage estimation is 102.69, and γ, the coefficient estimate of $\mathit{\Delta}\text{IPW}_{r,t}$ is negative and statistically significant, suggesting that increases in import penetration per worker reduces the share of workers with good health in the region. Dividing the coefficient estimate of -0.025 by the mean value of the good health share, we obtain that the elasticity of good-health share with respect to import penetration per worker is -0.0532.

This result is also illustrated in Figure A.1(a), which plots the change in the population share of good health, $\Delta\text{GHSH}_{r,t}$, against the predicted value of $\mathit{\Delta}\text{IPW}_{r,t}$ by its instrument, after netting out the period fixed effect, β_t. The numerical labels show the decile and the label "$*$" indicates the second period; e.g. "2" is the second decile from the first period,

Table A.2: Import Penetration and Health Distribution, Region-Level Results

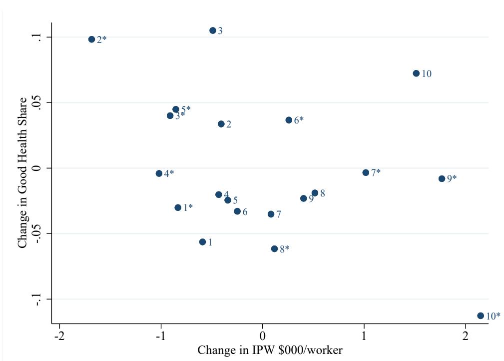
Dependent variable: Change in regional share of individuals with good health				
	(1)	(2)	(3)	(4)
Time Periods	1991-1999 & 2001-2007		1991-2007	
# Bins by ΔIPW	10	20	20	40
γ	-0.0253**	-0.0219**	-0.0295**	-0.0328**
	(-2.54)	(-2.01)	(-2.30)	(-2.22)
Implied Elasticity	-0.0532	-0.0480	-0.0692	-0.0781
First-Stage F-Statistic	102.69	79.36	39.41	46.14
Number of Observations	20	40	20	40

Note: The table reports regression coefficients γ from Equation (A.1) with t-statistic in parentheses. We use the number of observations in each region as weight. The first-stage F-statistics are for the $\Delta \text{IPW}_{r,t}$. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$

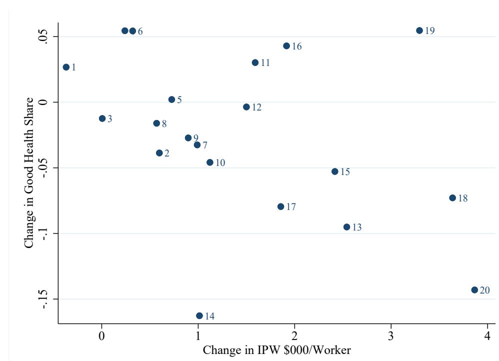
1991-1999, and "7∗" is the seventh decile from the second period, 2001-2007. The scatter plot clearly illustrates a negative relationship between $\Delta \text{GHSH}_{r,t}$ and the predicted value of $\Delta \text{IPW}_{r,t}$.

Figure A.1: Import Penetration and Health Distribution

(a) Two time periods, with 10 ΔIPW bins



(b) One time period, with 20 ΔIPW bins



Note: Each point in scatter plots represent each observation. Plot (a) and (b) correspond to specifications in columns (1) and (3) in Table A.2, respectively.

Columns (2) to (4) of Table A.2 show the results of different implementations of regression (A.1), where we use 20 bins (columns (2) and (4)) and/or use a single, longer, time period of 1991-2007 (columns (3) and (4)) similar to Autor et al. (2013). Figure A.1(b) illustrates the results in column (3), with one single time period and 20 bins. In all specifications, the coefficient estimate is negative and statistically significant, and its value is similar to column (1). These results suggest that the adverse effects of the China shock on workers' probability of good health are robust.

Overall, Table A.2 shows that the elasticity of the probability of good health with respect to IPW ranges between -0.048 and -0.078, with a mid-point of -0.060. These elasticities are similar to those reported for the benchmark individual-level analysis in Section 3.1.

