Care for the China Syndrome: Trade Shock, Sick Workers, and Access to Healthcare*

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[Preliminary]

Abstract

We investigate how the China shock affects workers' health through optimal health investment decisions. We empirically estimate the elasticity of import penetration per worker on future good health probability. In our quantitative model, workers make decisions on their health investments based on sickness shocks, income, and insurance status. They have the option to either partially treat sickness or invest in their health beyond just treating the sickness. In our quantitative evaluation of the China shock, we find that there is little (substantial) change in the probability of future good health of employed workers whose health is initially bad (good), in line with our empirical estimates. In addition, uninsured workers who encounter a severe sickness shock experience a significant decline in their health. Overall, the health investment mechanism accounts for over two-fifths of the estimated empirical elasticity, implying that the China shock pushes nearly half a million individuals in U.S. manufacturing into bad health through this mechanism. In our counterfactuals, we find that universal health insurance would have remedied over 80% of the adverse health effects from the China shock, with large heterogeneity across sickness shocks and across commuting zones with varying degrees of exposure to import penetration.

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1 Introduction

A large empirical literature finds that in response to the "China shock"—an increase in import penetration from China in the U.S. manufacturing sector—the local labor market adjustment was slow and that workers experienced long-term adverse effects in earnings and employment (e.g. Autor et al., 2013; Autor et al., 2014). Additional research has complemented these studies using dynamic models to quantify the mechanisms underlying the earnings and employment consequences of the China shock (e.g., Lyon and Waugh, 2018; Caliendo et al., 2019). Considering the significant economic effects on workers, recent empirical studies have also indicated that the China shock had adverse effects on workers' health (e.g., Adda and Fawaz, 2020; Pierce and Schott, 2020). However, the mechanisms behind these health effects remain unexplored. This is an important open question, because the China shock may have persistent effects on health, which in turn, would have significant implications for individual workers' well-being and potential government policies.

In order to better understand these mechanisms, it is important to recognize that many in the U.S. do not have health insurance coverage that may limit their healthcare utilization when they experience a sickness. According to the National Health Interview Survey (NHIS), 18.6% of working-age adults reports not receiving medical care in 2011-2012 due to financial constraints. 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. These features of "*under*-investment" or "*over*-investment" (relative to sickness) in health, however, have not been incorporated into the quantitative models of health transition dynamics in the literature (e.g. Cole et al., 2019; Fonseca et al., 2021).

In this study, we first estimate the effect of import penetration on the likelihood of good health at the regional and worker levels. Our empirical results show that exposure to the China shock decreases the probability of good health, complementing the previous studies discussed above. Given these empirical findings, we develop a quantitative dynamic model in which workers' probability of future good health is determined by sickness shocks and endogenous health investment. Importantly, when workers experience sickness shocks, they may optimally choose to under-invest (e.g., only partially treat their sickness) or over-invest (e.g., receive additional therapies beyond the treatment of sickness) in health. We calibrate the model to match the key empirical patterns including workers' health dynamics, and use the model as a laboratory to quantify the health effects of the China shock through the health investment mechanism, and evaluate the efficacy of potential policy responses, such as universal health insurance.

Our first goal is to estimate the effects of the China shock on the probability of good health, the dynamics of which is the focus of our model. Following Autor et al. (2013), we measure the magnitude of the China shock as import penetration per worker (IPW) in their commuting zones. We further combine the IPW data with the individual-level health and geographical data in the Panel Study of Income Dynamics (PSID). At the regional level, we find that the elasticity of good health share with respect to import penetration is around -0.060. Further utilizing the detailed individual-level characteristics and accounting for individual fixed effects, our analysis estimates the elasticity of future good health probability with respect to IPW at -0.054 for full-time manufacturing workers. The effects of the China shock are heterogeneous, with more pronounced effects on workers with lower income and those with good initial health.

Given these novel empirical findings, we incorporate both worker-level and sector-level analyses into our model. At the sector level, the manufacturing sector produces outputs from both domestic and foreign intermediate inputs, and the production of domestic inputs is exposed to import penetration, capturing the key features of the China shock. International trade affects both the sectoral wages and employment endogenously, as the labor market for the manufacturing sector clears. At the worker level, we explicitly model the endogenous evolution of workers' good-health probability as in Cole et al. (2019) and Fonseca et al. (2021), while also introducing distinctive features from theirs. In particular, workers face health transition risks in the form of sickness shocks. In response, they can choose health investment to improve the probability of future good health. Unlike in previous studies, workers may optimally choose to under-invest in health, where the medical expenditure is insufficient to fully treat the sickness. They may also choose to over-invest, above and beyond the full treatment (through, e.g., massages or therapies). In other words, the health transition depends on both the sickness shock the worker experiences and his choice of health investment, which could be different from each other.

The next step in our analysis is to calibrate the model. Using the Medical Expenditure Panel Survey (MEPS) data, we document empirical facts that relate health transitions, medical expenditures, and insurance statuses. Two key observations are first, that those with bad initial health and high current medical expenditures are less likely to transition into good health in the future; and second, that uninsured individuals have lower probabilities of transitioning into good health, conditional on current period's medical expenditures (and other health and demographic conditions). Motivated by these observations, we interpret high medical expenditures as severe sickness shocks, and use the medical expenditure distribution from MEPS to measure the health-dependent sickness shock distribution in our model. With these parameter values in hand, we specify a flexible Weibull function for the transition probability to good health (health production function) that differ by initial health status. The health production function and utility parameters are calibrated to match worker-level variables that include health transition probabilities, shares without medical utilizations, and average medical expenditures, by worker demographics. We then utilize labor market clearing conditions in the manufacturing sector and trade data to calibrate the sector-level parameters.

The calibrated health production function features a large heterogeneity across initial health statuses. In particular, for those with bad initial health, the marginal benefit of investment is higher at low amounts, inducing low share of zero medical utilizations and high share of partial treatment of sicknesses, but not necessarily over-investment. In contrast, individuals with good initial health have higher incentives to over-invest in health. As such, the calibrated model is able to match the empirical differences in medical expenditures and health transition probabilities across health statuses. The model also captures discrepancies in investment choices across insurance status of workers that are in line with empirical observations. We further validate our model's ability to match untargeted moments that govern health outcomes and health investment incentives, both for under- and over-investment. In particular, our model predicts that 16.7% of workers choose under-investment, which is similar to the 18.6% from NHIS.

Our simulation of the China shock induces a 5.75% drop in manufacturing sector wage, in line with Autor et al. (2014)'s estimates that range between 2.7% and 7.2%. The reduction in wage income, however, leads to very little change in the transition probability to future good health for employed workers with bad initial health, because their health production function implies low marginal benefits for the level of health investment that they choose. In contrast, employed workers with good health experience substantial reductions in their future good-health probability. These model predictions are consistent with our empirical estimates based on the PSID data. In addition, our model suggests that the adverse health effects of the China shock are especially pronounced for the uninsured workers with severe sickness shocks. For those with moderately (the most) severe sickness, the model predicted IPW elasticity of future good-health probability is about twice as large in magnitude as their insured counterparts. The non-linearity arises because a larger share of workers with the most severe sickness choose zero treatment in the pre-China economy, and so their transition probability to good health cannot decrease further.

In the aggregate, for all employed workers, the model-generated IPW elasticity of future good-health probability is -0.023, which is about two-fifths of the magnitude of our empirical estimates. This result suggests that the mechanism through optimal health investment, the only mechanism through which China shock affects health in our model, is quantitatively important. For all workers, both employed and unemployed, the model predicted good-health elasticity is -0.024. A back of the envelope calculation indicates 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 in-patient hospital days per year.

In order to explore the efficacy of potential policy responses, we simulate a post-China economy in which all individuals are covered by health insurance. In this counterfactual, universal health insurance would substantially reduce under-investment of health, relative to both the pre- and post-China equilibria, and induce all workers to seek (some levels of) treatment when facing a sickness shock. Therefore, universal health insurance would remedy over 80% of the overall adverse health effects of the China shock. These results of our counterfactual simulations are consistent with the empirical finding that under-investment in health is far more common in the U.S. than in the high-income countries with universal health insurance (e.g. Davis and Ballreich, 2014).

Given the large geographical variations in the exposure of import penetration, we further quantify the efficacy of universal health insurance across commuting zones and across sickness shocks. In commuting zones with high import penetration that led to large wage declines, workers' health investment decreases substantially. Because health insurance does not cover the amount of over-investment, universal health insurance would provide limited overall remedy for these commuting zones. For the individuals with the most severe sickness shocks, however, universal health insurance would still be highly effective in shielding their health from the negative impacts of the China shock.

Related Literature A number of recent studies have used quantitative dynamic models to explore how specific mechanisms, such as migration, labor force participation, and college education, contribute to the effects of the China shock on earnings, employment, and welfare (e.g., Lyon and Waugh, 2018; Caliendo et al., 2019; Carroll and Hur, 2020; Ferriere et al., 2021). Meanwhile, several empirical studies (e.g. Adda and Fawaz, 2020; Pierce and Schott, 2020) have documented that the China shock had detrimental effects on workers' health, increasing hospitalizations and mortality.[1] We bring these two lines of work together by studying how workers' optimal choice of health investment leads to the endogenous evolution of their health over time, and how much this mechanism contributes to the adverse health effect of the China shock. We also explore the efficacy of potential healthcare policy responses after the China shock.

There has also been a growing literature that use structural models to evaluate how healthcare policies and technology affect health and welfare, where the quantification is guided by micro data of health. Aizawa and Fang (2020), Hosseini et al. (2021), and De Nardi et al. (2023) abstract away from endogenous health investment decisions. On the other hand, Cole et al. (2019) and Lukas and Yum (2023) incorporate health investment through efforts (e.g., exercise), and Fonseca et al. (2021) model endogenous medical spending but abstract away from sickness shocks. Relative to this literature, our flexible health production function implies that workers may optimally choose to over-invest or under-invest in response to sickness shocks, and so our model is able to make contact with the shares of zero medical utilizations, a salient feature in the micro data of health that has been overlooked in the literature.

Lastly, empirical studies find mixed effects on how health insurance impacts health outcomes (see Baicker et al., 2023 for a recent survey of this literature). For example, an early study by Baicker et al. (2013) shows that Medicaid coverage in Oregon lowers the rate of depression but generates no significant improvements in measured physical heath outcomes. More recent empirical investigations have found positive effects of health insurance on health

[1] Pierce and Schott (2020) estimates the effects of trade liberalization on mortality due to the "deaths of despair" (e.g., drug overdose, suicide) introduced in Case and Deaton (2015). These are conditions for which the usual medical utilizations (e.g., hospital visits) may not be the most effective treatment. Our focus is on more general types of sicknesses that impact a broader population.

outcomes. These include Borgschulte and Vogler (2020), Goldin et al. (2021), and Miller et al. (2021), where health insurance is found to lower mortality rates. Relative to this literature, our theoretical model clarifies how health insurance affects health through the mechanism of optimal health investment, and our quantification shows that this mechanism is important in the context of the China shock.

The rest of the paper is organized as follows. In Section 2, we present empirical evidence of the effects of the China shock on heath of workers. Section 3 presents our model of heterogeneous agents with endogenous health evolution. The calibration strategy is detailed in Section 4 and its results are presented in Section 5. Our quantitative analyses, evaluating the effects of the China shock and the role of health insurance, are presented in Section 6.

2 Empirical Motivation: Effects of Import Penetration On Health Status

In this section, we combine the measures of import penetration with the Panel Study of Income Dynamics (PSID) data to estimate the causal effect of import penetration on the probability of good health. We conduct our estimation using both region-level and worker-level data. Our estimation results corroborate and enrich previous results from the literature, and provide both quantitative and qualitative benchmarks for the predictions of our model in Sections 5 and 6 below.

2.1 Data

In this subsection, we outline our data and the construction of our main variables, and then present 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):

$$\mathrm{IPW}_{cz,t} = \sum_{j} \frac{L_{cz,j,t}}{L_{cz,t}} \times \frac{M_{j,t}^{\mathrm{CHN}}}{L_{j,t}}. \tag{1}$$

In Equation (1), $M^{\text{CHN}}_{j,t}$ 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, $\text{IPW}_{cz,t}$ 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 $\text{IPW}_{cz,t}$:

$$\text{IPW}^{IV}_{cz,t} = \sum_{j} \frac{L_{cz,j,t-10}}{L_{cz,t-10}} \times \frac{M^{\text{OTH}}_{j,t}}{L_{j,t-10}}. \tag{2}$$

As compared with the IPW measure of (1), its instrument, (2), uses U.S. imports from eight other high-income countries (Australia, Denmark, Switzerland, Finland, Japan, Germany, New Zealand, and Spain) $M^{\text{OTH}}_{j,t}$ and 10-year-lagged labor employments $L_{cz,j,t-10}$, $L_{cz,t-10}$, and $L_{j,t-10}$ both at the commuting zone and the industry level.

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. 2023) and applied micro studies of health (e.g. Currie and Madrian, 1999), and recent studies show that self-reported health is also a good predictor of future health events, such as hospitalization (e.g. Nielsen, 2016). The use of self-reported health also fits well with our inquiry, because the PSID data for self-reported health span the years of the China shock, 1991 through 2011.[2] To be specific, in PSID, each respondent is asked to rate his health into five levels (from excellent to poor, or 1 through 5). We combine the top two levels into the single category of *good* health, and combine the other three levels into *bad* health.

We then obtain other worker characteristics from PSID, such as age, gender, income, and industry affiliation. In addition, we obtain the restricted commuting-zone identifiers, in order to combine the worker-characteristics data with the IPW data discussed above.

[2]The objective health measures in PSID (e.g., indicator variables of diabetes, asthma, etc.) start in 2003, which makes it impossible for us to exploit the IPW variations before 2003.

Table 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)
Health status (Good-Health Dummy)	0.65	0.68	0.67	0.65	0.61
	(0.48)	(0.47)	(0.47)	(0.48)	(0.49)
Manufacturing Dummy	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 PSID data in years from 1991 to 2011 using longitudinal individual sample weights. The sample is restricted to those who work more than 1,600 hours in their initial year of entry into the PSID. The averages of the sample are reported with standard deviations in parentheses. Labor income is expressed in 2015 dollars. Health status in five levels assigns a value between 1 and 5 with 1 being in excellent health. The Good-Health dummy assigns the value of one to the top two levels of health ("Good" health) and zero otherwise ("Bad" health).

Descriptive Statistics of the Merged IPW-PSID Data The merged data set includes 508 unique commuting zones and about 33,000 worker-year observations. Table 1 reports the summary statistics of the merged data set for the full sample and then by IPW quartiles. The average IPW in the data is $1,440 per worker and the IPW distribution features a large variation as seen by the quartile averages. 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, implying that exposure to import competition from China is associated with low probability of good health. In the rest of this section, we establish the causality of the effects of IPW.

2.2 Effects of Import Penetration: Region-Level Analyses

We first 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

$$\Delta\text{GHSH}_{r,t} = \beta + \beta_t + \gamma \cdot \Delta\text{IPW}_{r,t} + \varepsilon_{r,t}, \tag{3}$$

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 $\Delta\text{IPW}_{r,t}$ is the change in the IPW in region r in period t. Because we instrument the change in import penetration per worker, $\Delta\text{IPW}_{r,t}$, using the change in its instrument, (2), 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 2, we report results using two time periods, 1991-1999 and 2001-2007, and 10 decile bins of IPW exposure per period. The F-statistic of the first-stage estimation is 102.69, and γ, the coefficient estimate of $\Delta\text{IPW}_{r,t}$ 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.

Table 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

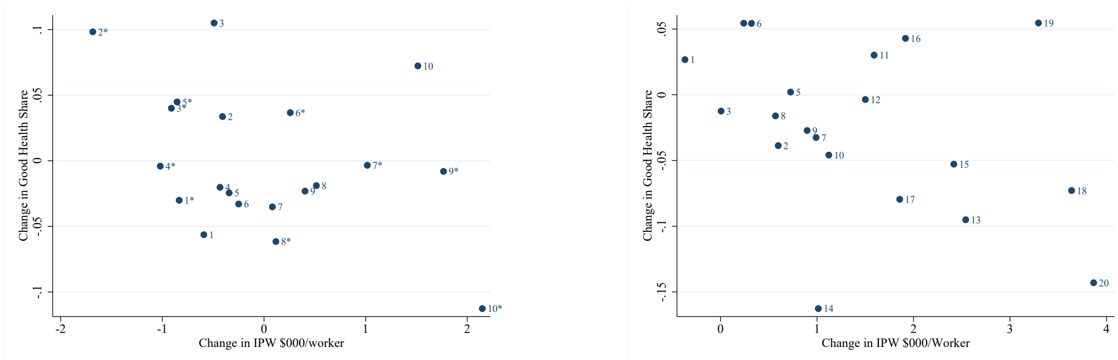
Note: The table reports regression coefficients γ from Equation (3) with t-statistic in parentheses. We use the number of observations in each region as weight. The first-stage F-statistics are for the $\Delta\text{IPW}_{r,t}$. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$

This result is also illustrated in Figure 1(a), which plots the change in the population share of good health, $\Delta\text{GHSH}_{r,t}$, against the predicted value of $\Delta\text{IPW}_{r,t}$ by its instrument.[3] The numerical labels show the decile and the label "*" indicates the second period; e.g.

[3]The period fixed effect, β_t, has been netted out of the values from both axes.

Figure 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 2, respectively.

"2" is the 2nd decile from the first period, 1991-1999, and "7∗" is the 7th 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 $\mathit{\Delta}\text{IPW}_{r,t}$.

Columns (2) to (4) of Table 2 show the results of different implementations of regression (3), 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 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 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. We interpret this elasticity as the estimated total effect of the China shock on workers' health status, from the pre-China-shock equilibrium to the post-China-shock equilibrium, and will use it as the quantitative benchmark of our model's predictions in Sections 5 and 6 below.

2.3 Effects of Import Penetration: Worker-Level Analyses

In the previous subsection, we have utilized long-differences (8 to 16 years) and cross-sectional variations to identify health effects. Here, we complement our region-level analysis by exploiting the rich worker-level panel data to estimate the causal effects of IPW, as well as their heterogeneity across worker characteristics.

The econometric specification for our worker-level analysis is:

$$\mathrm{GH}_{i,cz,t} = \beta_i + \beta_t + \sum_k \gamma_k \cdot \mathbb{I}_{k,t_0} \cdot \mathrm{IPW}_{i,cz,t-1} + \alpha \cdot Z_{i,t} + \varepsilon_{i,cz,t}. \tag{4}$$

In Equation (4), 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. The coefficients 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. Additionally, we estimate the model incorporating manufacturing-by-year fixed effects instead of year fixed effects, to address concerns that workers in manufacturing and non-manufacturing sectors could have experienced different trends in overall health status during our sample period.

The following features of the estimation of Equation (4) 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 $IPW_{cz,t-1,k}$ using the exogenous variations in $IPW^{IV}_{cz,t-1,k}$. 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, birth weight, and genetic differences, some of which have been emphasized in previous studies.[4] While the first two features have been used in previous studies, the use of worker fixed effects is novel. It implies that regression (4) asks the following question: as import penetration increases in commuting zone for exogenous reasons, relative to the sample mean, do the 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 $\varepsilon_{i,cz,t}$ might be correlated across workers within cz by year, we cluster standard errors by cz in all our estimation.

Table 3 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 signifi-

[4] See, e.g. Maccini and Yang (2009) and De Nardi et al. (2023).