B.2 Robustness Checks: Individual-Level Analysis

In Table A.3, we include manufacturing-by-year fixed effects in the estimation of Equation (10), and obtain very similar results relative to Table 1. In Tables A.4 and A.5, we present results of estimating Equation (10) in subsamples, male workers and manufacturing sector workers, respectively. We include manufacturing-by-year fixed effects for male worker analysis, and year fixed effects for manufacturing sector analysis. In both subsamples, we find that our results are robust. Among male workers, those in the manufacturing sector, with low income, and with initially good health experience larger and statistically significant adverse effects of health from import penetration. These results hold when we restrict our sample to only manufacturing sector workers in Table A.5. We find that the effect among all manufacturing workers, when analyzed separately, shows an even larger coefficient of -0.038, compared to -0.027, the manufacturing-sector-specific effect using all workers in the benchmark regression. These additional results suggest that the causal impact of IPW on workers' health is robust.

Table A.3: Import Penetration and Health, Manufacturing-Year Fixed Effects

γ_k	Probability of good health			
	(1)	(2)	(3)	(4)
All	-0.019			
	(-1.60)			
Manufacturing		-0.027**		
		(-2.12)		
Non-Manufacturing		-0.012		
		(-1.11)		
Income Q1			-0.051***	
			(-2.87)	
Income Q2			-0.025	
			(-1.36)	
Income Q3			-0.022*	
			(-1.75)	
Income Q4			-0.012	
			(-0.98)	
Initial Health Good				-0.031**
				(-2.42)
Initial Health Bad				0.018
				(1.54)
First-Stage F	12.65	6.97	2.91	6.41
Number of Obs.		32,519		

Note: The standard errors are clustered by commuting zone and t-statistics are in parentheses. All regressions include worker and manufacturing-by-year fixed effects and the vector of time-varying worker characteristics as controls. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

Table A.4: Import Penetration and Health, Male Workers

γ_k	Probability of good health			
	(1)	(2)	(3)	(4)
All	-0.019			
	(-1.60)			
Manufacturing		-0.030**		
		(-2.12)		
Non-Manufacturing		-0.010		
		(-0.90)		
Income Q1			-0.056***	
			(-2.73)	
Income Q2			-0.026*	
			(-1.75)	
Income Q3			-0.021	
			(-1.60)	
Income Q4			-0.014	
			(-1.06)	
Initial Health Good				-0.029**
				(-2.32)
Initial Health Bad				0.019
				(1.42)
First-Stage F	14.70	8.13	3.88	7.01
Number of Obs.	24,238			

Note: The standard errors are clustered by commuting zone and t-statistics are in parentheses. All regressions include worker and manufacturing-by-year fixed effects and the vector of time-varying worker characteristics as controls. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

Table A.5: Import Penetration and Health, Manufacturing Sector Workers

γ_k	Probability of good health		
	(1)	(2)	(3)
All	-0.038*		
	(-1.77)		
Income Q1		-0.073	
		(-1.34)	
Income Q2		-0.042	
		(-1.50)	
Income Q3		-0.036	
		(-1.40)	
Income Q4		-0.036*	
		(-1.70)	
Initial Good			-0.048**
			(-2.24))
Initial Bad			-0.012
			(-0.60))
First-stage F	5.65	1.57	3.03
Number of Obs.		7,103	

Note: The standard errors are clustered by commuting zone and t-statistics are in parentheses. All regressions include worker and year-fixed effects and the vector of time-varying worker characteristics as controls. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$

C Equilibrium of the Trade Model

Given government policies, a stationary equilibrium in the manufacturing sector consists of prices $\{w_m, p_m, P_m\}$, value and policy functions for workers $\{V(\mathbf{s}), c(\mathbf{s}), a'(\mathbf{s}), H(\mathbf{s})\}$, policies for firms $\{L_m, n_m, n_m^*, x_m\}$, government expenditures $\mathcal{G}$, and a stationary measure $\mu(\mathbf{s})$ where $\mathbf{s} = \{l, x, a, in, \varepsilon, z\}$ such that:

1. Value and policy functions solve the household's optimization problem specified in (2).

2. Prices in the manufacturing sector satisfy the following conditions.

$$\begin{aligned}
\text{Final good demand :} \quad & x_m = \frac{\phi_m Y}{P_m} \\
\text{Final good supply :} \quad & x_{mS} = A\left[\omega_m^{\frac{1}{\sigma}} n_m^{\frac{\sigma-1}{\sigma}} + (1-\omega_m)^{\frac{1}{\sigma}} (n_m^*)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
\text{Demand for inputs:} \quad & n_m = \omega_m (p_m)^{-\sigma} X_{mS} P_m^{\sigma-1} \\
& n_m^* = (1-\omega_m)(\tau_m^* p_m^*)^{-\sigma} X_{mS} P_m^{\sigma-1} \\
\text{Supply of domestic inputs:} \quad & p_m = \frac{w_m}{\psi_m}.
\end{aligned}$$