Table 3: Import Penetration and Future Health, Worker-Level Results

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 (4). The standard errors are clustered by commuting zone and t-statistics are in parentheses. All regressions include year fixed effects and the vector of time-varying worker characteristics, $Z_{i,t}$, as controls. Columns (2)-(4) report the coefficient estimates by subgroup (γ_k). In addition, the first-stage F-statistics are for the first endogenous variables. The F-stats of the other endogenous variables are similar, and often times larger in magnitude. The Δ75-25% are obtained from comparing predicted good health probabilities of workers in 75-percentile IPW commuting zone compared to those in 25-percentile IPW commuting zone. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

cant. In columns (2) through (4), we divide the workers into their initial-year-characteristics subgroups, 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 with 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) implies that the elasticity of IPW on the Good health probability is -0.054 for manufacturing workers and -0.026 for non-manufacturing workers (although the latter is statistically insignificant), 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 align with our earlier results in Table 2, using region-level data, where the implied elasticities range between -0.048 and -0.078. They also 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 3 indicates a particularly pronounced effects of import penetration on workers whose initial-year income is in the first quartile. This result is consistent with the results from Autor et al., 2014, indicating that the China shock has a more adverse effect on the earnings of low-income workers. Lastly, in Column (4), we see that the IPW had more adverse health effects on the workers with good initial health than on those with bad initial health. We will show, in Section 5 below, that this result is consistent with the qualitative predictions of our model.

In summary, we have shown that the increase in import penetration from the China shock caused statistically and economically significant adverse impacts on the workers' probability of good health. These results raise a number of novel questions. For example, why is the effect of the China shock strong for the initially-good-health workers, but statistically insignificant for those with initial bad health? Through which mechanism does the China shock impact workers' health? How important are such mechanisms, quantitatively? These questions call for the development of a quantitative model for how workers' health evolves over time. We turn to this task now.

3 Model

In this section, we develop a trade model with endogenous health dynamics, by sketching the economy's trade and production, the workers' optimization problem, the government's role, and finally, the economy's competitive equilibrium. We also zoom in on the key features of the model that allow us to make contact with the data.

3.1 Production and Trade

We start with the production and trade side of the economy, where all markets are competitive. 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,

$$x_m = \frac{\phi_m Y}{P_m}. \tag{5}$$

Equation (5) is 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.[5]

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

$$x_{mS} = A \left[\omega_m^{\frac{1}{\sigma}} z_m^{\frac{\sigma-1}{\sigma}} + (1-\omega_m)^{\frac{1}{\sigma}} \left(z_m^*\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where A is the TFP, ω_m is the weight of the domestic input, z_m and z_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 $\tau^* \geq 1$ represents the trade cost of manufacturing inputs. It is straightforward to show that

$$z_m = \omega_m \left(p_m\right)^{-\sigma} X_{mS} P_m^{\sigma-1}, \qquad z_m^* = (1-\omega_m)\left(\tau_m^* p_m^*\right)^{-\sigma} X_{mS} P_m^{\sigma-1}, \tag{7}$$

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

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

relates the prices of the manufacturing good to the prices of its domestic and imported inputs. Equation (7) is the demand for these inputs by the manufacturing sector.

Turning to 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 efficiency

[5]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 want to focus on outcomes of manufacturing workers, we choose to abstract away from production in other sectors. However, as we describe in Section 4.3, we impose equilibrium conditions in the manufacturing sector, endogenizing the equilibrium wage effect in the manufacturing sector in response to the China shock.

equivalent units) of the manufacturing sector. We assume that manufacturing labor is immobile to the rest of the economy, as in the specific factors model in the trade literature. The price of the domestic input is thus proportional to the wage rate w_m:

$$p_m = \frac{w_m}{\psi_m}. \tag{8}$$

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, we assume that our economy is a small open economy with respect to the rest of the world, and so the supply of imported manufacturing inputs z_m^*, is elastic.

In summary, the manufacturing-sector setup of our model allows 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-shock equilibrium (see Subsection 4.3 below). We now move on to describe the workers in our model.

3.2 Workers

In a nutshell, when workers make decisions about health investments given today's health status, they face the trade-off between today's costs in terms of consumption and the future benefits of good health. We incorporate the main elements of both good-health benefits (e.g. in terms of wage, sickness shock, and employment status) and consumption costs (e.g. asset and insurance status), in order for our model to match key features of the data.

Endowments and Preferences The economy is populated by a measure one of workers who are infinitely-lived. Workers are endowed with a unit of time that they can use for work or leisure. A worker's employment status is denoted as $l \in \{0 \text{ (unemployed)}, 1 \text{ (employed)}\}$. Individuals differ in their health status $x \in \{G\text{(ood)}, B\text{(ad)}\}$ that affects sickness shock process, labor income, job transition probability, and utility.

Each period, a worker receives a sickness shock $\varepsilon(x)$ with probability $f(\varepsilon; x)$, and draws his labor endowment z, from an AR(1) distribution in logs with persistence ρ_z and standard deviation σ_z. The productivity effect of health is captured by $\nu(x)$, and the worker's labor income, if he is employed, is $w \cdot \nu(x) \cdot z$. Workers face exogenous job separation rate of

$\delta(x,l)$ and have preferences over consumption represented by $U(c;l,x)$, in which we allow marginal utility of consumption to depend on health and employment statuses. Workers face borrowing constraints and have access to risk-free asset with return r.

Health Production and Insurance Probability of being in good health in the next period $Pr(x'=G)$ is determined by a function $F(H;x,\varepsilon)$. It depends on health status in the current period x, sickness shock ε,and health investment H. As we have two health statuses, $Pr(x'=B)=1-Pr(x'=G)$. We do not impose any restrictions on the amount of health investment relative to the size of the sickness shocks. However, we assume first, that any health investment that is smaller than the size of the sickness shock is used to treat the sickness shock (and later measure it using medical expenditures from the data), and second, that investments used to treat sickness shocks and other monetary investments (e.g., massage or healthy food) are perfect substitutes.

Individuals have access to health insurance with probability $\zeta(l)$ specifying the linkage between employment and health insurance under the prevalence of Employer Sponsored Health Insurance (ESHI) in the US. Health insurance premium is π and it covers a $\chi(\varepsilon;x)$ share of health investment used for treating sicknesses. Any other monetary investments are not covered by insurance.

3.3 Government

The government does not consume final goods, but makes transfers. To be specific, it pays unemployment benefits b, guarantees workers a minimum consumption floor of amount $\underline{c}$, and ensures that health insurance sector makes zero profits through lump-sum subsidies (either positive or negative). These transfers are financed using taxes on labor income $T(y)$. The consumption floor captures various means-tested government programs, in a similar manner as in studies with medical expenditure risks, e.g., De Nardi et al. (2023). We denote the transfers made to ensure a minimum consumption floor as tr, and individuals for whom $tr>0$ are not allowed to save or invest in health. Note health insurance companies collect premium π and pay the insured at coinsurance rate of $\chi(\varepsilon;x)$ up to ε (the sickness shock). That is, their profit on each insured individual is $\pi-\chi(\varepsilon,x)\min\{H,\varepsilon\}$, which is zero if the premium is actuarially fair. We assume that premium is exogenous, which does not guarantee that health insurance companies make zero profits. Instead, we assume that the government makes transfers to insurance companies to ensure zero profit.[6] Lastly, we denote $\mathcal{G}$ as exogenous expenditures.

3.4 Optimization Problem

Let state variables for worker problems be $\mathbf{s} \equiv \{x, a, in, \varepsilon, z\}$, denoting health, asset, insurance status, sickness shock, and labor productivity shock (only relevant for the employed) respectively. Worker problem is

$$
\begin{aligned}
V^{l}(\mathbf{s}) \quad = \quad & \max_{c \geq 0, a' \geq 0, H \geq 0} U(c + tr, l; x) && (9) \\
& + \beta \sum_{x'} Pr(x') \, \delta(l, x') \, \mathbb{E}_{in', \varepsilon'} V^{0}(x', a', in', \varepsilon') + \\
& + \beta \sum_{x'} Pr(x') \left(1 - \delta(l, x')\right) \mathbb{E}_{in', \varepsilon', z'} V^{1}(x', a', in', \varepsilon', z') \\
\text{s.t.} \quad & c + a' + \tilde{H} = I(l, x) + (1 + r) a + tr && (10) \\
& tr = \max\{0, \underline{c} - (I(l, x) + (1 + r) a)\} && (11) \\
& \tilde{H} = \begin{cases} H & \text{if uninsured} \\ \pi + (1 - \chi(\varepsilon; x)) \min\{\varepsilon, H\} + \max\{H - \varepsilon, 0\} & \text{if insured} \end{cases} && (12) \\
& Pr(x' = G) = F(H; x, \varepsilon), \quad Pr(x' = B) = 1 - F(H; x, \varepsilon) && (13) \\
& I(l, x) = \begin{cases} w \cdot \nu(x) \cdot z - T(w \cdot \nu(x) \cdot z) & \text{if } l = 1 \\ b & \text{if } l = 0. \end{cases} && (14)
\end{aligned}
$$

The worker maximizes his utility (9), which consist of his utility in the current period plus his discounted utility that depend on his employment status in the next period. The expectation for the realization of statuses in the next period include probability of being insured $\xi(l')$, the sickness shock probability $f(\varepsilon'; x')$, and labor productivity $f(z'; z)$ (if employed). In the budget constraint (10), his expenditures are consumption c, tomorrow's asset a',and out-of-pocket health investment expenditures $\tilde{H}$, and government transfers (11) that guarantee a minimum consumption floor of amount $\underline{c}$. The worker's resource on the right hand side of the budget constraint (10) is his income $I(l, x)$—after-tax labor income if employed and

[6] In reality, Employment Sponsored Insurance system is tax-deductible for employers and employees, so this may reflect such policy. Effectively, this is equivalent to government running the health insurance system.

unemployment insurance if unemployed as expressed in (14)—and assets $(1 + r)\,a$.

Equation (13) shows that the transition probability into future good health depends on both the sickness shock ε and endogenously chosen health investment H. Upon receiving a sickness shock, we say that an individual *"under*-invests" in health if the total amount of health investment H is smaller than the sickness shock ε; i.e. $H < \varepsilon$. Under-investment can be due to partial treatment (i.e. $0 < H < \varepsilon$) or zero treatment (i.e. $0 = H < \varepsilon$). If $0 < H = \varepsilon$, an individual has chosen full treatment of the sickness shock. If $H > \varepsilon$, we say that an individual "*over*-invests" in health in the amount of $H - \varepsilon$. Thus, we categorize an individual's medical expenditure to be of the amount $\min\{\varepsilon, H\}$ and his over-investment, or monetary investment in health not in the form of medical expenditures, to be of the amount $\max\{H - \varepsilon, 0\}$. Given total health investment H, we elaborate on the individual's out-of-pocket health investment expenditures $\tilde{H}$ by insurance status in (12). Uninsured individuals incur all investment amounts out of pocket. Insured individuals pay premium π and $1 - \chi(\varepsilon; x)$ share of the medical expenditures, $\min\{\varepsilon, H\}$, but they pay 100% of the over-investment amount $\max\{H - \varepsilon, 0\}$.

Intuitively, the dynamic asset and health investment choices of workers weigh the trade-offs between today's consumption costs, returns to asset holding, and the future benefits of good health. In particular, the health investment choices vary across worker characteristics including the insurance status and the size of the sickness shock, which are the key features of our model.

3.5 The Competitive Equilibrium

Because the workers in our model are infinitely-lived, our equilibrium refers to the steady state. Let the (steady-state) distribution of workers in the manufacturing sector over the state variable $\mathbf{s}$ be $\mu(\mathbf{s})$.

Market Clearing The labor market clearing condition is

$$L_m = \sum_{\mathbf{s}} \nu(x) \cdot z \cdot \mathbb{I}_{l=1} \mu(\mathbf{s}), \tag{15}$$

where effective labor supply depends on workers' health and productivity and the stationary distribution.

The market for the domestic variety of manufacturing inputs also clears

$$z_{mS} = z_m + D_m^* \cdot (p_m)^{-\sigma}, \tag{16}$$

and the market clearing condition for the manufactured good is simply

$$x_{mS} = x_m. \tag{17}$$

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

1. Value and policy functions solve the household's optimization problem (9).

2. Prices follow (5), (6), (7), and (8).

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

$$\begin{aligned} &\sum_{\mathbf{s}} b \cdot \mathbb{I}_{l=0}\mu(\mathbf{s}) + \sum_{\mathbf{s}} tr(\mathbf{s}) \cdot \mu(\mathbf{s}) \\ &\quad + \sum_{\mathbf{s}} [\chi(\varepsilon, x) \min\{H, \varepsilon\} - \pi] \cdot \mathbb{I}_{in=1}\mu(\mathbf{s}) + \mathcal{G} = \sum_{\mathbf{s}} T(y(\mathbf{s}))\mu(\mathbf{s}) \end{aligned} \tag{18}$$

4. Markets clear; i.e., (15), (16), and (17) hold.

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

4 Calibration Procedure

In this section, we map our model to the data to quantify the effects of the China shock on workers' health. In addition to PSID, we use the following standard data sources to both set parameter values exogenously and generate target moments: Medical Expenditure Panel Survey (MEPS), Current Population Survey (CPS), STructual ANalysis Database (STAN), and World Development Indicators (WDI).

We first lay out the parameters whose values we treat as determined (Subsection 4.1). We then discuss how we calibrate the parameters of the health production function and utility function in Subsection 4.2. For this part, we first document motivating empirical patterns for our choice of sickness shock parameters and functional form of the health production function. We then show how we choose certain parameters exogenously but calibrate the others within the model (the inner loop). Finally, we describe how we calibrate the production and export-related parameters in the pre- and post-China economies (the outer loop) in Subsection 4.3.

4.1 Predetermined Parameters

The top panel of Table 4 lists the household parameters whose values we take from outside the model. To be specific, 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 fairly standard values in the literature. Then, we use the PSID data in pre-China years (1991–1996) to obtain the average income of workers by health status in the manufacturing sector. In our model, the average labor income of a worker with health type x is $w_m \cdot \nu(x)$. We normalize $\nu(x = G) = 1$, to obtain obtain $\nu(x = B) = 0.81$ from the income gradient of health. We also obtain w_m for the pre-China-shock equilibrium from the average income of workers with good health. 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 Current Population Survey (CPS-ASEC) data in years 1996-1999.[7]

We set the unemployment benefit to 20% of average wage income across health statuses which amount to \$9,086. Additionally, the consumption floor guaranteed by the government is \$3,000, similar to one estimated in De Nardi et al. (2023), and the proportional income tax rate is 20%.

4.2 Sickness Shocks, Health Production, and Preferences

On the household side, the remaining parameters are those governing (i) the sickness shock process $\{\varepsilon(x), f(\varepsilon; x)\}$; (ii) the health production $F(x' = G; x, \varepsilon, H)$; and (iii) the preferences $\{\iota(x, l)\}$. In addition to the PSID data, we use Medical Expenditure Panel Survey

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

Table 4: Predetermined Parameters

Parameter	Description	Values
Household and Labor Market		
σ	Risk aversion	1.5
β	Discount factor	0.9
r	Interest rate	0.02
w_m	Pre-China wage (earnings)	\$50,211
$\nu(x = B)$	Health effect on wage	0.81
(ρ_z, σ_z)	Income shock process: Persistence, St.Dev.	0.95, 0.15
$1 - \delta(E, x)$	Job continuation rate: Bad; Good	0.87; 0.92
$1 - \delta(U, x)$	Job finding rate: Bad; Good	0.18; 0.32
Government Policies		
b	Unemployment benefit	\$9,086
$\underline{c}$	Consumption floor	\$3,000
τ	Income tax rate	20%
Production		
ω_m	Home bias	0.5
$\sigma - 1$	Trade elasticity	3
ϕ_m	Cobb-Douglas share of manufacturing	0.17
$\pi^D_{m,pre/post}$	Domestic share of manufacturing: Pre; Post	0.85; 0.71

(MEPS) data that contains individual-level medical expenditures to establish stylized facts to guide us through the calibration process.[8]

Motivating Empirical Patterns We document key empirical patterns from MEPS in two areas: firstly, medical expenditures and medical utilizations, and secondly, transition probabilities to good health, by worker characteristics.[9] These stylized facts motivate the way we measure sickness shocks from the data and parameterize and identify the health production function.

In Table 5, we document average medical expenditures and the shares of individuals with zero medical utilizations by eight groups—current health status (2) $\times$ employment status (2) $\times$ insurance status (2). For the latter, we use the Household Component Event files (MEPS-HC) of the MEPS Medical Conditions data to identify individuals who never

[8]PSID only includes family-level medical expenditures, which is not ideal for our purpose. Further, MEPS contains the same health variables as in PSID, allowing us to be consistent in measurement.

[9]For parameters governing health production, we calculate moments using all workers in the sample without restricting the sample to those in the manufacturing sector (as 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.[10]

Table 5: Medical Expenditures and Medical Utilizations

Average medical expenditures (positive only)				
Bad	Emp/Ins	\$3,689	Emp/Unins	\$2,412
	Unemp/Ins	\$3,493	Unemp/Unins	\$2,148
Good	Emp/Ins	\$2,318	Emp/Unins	\$1,625
	Unemp/Ins	\$2,376	Unemp/Unins	\$1,591
Share of individuals without medical utilizations				
Bad	Emp/Ins	0.05	Emp/Unins	0.20
	Unemp/Ins	0.06	Unemp/Unins	0.20
Good	Emp/Ins	0.08	Emp/Unins	0.29
	Unemp/Ins	0.08	Unemp/Unins	0.27

Note: For medical expenditures in Table 5, 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. We construct medical utilizations using household-reported medical events in MEPS-HC data. 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.

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

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

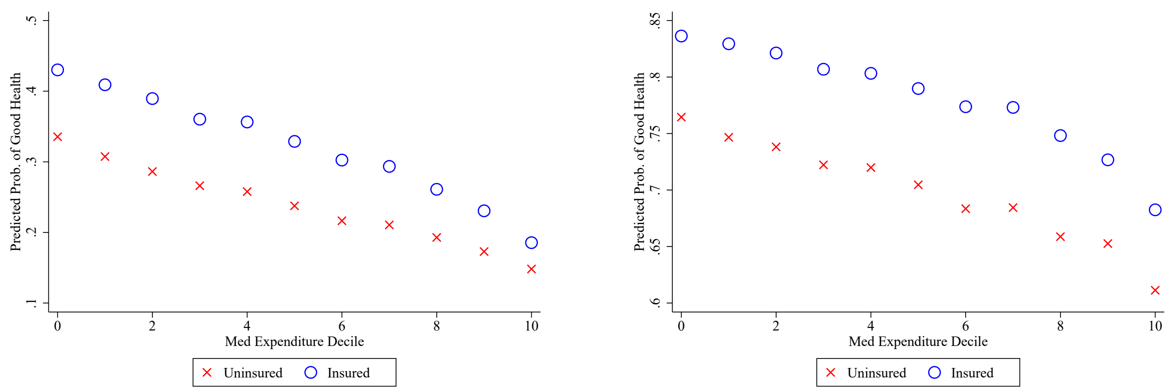
The variable $\text{Health}_{i,t(t+1)}$ takes a value of 1 if the individual is in Good health, and 0 otherwise in year t $(t+1)$. We then construct deciles of medical expenditures among insured individuals with positive expenditures, and assign each individual i with a dummy variable $D_{i,t,k}^{med}$ 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 the number of reported medical conditions, employment, and insurance status. In Figure 2 are predicted probabilities of being in good health in the future by this period's health status ((a) for initially bad health individuals and (b) for initially good health individuals), this period's medical expenditure decile (x-axis), and insurance status ($\circ$ for insured and $\times$ for uninsured). The first notable feature of both panels in Figure 2 is the monotonically decreasing future good health probabilities in current medical expenditure deciles for all groups. It implies that a

[10] 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.

large expenditure this period reflects the severity of the sickness shock a worker experienced.

Figure 2: Medical Expenditures, Insurance, and Future Health

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



We now examine the heterogeneity across different worker characteristics. From Table 5, 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. Further, conditional on characteristics and current medical expenditures, their probabilities of being in good health in the future are higher than those with bad initial health: In Figure 2, the predicted probabilities of being in good health for bad initial health in panel (a) range from 0.15 to 0.42, relative to 0.60 and 0.84 for those with good initial health in panel (b). These patterns suggest that individuals with good health experience milder sickness shocks and that health status is persistent.