3. Government expenditures $\mathcal{G}$ are such that the government's budget constraint holds:

$$\begin{aligned}
&\sum_{\mathbf{s}} b \cdot \mathbb{I}_{l=U} \mu(\mathbf{s}) + \sum_{\mathbf{s}} tr(\mathbf{s}) \cdot \mu(\mathbf{s}) \\
&\quad + \sum_{\mathbf{s}} \left[\chi(\varepsilon, x) \min\{H, \varepsilon\} - \pi\right] \cdot \mathbb{I}_{in=1} \mu(\mathbf{s}) + \mathcal{G} = \sum_{\mathbf{s}} T(y(\mathbf{s})) \mu(\mathbf{s})
\end{aligned}$$

4. The following market clearing conditions hold for the manufacturing sector.

$$\begin{aligned}
\text{Aggregate labor supply:} \quad & L_m = \sum_{\mathbf{s}} \nu(x) \cdot z \cdot \mathbb{I}_{l=E} \mu(\mathbf{s}) \\
\text{Domestic input:} \quad & z_{mS} = n_m + D_m^* \cdot (p_m)^{-\sigma} \\
\text{Final good:} \quad & x_{mS} = x_m
\end{aligned}$$

5. The probability distribution $\mu(\mathbf{s})$ is a stationary distribution associated with policy functions.

D Calibration and Quantitative Analysis

D.1 Effects of Health on Income: Calibration of $\nu(B)$

We estimate the health effect of income $\nu(B)$ outside the model using the PSID data. In doing so, we address the selection bias using a standard two-stage procedure introduced by Heckman (1979). We follow Low and Pistaferri (2015) and use geographical (state) and temporal policy variations to construct instrumental variables for employment decisions. In particular, we incorporate benefits from the Earned Income Tax Credit, Unemployment Insurance, the Supplemental Nutrition Assistance Program, and Aid to Families with Dependent Children (that became Temporary Assistance of Needy Families) to construct benefits that a "representative" earner would receive from his residential state in a given year. The use of benefits of a representative earner, not that of the specific individual, ensures that the benefits we use as an instrument are not endogenous. Using the instrumental variable, we estimate the effect of health on hourly wage, and use annual hours worked to calibrate the health effect on annual income.

In Table A.6, we report the coefficient estimates from using two-step and FIML (with and without weights) procedures. We observe that the selection term is statistically significant and that the estimated effects of bad health on manufacturing sector workers, after controlling for selection, are similar in magnitude across different specifications. We then use predicted hourly wages of bad and good health workers in the manufacturing sector from the two-step estimation (3.20 and 3.00 for good and bad health, respectively) and annual hours worked by full-time workers (2,200 and 2,136 for good and bad health, respectively) to obtain the income ratio of bad health workers $\nu(B)$ of value 0.8. This value, together with the average manufacturing worker's annual income from the data of \$50,211 are used as labor income in the quantitative model.

Table A.6: Effects of Health on Wage

	Two-Step	FIML, no weights	FIML, weights
log Hourly wage			
Manufacturing× Bad	-0.112***	-0.112***	-0.109***
	(0.014)	(0.016)	(0.026)
Non-Manufacturing × Good	-0.262***	-0.259***	-0.257***
	(0.018)	(0.017)	(0.025)
Non-Manufacturing × Bad	-0.358***	-0.350***	-0.371***
	(0.020)	(0.018)	(0.028)
Age	0.073***	0.072***	0.070***
	(0.003)	(0.004)	(0.006)
Age-squared	-0.001***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)
High school graduates	0.250***	0.244***	0.248***
	(0.012)	(0.016)	(0.027)
Some college	0.388***	0.382***	0.373***
	(0.013)	(0.018)	(0.031)
College graduates	0.624***	0.616***	0.619***
	(0.015)	(0.023)	(0.036)
More than college	0.701***	0.693***	0.689***
	(0.016)	(0.010)	(0.014)
Selection			
Manufacturing × Bad	-0.115	-0.123	-0.120
	(0.086)	(0.086)	(0.126)
Non-Manufacturing × Good	-0.367***	-0.351***	-0.327***
	(0.122)	(0.122)	(0.163)
Non-Manufacturing × Bad	-0.624***	-0.623***	-0.581***
	(0.122)	(0.124)	(0.168)
log Welfare benefits	-0.086**	-0.098**	-0.136**
	(0.037)	(0.039)	(0.060)
Mills	0.305***	0.192***	0.122***
	(0.118)	(0.038)	(0.072)
Observations	24,956	24,956	17,062

Note: The table reports regression coefficients from Heckman's (log) wage estimation procedures. Additional controls include race, sex, marital status, region, family size, number of children, and (non)-manufacturing × year fixed effects. Standard errors, reported in parentheses, are clustered at the individual level. $* p < 0.10$, $** p < 0.05$, $* * * p < 0.01$

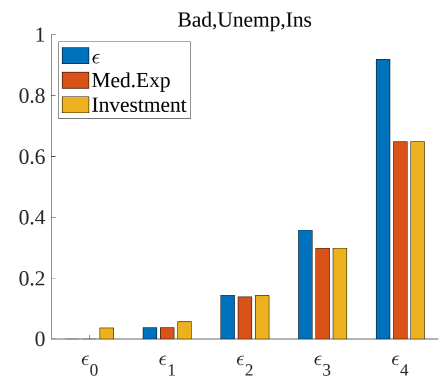
D.2 Model Feature: Health Investment of Unemployed Workers

In Figure A.2, we present health investment decisions of unemployed workers, analogous to employed workers' decisions presented in Figure 5. Each plot summarizes the size of the sickness shock ε, the average medical expenditures $\min\{H^*, \varepsilon\}$, and the average health investment H^* by initial health status and sickness shock. The qualitative investment patterns of unemployed workers are similar to those of employed workers. Non-medical health investment is common across all types of workers when individuals do not face a sickness shock or a mild sickness shock. In contrast, when experiencing a severe sickness shock, the extent of foregone or partial sickness treatment increases sharply, especially more so for those who are uninsured.

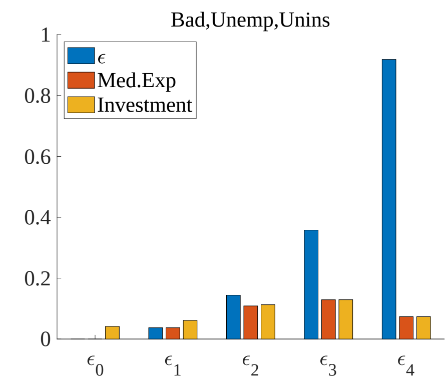
Figure A.2: Health Investment of Unemployed Workers

Bad Initial Health

(a) Insured

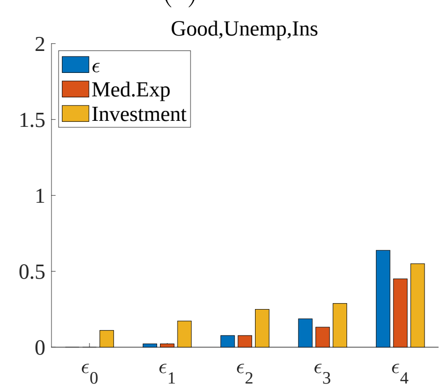


(b) Uninsured

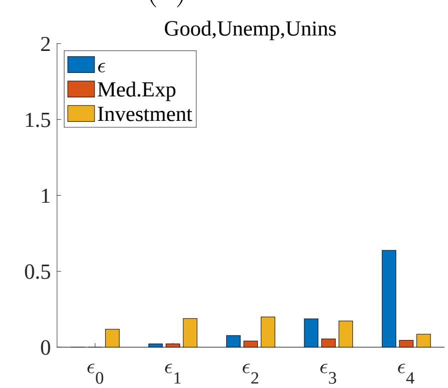


Good Initial Health

(c) Insured



(d) Uninsured



D.3 Model Validation: The Value of Health

We provide the details of the model validation in subsection 5.2, where we compare the model-predicted value of a statistical injury (VSI) with our empirical estimates.