Second, we compare expenditures and health outcomes of individuals across insurance statuses. A salient feature of Table 5 is the large variations in medical expenditures and utilization shares across insurance status: 8% of the employed and good-health individuals report zero medical utilization if they are insured, but 29% do so if they are uninsured. Conceptually, these variations may arise because the uninsured are healthier, or because they are not able to receive sufficient medical care due to their lack of resources and access. Figure 2 suggests that the latter is likely the main reason. It clearly shows that the uninsured individuals have lower probability of being in good health in the future than the insured ones in every single medical-expenditure decile, for both bad initial health (panel (a)) and good initial health (panel (b)), even after controlling for various individual-level characteristics.

We summarize these patterns as the following empirical facts.

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

(a) *Individuals with good initial health have lower medical expenditures and are less likely to utilize medical services than those with bad initial health* (Table 5).

(b) *Conditional on demographic characteristics, individuals with good initial health have a higher probability of being in good health in the next period 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 5).

(b) *Conditional on medical expenditures and demographic characteristics, insured individuals have higher probabilities of being in good health than uninsured individuals* (Figure 2).

Sickness Shocks and Health Insurance The declining future good health probabilities in current medical expenditures in Figure 2 suggests that high medical expenditures in MEPS imply large (severe) values of the sickness shock ε in our model. In order to quantify ε, however, we face the following two difficult problems with data availability. First, although in the model, sickness shock, ε, is distinct from medical expenditures, $\min\{H, \varepsilon\}$, we only observe medical expenditures in the data.[11] Second, although we observe whether an individual utilized medical services or not (lower panel of Table 5), it does not perfectly coincide with whether an individual experienced a sickness shock this period. To make progress, we assume that individuals who are insured and employed (those who are most likely to have sufficient resources) choose full treatment of sicknesses. In addition, we also assume that the uninsured face the same distribution of sickness shocks as the insured.[12] These assumptions are consistent with *Empirical Fact 2*, where insured workers incur higher medical expenditures and experience better health outcomes conditional on current period's medical expenditures (that reflect the severity of the sickness shock).

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

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

Given these assumptions, we use medical expenditures for the insured and employed individuals to parameterize the sickness shock distribution in our model. As reported in Table 6 below, we discretize the sickness shock into five events, whose values differ by health status consistent with *Empirical Fact 1* showing a large discrepancy in expenditures and outcomes across initial health statuses. In it, ε_0 refers to the event of being sickness free (i.e. $\varepsilon = 0$), 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 5 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. As reported in Table 6, the size of sickness shocks are larger ($\varepsilon(x = B) \geq \varepsilon(x = G)$) and the probability of not getting any shock ($f(\varepsilon_0; B) < f(\varepsilon_0; G)$) is smaller for those with bad health relative to their good health counterparts.

Table 6: 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	\$420	\$1,490	\$3,530	\$9,320
		Good	\$0	\$270	\$840	\$1,870	\$6,290
$f(\varepsilon; x)$	Probability	Bad	0.05	0.24	0.24	0.24	0.24
		Good	0.08	0.23	0.23	0.23	0.23
$\chi(\varepsilon; x)$	Coinsurance rate	Bad	-	0.27	0.22	0.18	0.12
		Good	-	0.28	0.27	0.24	0.17
$\zeta(l)$	Insurance Prob.	Emp.			0.81		
		Unemp.			0.57		
π	Insurance Premium				\$2,820		

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 5. Coinsurance rate is calculated from MEPS using out-of-pocket expenditures and total medical expenditures, and insurance premium is defined as an weighted average of sickness shocks, using $f(\varepsilon; x)$ as weights.

For the insured, we use MEPS to obtain the coinsurance rate by sickness shock, $\chi(\varepsilon; x)$, the insurance coverage rates by employment status, $\zeta(l)$, and the average health insurance premium, π. We summarize these values in Table 6, and make the following observations about them. First, we use expenditure-dependent coinsurance rates that help us capture various components of insurance plans, such as deductibles and out-of-pocket maximum, in a parsimonious way. Second, although we do not directly model insurance for low-income people, such as Medicaid, we allow for the unemployed to have health insurance, along with other social insurance policies through the consumption floor. Finally, the insurance premium stays constant across sickness shocks while the insurance coinsurance rate decreases, and so health insurance is more useful for severe sickness shocks than for mild ones in our model. These features of health insurance help our model predictions match the pattern in the upper panel of Table 5 that the mean medical expenditure is higher for the insured, and generate heterogeneous effects of the China shock across workers (see Section 6).

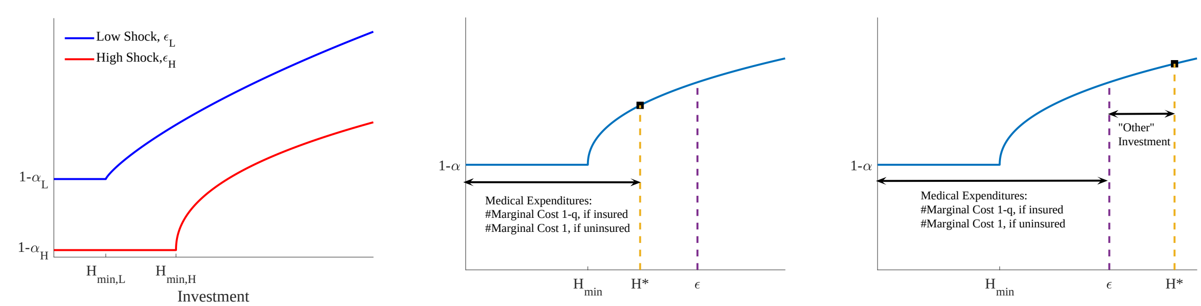
Health Production Function We use the following flexible Weibull function to describe how the probability of future good health $Pr\left(x'=G\right)$, relates to today's health x, sickness shock ε, and health investment H:

$$F\left(x'=G;x,\varepsilon,H\right)=\begin{cases}1-\alpha\left(x,\varepsilon\right) & \text{if } H\leq H_{min}\left(x,\varepsilon\right)\\ 1-\alpha\left(x,\varepsilon\right)\exp\left[-\frac{\left(H-H_{min}\left(x,\varepsilon\right)\right)^{\gamma(x)}}{\lambda(x)}\right] & \text{if } H>H_{min}\left(x,\varepsilon\right).\end{cases} \tag{19}$$

Motivated by *Empirical Fact 1*, we let all parameters of the health production function (19) to vary by health status, x. On the other hand, none of the parameters depends on health insurance or employment status. This means that health insurance and employment status affect health only through workers' optimal choice of health investment.

Figure 3: Health Production and Investment

(a) Health Production (b) Under-Investment (c) Over-Investment



The health production function in Equation (19) has the following properties. First, $1-\alpha\left(x,\varepsilon\right)$ represents the baseline probability; i.e. even if $H=0$, the probability of future good health is $1-\alpha\left(x,\varepsilon\right)>0$. We incorporate $\alpha\left(x,\varepsilon\right)$ because in the data, the probability of future good health varies a lot across current health status (Figure 2). Intuitively, $\alpha\left(x,\varepsilon\right)$

increases with ε, given health status x (as illustrated in Figure 3(a)), because a large sickness shock (e.g., cancer) may lower one's baseline probability of being in good health. Second, $H_{min}(x,\varepsilon)$ represents the minimum investment, below which health investment leaves the probability of future good health unchanged at $1-\alpha(x,\varepsilon)$. The flat portion of the health production function in Figure 3(a) helps visualize $H_{min}(x,\varepsilon)$. We incorporate $H_{min}(x,\varepsilon)$ because in the data, many uninsured individuals report zero medical utilizations, and intuitively, when one is severely ill (e.g. cancer), a small amount of investment is not effective. In order to limit the number of parameters to calibrate, we parameterize $H_{min}(x,\varepsilon) = s(x)\cdot\varepsilon$, with $s(x) \leq 1$; i.e., within health status x, the level of minimum health investment increases as ε increases, but its share relative to ε stays unchanged. Third, when health investment exceeds the minimum, $F(\cdot)$ is increasing in H, $\partial F(\cdot)/\partial H > 0$ approaches $+\infty$ as H approaches $H_{min}(x,\varepsilon)$ from above, and $F(\cdot)$ is concave with respect to H, as long as $\gamma(x) < 1$ (which is the case in our calibration).

These features of the health production function, (19), imply that the optimal health investment is $H^* = 0$, $H_{min}(x,\varepsilon) < H^* < \varepsilon$ (under-investment), $H^* = \varepsilon$ (full treatment), or $H^* > \varepsilon$ (over-investment), but never $H^* \in (0, H_{min}(x,\varepsilon))$. Figures 3(b) and (c) illustrate under- and over-investment, as well as the medical expenditure of $\min\{H^*,\varepsilon\}$, and non-medical health investment of $\max\{H^*-\varepsilon, 0\}$. Below, we further discuss how the flexibility of health production function is useful in matching our model to the data moments of mean medical expenditures, shares of zero medical events, and probabilities of good health.

Preferences We assume that the utility function is

$$U(c,l;x) = \frac{[c\cdot\exp\iota(x,l)]^{1-\rho}}{1-\rho}, \tag{20}$$

in which c denotes consumption and ρ is the relative risk-aversion parameter. The parameter $\iota(x,l)$ captures how health and work affects both the utility and marginal utility of consumption (e.g., Low and Pistaferri, 2015). We normalize $\iota(x=G, l=1) = 0$, thus $\iota(x,l)$ for $x = B$ and $l = \{0,1\}$ represent differences in marginal utility of consumption from health and/or employment statuses. If $\iota(x=B,l) < 0$, being in the unhealthy state lowers utility, and this provides incentives for health investment.

Target Moments and Identification The parameters to be calibrated on the worker side are health production parameters $\{\alpha(x,\varepsilon), s(x), \gamma(x), \lambda(x)\}$ (16 parameters) and preference parameters $\iota(x,l)$ (3 parameters). Meanwhile, our data targets are group-specific averages of (i) the sickness shock-dependent probabilities of tomorrow's good health (analogous to Figure 2 but with five sickness shocks, 20 moments); (ii) the share of population with zero medical utilizations (as reported in Table 5, 8 moments); and (iii) the average medical expenditures (as reported in Table 5, 8 moments). We jointly calibrate the 19 model parameters to target the 36 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 the model moments of probabilities of future good health, zero-utilization shares, and mean medical expenditures. First, from Figure 3(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 the 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, $s(x) = H_{min}(x,\varepsilon)/\varepsilon$, directly impacts the share of workers who choose zero utilizations. It also decreases the probabilities of future good health for large sickness shocks, like ε_3 and ε_4, but has more limited effects on those of small sickness shocks. On the preference side, $\iota(x,l)$ affects the marginal utility of consumption by health and employment statuses impacting worker's investment choices, e.g., an increase in $\iota(B, l=0)$ increases the zero shares for the uninsured. Overall, $s(x)$ and $\iota(x,l)$ (particularly $\iota(B,0)$) are identified from the levels of the population shares of zero medical utilizations across health and employment statuses.

Overall, while all 19 parameters contribute to the quantitative fit of the model, the more parsimonious set of 7 parameters — $\gamma(x)$, $\lambda(x)$, $s(x)$ and $\iota(B,0)$ — govern the shape of the health production function and utility function, and play important roles in both model mechanisms and calibration results, which we detail in Subsections 5.3 and 6, respectively.

4.3 Production Parameters and the China Shock

In the previous subsection, we described how we calibrate the parameters of the health production function (19), and utility function (20), and solve the workers' optimization problem (9), given the predetermined household parameters in the top panel of Table 4. These procedures are the inner loop of our computation. We now relate the inner loop to the market clearing conditions of the manufacturing sector, equations (16)—(17), and clarify how we introduce the China shock into our model. These steps, below, form the outer loop of our computation.

First, as described in the bottom panel of Table 4, we take the values of the following parameters from outside the model. We normalize the manufacturing sector productivity ψ_m and the final goods price P to one. The sectoral home bias, ω_m, is set to 0.5, and the trade elasticity, $\sigma - 1$, to 3, following Simonovska and Waugh (2014).

Next, consider the pre-China-shock equilibrium. Equations (16)—(17) imply that

$$w_m L_m = \pi_m^D \phi_m Y + D_m^* p_m^{1-\sigma}, \quad \pi_m^D = \frac{\omega_m \left(p_m\right)^{1-\sigma}}{\omega_m \left(p_m\right)^{1-\sigma} + \left(1-\omega_m\right)\left(\tau_m^* p_m^*\right)^{1-\sigma}}, \tag{21}$$

where π_m^D is the domestic share of the manufacturing sector. Equation (21) is the labor market clearing condition for the manufacturing sector. On its left-hand side, w_m, the equilibrium wage, has its value set in Table 4. The equilibrium labor supply, L_m, is completely pinned down by the inner loop, from the workers' optimal choices and the stationary distribution, as expressed in Equation (15). For example, if a large fraction of workers are in good health, L_m tends to be high, because unhealthy workers have fewer effective labor units than healthy ones ($\nu\left(x = B\right) = 0.81$ in Table 4). Our remaining task, then, is to ensure that the right-hand side of Equation (21) stays in balance.The first term on the right-hand side represents domestic demand for manufacturing labor, and the second term represents foreign demand, through exports. As listed in Table 4, ϕ_m is set to 0.17, the mean of manufacturing value added as a share of U.S. GDP for 1990-1992 (WDI), and $\pi_m^D = 0.85$ is the average for the years 1990-1992 (STAN). 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 (21).

We thus bring in the extra equation of the model-implied ratio of manufacturing export to Gross National Expenditure (GNE),

$$\frac{\text{Manufacturing Export}}{GNE} = \frac{D_m^* \cdot {p_m}^{1-\sigma}}{Y}. \tag{22}$$

From STAN, we obtain that this ratio is 0.057 (the average for 1990-1992). We then use equations (21) and (22) to back out the values of D_m^* and Y that are consistent with the solutions from the inner loop.

We now move on to the post-China-shock equilibrium. We start by following 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 these drops. On the other hand, because we have remained agnostic about the non-manufacturing part of the economy, our model is unable to predict how the China shock affects total output, Y.[13] We expect such effects to be small, however, because the trade literature estimates limited welfare gains from trade relative to autarky, a much larger change than the China shock we model (e.g. Costinot and Rodriguez-Clare, 2014).[14] Therefore, we make the assumption that there is no change in Y. We also assume that D_m^* remains unchanged.

Under these assumptions, there are two endogenously determined outcomes in Equation (21), the wage rate w_m and the total labor supply in the equilibrium 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 (21) allows us to solve for the post-China-shock equilibrium wage, w_m, because the inner loop pins down the aggregate labor supply, L_m, as a function of w_m, via Equation (15), and that $p_m = w_m$, by equation (8). 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

[13] An extension of our model to a multi-sector general equilibrium would allow us to endogenize the aggregate output in equilibrium, but at the expense of more assumptions on the production side with limited effects on workers facing the China shock, a focus of our work.

[14] This literature examines the change in real GDP, which is closely related to the total output, Y, or real GNE.

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 (21). For both approaches, we compare the model predictions of the export-GNE ratios with data.

5 Calibration Results

In this section, we focus on our calibration results for the pre-China equilibrium. We report parameter values and model fit in Subsection 5.1 and discuss how we validate our model in Subsection 5.2. Then in Subsection 5.3, we clarify how our calibrated parameters help our model match the key patterns of the data targets, *Empirical Facts 1* and *2*. Quantitative assessment of the China shock is presented in Section 6.

5.1 Parameter Values and Model Fit

Table 7 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 initial health status and sickness shock, in Figure 4.

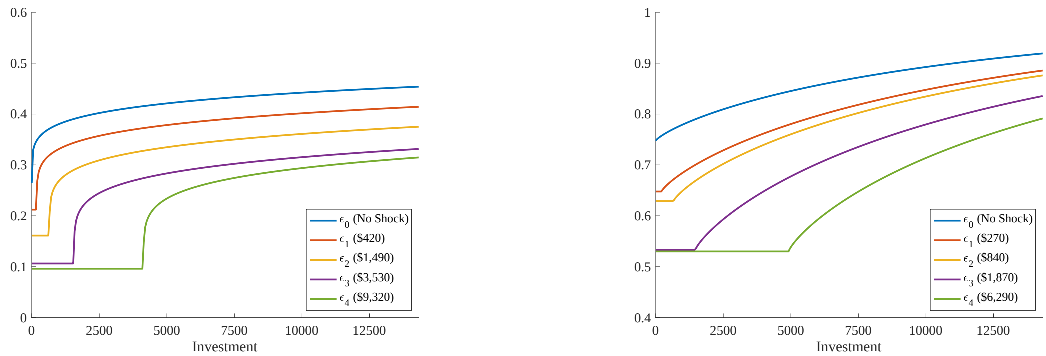
Table 7: Parameters Calibrated in the Model

Parameter	Description		Values				
Health production							
			ε_0	ε_1	ε_2	ε_3	ε_4
$1-\alpha(x,\varepsilon)$	Baseline probability	Bad	0.265	0.212	0.161	0.106	0.096
		Good	0.748	0.648	0.629	0.533	0.530
$\lambda(x)$	Scale: Bad; Good		3.625; 1.173				
$\gamma(x)$	Concavity: Bad; Good		0.208; 0.802				
$s(x)$	Min. inv. share: Bad; Good		0.444; 0.782				
Worker Utility							
$\iota(x,l)$	Marginal utility: Bad; Good	Emp.	-0.000; 0 (norm.)				
		Unemp.	-0.030; -2.689				

First, the group of 10 baseline probability parameters, $1-\alpha(x,\varepsilon)$, determine the vertical intercept of the health production function, $F(\cdot)$. Since $1-\alpha(x,\varepsilon)$ increases with x and decreases with ε, we see, from Figure 4, that $F(\cdot)$ shifts down as the sickness shock ε becomes more severe or health status x becomes worse. In words, the probability of future good health is higher when current health is good and lower when a severe sickness shock is realized.

Figure 4: Calibrated Health Production

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



Second, the remaining six parameters of the health production function determine its shape. As can be seen from Figure 4, the shape of $F(\cdot)$ differs substantially across initial health status. This happens for two reasons. One, the curvature of $F(\cdot)$ for $H > H_{min}$ is much more concave for bad initial health, because $\gamma(B)$ is smaller and $\lambda(B)$ is larger than their counterparts for good health. Two, $s(B)$, the ratio of minimum health investment to ε for bad health, is smaller than that for good health, $s(G)$, and so the kink point of $F(\cdot)$ under bad initial health is farther away from ε. The shape differences in $F(\cdot)$ imply that under bad initial health, it is important to alleviate the sickness through medical expenditures, whereas under good initial health, there is more scope for forgoing treatment (choose zero) or doing over-investment.

Lastly, among the parameters of the utility function, $\iota(B, 0)$ is substantially smaller than the $\iota(\cdot, \cdot)$ values in the other states, which are close to 0, signifying low marginal utility of consumption among the unemployed workers with bad initial health, consistent with Low and Pistaferri (2015).