D.3.1 Model-Predicted VSI

Hall and Jones (2007) We start with Hall and Jones (2007)'s prediction for value of a statistical life (VSL), whose approach we closely follow, by using their notation and equation numbers. Hall and Jones (2007)'s value function, $v_{a,t}$, is given by their equation (21), where a is age and t is year. If we apply the Envelope theorem to equation (21), we have

$$\frac{\partial v_{a,t}}{\partial p_{\text{death}}} = -\beta v_{a+1,t+1}, \frac{\partial v_{a,t}}{\partial y_t} = \lambda_t = c_t^{-\gamma},$$

where $\lambda_t = c_t^{-\gamma}$ comes from their equation (18) and y_t denotes income. As a result,

$$VSL = -\frac{\partial v_{a,t}/\partial p_{\text{death}}}{\partial v_{a,t}/\partial y_t} = \frac{\beta v_{a+1,t+1}}{c_t^{-\gamma}}. \tag{A.2}$$

Equation (A.2) matches lines 148 and 220 of their posted Matlab codes in the file "estimateb.m".

Our Model We now show our model's prediction for VSI, and switch to the notation and equation numbers in our model. Let the superscript "*" denote the steady-state value. To be specific, V^* is the steady state value function, given by equation (2), I^* is the steady-state income, and F^* is the steady-state probability of future good health.

Applying equation (A.2), we have:

$$\frac{\partial I^*}{\partial F^*} = \frac{\partial V^*/\partial F^*}{\partial V^*/\partial I^*}. \tag{A.3}$$

Both derivatives on the right-hand side of equation (A.3) are envelope types. $\partial V^*/\partial F^*$ is the change in the value function in response to an exogenous change in the good-health probability that comes from the change in the health production technology. $\partial V^*/\partial I^*$ is the change in the value function in response to an exogenous change in income. Our model predicted VSI is then:

$$\text{VSI} = -\frac{\partial I^*}{\partial \text{Prob(Injury)}} = -\frac{\partial I^*}{\partial F^*} \cdot \frac{\partial F^*}{\partial \text{Prob(Injury)}}. \tag{A.4}$$

Computation Equations (A.3) and (A.4) say that we can compute the value of our model predicted VSI from the values of $\partial V^*/\partial F^*$, $\partial V^*/\partial I^*$, and $\partial F^*/\partial \text{Prob(Injury)}$. For $\partial V^*/\partial F^*$, we perturb the pre-China economy by increasing $\alpha(x, \varepsilon)$ uniformly by 0.05. For $\partial V^*/\partial I^*$, we perturb the pre-China economy by increasing w_m by 5%. Finally, we have shown that $\partial F^*/\partial \text{Prob(Injury)}$ = -0.37 in the text (we explain how we obtain this estimate below). Plugging the values of $\partial V^*/\partial F^*$, $\partial V^*/\partial I^*$, and $\partial F^*/\partial \text{Prob(Injury)}$ into equations (A.3) and (A.4), we obtain that the model predicted VSI is $176,000.

D.3.2 Estimating VSI and $\partial F^*/\partial$Prob(Injury)

We start with the BLS data for non-fatal injury by industry from 1996-2000, as in https:// www.bls.gov /iif/ nonfatal-injuries-and-illnesses-tables /soii-summary-historical.htm. The industry codes in these data are 1987 SIC (Standard Industry Classification), and we map them into the 1990 Census industry codes used in the CPS data by using the mapping of Autor et al. (2019), downloaded from https://www.ddorn.net/data.htm (C8). We then merge the non-fatal injury data with our CPS data. The mean non-fatal injury rate is 2.41 per hundred in our sample.

Our estimation of VSI follows the literature (e.g. Viscusi and Aldy, 2003). To be specific, we estimate a Mincer wage regression augmented by the industry-specific non-fatal injury rate, controlling for age, age square, race, gender, marital status, education, as well as state fixed effects. We cluster our standard errors by industry. We obtain the log-wage-injury gradient of 3.31 (s.e. = 1.49), where the regression $R^2 = 0.38$ and N = 76,192. This result says that the VSI is about 3.3 times the average wage of $46,300 in our sample, or about $153,000.

To estimate $\partial F^*/\partial \text{Prob(Injury)}$, we change the dependent variable from log wage to the indicator variable for being in good self-reported health. The coefficient estimate for the injury rate is -0.37 (s.e. = 0.18), where the regression $R^2 = 0.074$ and N = 83,702. This result says that conditional on the demographics controls, an increase in the industry injury rate of one per hundred, or $1pp$, is associated with a $0.37pp$ decrease in the probability of good health, implying that $\partial F^* / \partial \text{Prob(Injury)} = -0.37$.

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