Table 8 shows that our model generates reasonable fits on thetarget moments reported in Table 5. First, the model predicted population share of zero medical utilizations is the sum of the probability of not being sick (i.e. experiencing $\varepsilon_0 = 0$), and the share of endogenously chosen zero treatment ($H^* = 0 < \varepsilon$). For example, for the unemployed and uninsured workers of bad initial health, ε_0 happens 5% of the time (see Table 6) and the zero-treatment share is 14%, and so the model predicted share of zero medical utilizations is 19%, which is close to the data target of 20%. On the other hand, the model predicted medical expenditure, $\min\{H, \varepsilon\}$, is positive only if the individuals endogenously choose positive health investment ($H^* > 0$),

Table 8: Model Fit on Targeted Moments

Moments	Model	Data	Moments	Model	Data
Share of individuals with zero medical utilizations					
Bad, Emp, Ins	0.05	0.05	Bad, Emp, Unins	0.16	0.20
Bad, Unemp, Ins	0.05	0.06	Bad, Unemp, Unins	0.19	0.20
Good, Emp, Ins	0.08	0.08	Good, Emp, Unins	0.30	0.29
Good, Unemp, Ins	0.08	0.08	Good, Unemp, Unins	0.26	0.27
Average medical expenditures (conditional on positive)					
Bad, Emp, Ins	\$3,689	\$3,689	Bad, Emp, Unins	\$2,223	\$2,412
Bad, Unemp, Ins	\$3,495	\$3,493	Bad, Unemp, Unins	\$2,022	\$2,148
Good, Emp, Ins	\$2,318	\$2,318	Good, Emp, Unins	\$1,723	\$1,625
Good, Unemp, Ins	\$2,318	\$2,376	Good, Unemp, Unins	\$1,753	\$1,591

Note: Model values are from Table 5, where we provide detailed descriptions on their construction procedures.

and excludes their over-investment above and beyond full treatment, $\max\{H^* - \varepsilon, 0\}$. For example, for the unemployed and uninsured workers of bad initial health, the mean of model predicted positive medical expenditure is \$2,022, close to the data target of \$2,148. Finally,

Figure 5: Model Fit on Good Health Probability

Bad Initial Health | Good Initial Health

(a) Insured | (b) Uninsured | (c) Insured | (d) Uninsured

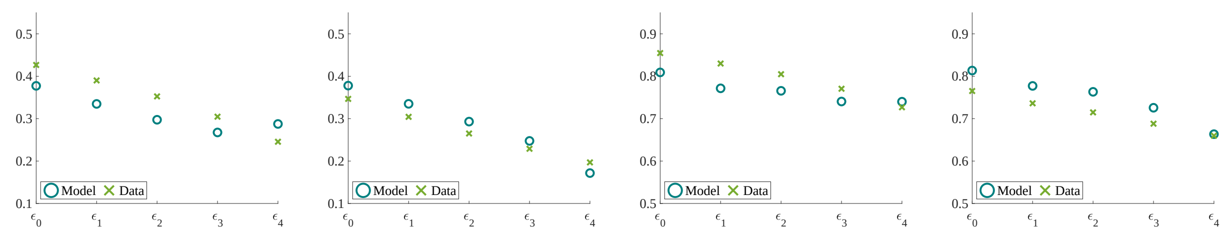


Figure 5 plots the future good health probabilities by initial health status by insurance status by sickness shock. We see that the model predictions ($\circ$) track the data targets ($\times$) fairly well.

In summary, Table 8 and Figure 5 show that our model is successful in generating both the qualitative and quantitative heterogeneity across worker groups in our data targets. We now move on to compare our model predictions with untargeted data moments.[15]

[15] Given the workers' choice of health investment and coinsurance rates, the actuarially fair health insurance premium in the equilibrium is \$2,260. This is close to the exogenously set premium of \$2,820 (Table 6) from the MEPS data. In counterfactual analyses, we use transfers to ensure budget neutrality of the government, whose budget incorporates changes in the gap between the exogenous health insurance premium and endogenously determined medical expenditures (Equation (18)).

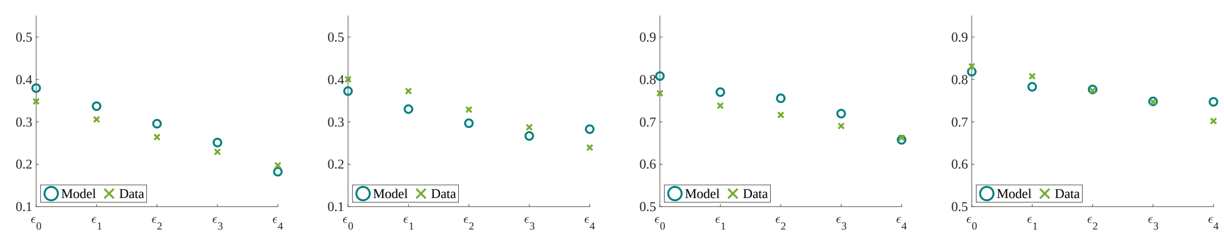
5.2 Validation of the Model

In this subsection, we externally validate our model by comparing the following worker-level model predictions to their empirical counterparts: (i) more disaggregated (and so untargeted) future good health probabilities; (ii) the income elasticity of health investment; (iii) the share of workers who under-invest in health; and (iv) the ratio of non-medical consumption to income. We focus on these untargeted moments because they are related to the quantitative magnitudes of the health investment mechanism and its effectiveness in the calibrated model. We provide additional validation by examining the model predicted aggregate effects of the China shock in Section 6.

First, Figure 6 compares the model predicted future probabilities of good health with data, where we use more disaggregated demographic groups — by initial health by employment by insurance statuses — than our target moments (see Figure 5). Figures 6(a) and (c) are for the employed and uninsured workers with initially bad and good health respectively, and Figures 6(b) and (d) are for the unemployed and insured workers. Figure 6 clearly shows that our model predictions (circles) track these untargeted moments (crosses) well.

Figure 6: Good Health Probability by Employment/Insurance

Bad Initial Health		Good Initial Health	
(a) Emp. & Uninsured	(b) Unemp. & Insured	(c) Emp. & Uninsured	(d) Unemp. & Insured



Second, 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 elasticities in our model are 0.12 and 1.06, depending on whether we focus on medical expenditures only or total health investment, in line with the range of estimates from previous studies (e.g. Acemoglu et al., 2013) of 0.3 to 1.1.[16]

[16] 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.

Third, an important model prediction is that workers may endogenously choose to under-invest in health. To measure the prevalence of under-investment in the data, 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.[17] If an individual's answer to any of these questions is "Yes", our indicator variable for under-investment in health turns on the value of 1. We obtain that, among the working-age adults (18-64) in the U.S., 18.6% under-invest in health. In comparison, our model predicted share of under-investment is 16.7% for the pre-China equilibrium, close to the empirical share from the NHIS.

Fourth, the model also predicts that workers may endogenously choose to over-invest in health, 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 (years 1999-2013) that include detailed consumption data, we show that among the employed, the ratio of non-medical consumption to income is 70% for those with bad health and 60% for those with good health,[18] which are similar to our model predictions of 68% and 71%. In other words, our model generates a reasonable non-medical consumption to income ratio, even though this ratio is not directly targeted.

Overall, we are able to validate the model's ability to generate health outcomes (transition probabilities) and health investment incentives, as measured by the elasticity and the quantitative magnitudes of both under- and over-investment in health, that are in line with the data.

[17] These questions are not available for earlier years, and we stop in 2012 because the Affordable Care Act (ACA) went into effect in 2014. Examples of these questions include: "DURING THE PAST 12 MONTHS, was there any time when {person} needed medical care, but did not get it because {person} couldn't afford it?", and "DURING THE PAST 12 MONTHS, was there any time when you needed any of the following, but didn't get it because you couldn't afford it? ... Prescription medicines."

[18] 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.

5.3 Key Model Features

Our main model mechanisms revolve around the optimal health investment, H^*, which, in turn, consists of both medical expenditures, $\min\{H^*, \varepsilon\}$, and over-investment, $\max\{H^* - \varepsilon, 0\}$. While all model parameters and settings affect H^*, the shape of the health production function, the health insurance structure, and the utility cost of the state of unemployment and bad health play important roles.[19]

For expositional purpose, we discuss in detail the decisions of employed workers, after which we summarize how unemployed workers' decisions differ. Figure 7 illustrates the averages of medical expenditures and total health investment of employed workers by health status, insurance status, and sickness shocks, where the averages are taken across other states of workers (i.e., the labor productivity shock, z, and financial asset, a). The figure also shows the values of the sickness shock ε (that differ only by health status), as the benchmark for comparison, and the unit of the vertical axis is \$10K.

Over/Under-Investment and Insurance Status Figure 7(c) plots the choices of employed and insured workers with good initial health, by sickness shock (x-axis). A noticeable pattern among these workers is that total health investment exceeds sickness shocks ($H^* > \varepsilon$) for all sickness shocks. That is, the most resource-rich types in our economy opt to mitigate against future risks of falling into bad health by over-investing in health, beyond fully treating their sickness. This is an important aspect of our model: in addition to self-insurance through savings, we incorporate an additional self-insurance channel through health investment choices. Such a mechanism cannot be captured in models with exogenous health dynamics or models that equate the amount of health investment with observed medical expenditures.

Figures 7 (a), (b) and (d) show that over-investment is also common among workers who do not experience a sickness shock (ε_0) or experience a mild sickness shock (ε_1 and ε_2), including the workers with no health insurance. This happens for two reasons. One, the insurance premium is the same for all sickness shocks, and so the (ex-post) financial benefit of health insurance coverage is limited for the workers with mild sickness. Two, these workers are faced with the future risks of severe sickness, and so they self-insure by over-investing in

[19] For example, the baseline probability parameters, $1 - \alpha(x, \varepsilon)$, shift the health production function vertically (Figure 4) and contribute to the quantitative model fit with the probability of future good health.

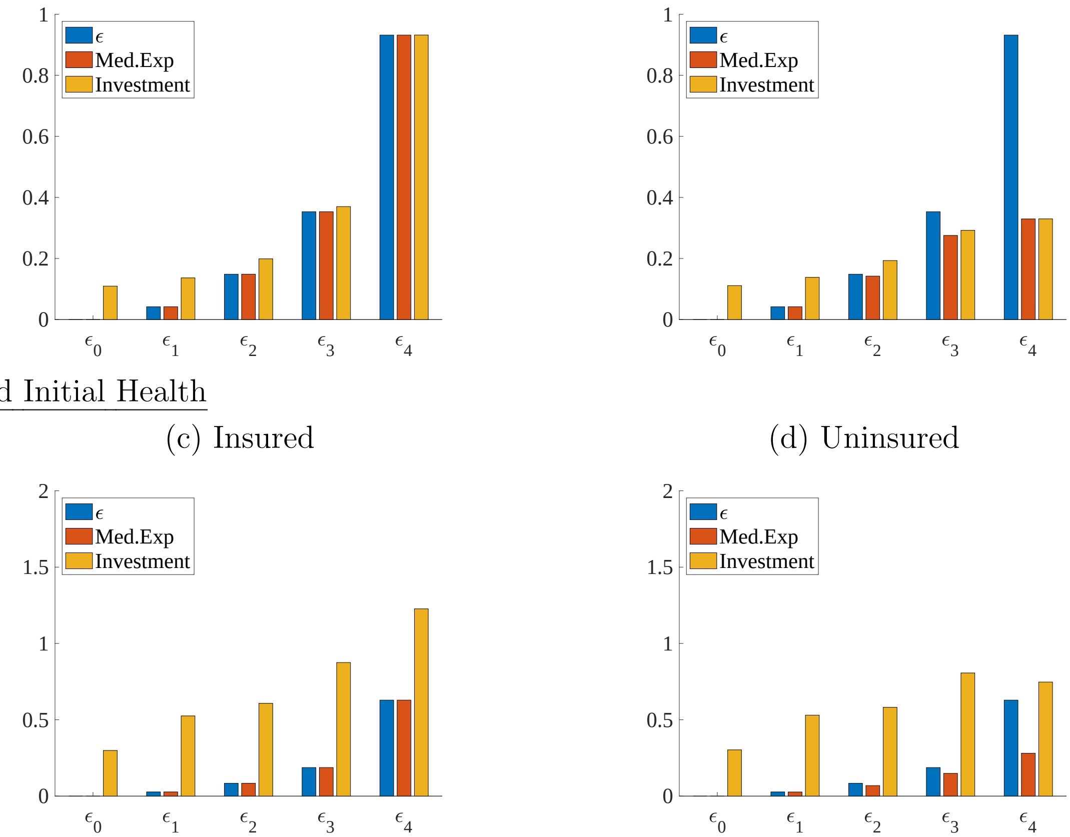
Figure 7: Health Investment of Employed Workers

Bad Initial Health

(a) Insured (b) Uninsured

Good Initial Health

(c) Insured (d) Uninsured



health.

On the other hand, Figures 7 shows that for the uninsured workers of bad initial health, total investment is lower than the sickness shock ($H^* < \varepsilon$) in the cases of severe sickness, ε_3 and ε_4. Under-investment happens due to the combination of resource constraints and consumption smoothing. In terms of resources, health insurance coverage carries large (ex-post) financial benefits for severe sickness, especially given the low coinsurance rates in our model (Table 6). Lacking such resources, uninsured workers with bad initial health choose to under-invest in health for the sake of current-period consumption.

Overall, the health insurance structure and endogenous and flexible investment choices help our model match the heterogeneity in the targeted moments across insurance status, as summarized in *Empirical Fact 2*.[20]

[20] Note that the baseline probabilities in Table 7 are substantially lower than the transition probabilities in Figure 5.

Heterogeneity Across Initial Health Status Figure 7 also shows substantial heterogeneity in optimal health investment by initial health status that arise due the their different shapes of health production function, $F(.)$ (Figure 4).

First, above the minimum investment, $H_{min}(x)$, $F(\cdot)$ is more concave for bad health individuals; i.e. the marginal benefit of health investment is high initially but decreases rapidly as H increases. Thus, bad health individuals who choose partial treatment still expend a significant amount of medical expenditures, consistent with their high mean medical expenditures conditional on positive expenditures, documented in Table 8. This also implies that among the insured, the amount of over-investment tends to be small for bad health individuals (Figures 7(a) and 7(c)). For example, while the amount of over-investment is almost as large as $\varepsilon_4(G)$ for $\varepsilon_4(G) = \$6,290$, it is fairly small even for $\varepsilon_2(B) = \$1,490$, and it drops to zero for $\varepsilon_4(B) = \$9,320$.

Second, $F(.)$ has a short flat segment relative to ε for the workers with bad initial health (because $s(B) = H_{min}(B)/\varepsilon(B)$ is small), and so they are more likely to choose partial treatment ($0 < H^* < \varepsilon$) than zero treatment ($H^* = 0$). In comparison, the workers with good initial health do not choose partial treatment when they experience a sickness shock. Such compositional differences interact with the differences in the concavity of $F(\cdot)$, and the total effects of these interactions are manifested in Figures 7(b) and 7(d). For the good initial health individuals with no insurance (Figure 7(d)), 22% choose zero treatment (but not partial treatment) and the remaining 78% choose over-investment. The amount of over-investment is substantial given the low concavity of $F(\cdot)$. Therefore, the average total investment is substantially higher than the average medical expenditure. In comparison, only 10.7% of bad health individuals without insurance choose zero treatment. The remaining 41.0% choose partial treatment and 48.3% choose over-investment. Due to the high concavity of $F(\cdot)$, medical spending is high under partial treatment but the amount of over-investment is small. Therefore, the average total investment is similar to the average medical expenditure (Figure 7(b)).

Together, these features of the health production function help the model match the heterogeneity in the targeted moments across health status, as summarized in *Empirical Fact 1*.

Unemployed Workers For the unemployed workers, under-investment and over-investment continue to work in the ways discussed above, and they also work through the utility channel. Due to the high utility cost of the state of bad health and unemployment ($\iota(B, l = 0) < 0$), the unemployed workers with good health are strongly incentivized to over-invest, and this effect amplifies the effect through the low concavity of the health production function, discussed above. In addition, the unemployed workers with bad health are also incentivized to invest in health, in order to transition out of this state, and this effect amplifies the low marginal utility of consumption in this state. Therefore, our model predicts small differences in both population shares of zero medical utilizations and mean medical expenditures across employment status, as consistent with the data targets shown in Table 8.

In summary, over-investment and under-investment, illustrated in Figure 7 and discussed above, underlie the model predicted outcomes that we described in Subsections 5.1 and 5.2. They also play an important role in the way in which exposure to the China shock may impact the workers' probability of good health.

6 Quantitative Analysis

In the previous section, we have shown that the calibrated model matches the key quantitative patterns of the data, and clarified the key model features in the pre-China economy. Now, we use the model as a laboratory to quantify the effects of the China shock on workers' probability of being in good health, and to evaluate the effectiveness of potential policy responses.

6.1 China Shock and Health

In this subsection, we present the model's predictions about the effects of the China shock on aggregate manufacturing sector outcomes, health transition probabilities at the worker level, and sector-wide health distribution to quantify the economic significance of our results.

Manufacturing Sector Outcomes in the Post-China Economy To recap our earlier discussions, we model the China shock as an exogenous drop in the domestic share of the manufacturing sector from 0.85 to 0.71. Table 9 summarizes the model-implied effects of the China shock. In the first experiment in which only wage adjusts and the job-destruction

Table 9: Manufacturing Sector Outcomes in the Post-China Economy

	Income	Employment	Export-GNE
Pre-China economy	\$50,211	71.8%	0.057
Post-China 1: Wage adjustments	\$47,322	71.5%	0.068
Change from Pre-China	-5.75%	-0.3*pp*	+19.30%
Post-China 2: Wage & employment adjustments	\$49,056	68.4%	0.061
Change from Pre-China	-2.30%	-3.4*pp*	+7.02%

rate remains fixed, we observe that the model predicts a 5.75% drop in the wage rate of manufacturing workers. Intuitively, this is because the increase in import competition from the China shock reduces demand for manufacturing labor, as can be seen from Equation (21). The magnitude of the wage decline is in line with the upper end of the estimates from Autor et al. (2014), 7.2%. 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.

In the second experiment, we fix the wage drop at 2.3% (the lower end of the estimates from Autor et al., 2014), and attain the labor market equilibrium condition (21) by a uniform increase in the job destruction rate $\delta(E, x)$ of 1.12*pp*, resulting in a 3.4*pp* drop in the manufacturing sector employment rate. This implies that the ratio of manufacturing employment to population declines by 0.51*pp* (assuming that the manufacturing sector accounts for 15% of the population), accounting for a substantial portion of the effect of the China shock on this ratio, 0.88*pp*, as reported by Autor et al. (2013).

Overall, our model's predicted effects of the China shock on manufacturing sector outcomes are quantitatively consistent with previous findings, further validating our model.

Effects on Workers' Health Statuses Table 10 gathers the change in the probability of transitioning to good health in the post-China economy by workers of different characteristics. Before we compare these model predictions with our estimates from Table 3, we clarify that in our stylized model, economic shocks affect health status through workers' optimal choices of monetary health investment, but other channels (e.g., mental stress) have been assumed away. As a result, the comparisons below show the contribution of the single mechanism of optimal health investment.

First, among the employed, the probability of being in good health decreases by 2.15%,

Table 10: Heterogeneity in Health Effects of the China Shock

% Change in Transition to Good Health (from Pre-China)			
By Initial Health and Employment Statuses			
Health Status	All	Unemployed	Employed
All	-2.23	-2.33	-2.15
Bad	-0.78	-1.32	-0.49
Good	-1.36	-1.20	-1.41
By Sickness Shock and Insurance Statuses			
Sickness Shock	All	Uninsured	Insured
All	-2.23	-2.72	-2.07
ε_0 (no shock)	-1.36	-1.39	-1.35
ε_1	-1.91	-1.94	-1.90
ε_2	-2.10	-2.24	-2.04
ε_3	-2.81	-4.22	-2.34
ε_4 (severe shock)	-2.44	-3.17	-2.22

which translates into good-health elasticity of IPW for the employed of -0.023.[21] In our empirical analysis in Section 2, where we estimate the elasticity among initially employed workers, we find the elasticity of -0.054 (Table 3) and -0.06 (Table 2) using individual-level and region-level data, respectively. This implies that the optimal-health-investment mechanism is quantitatively important, accounting for roughly two-fifths of our empirical estimate. Next, for employed workers with good initial health, transition probability to future good health drops by 1.36% (elasticity -0.0149), suggesting that the investment mechanism accounts for more than one-fifth of the estimated elasticity of -0.068 (Table 3). For the employed with initial bad health, the model predicted elasticity is -0.0052, very close to 0, consistent with the finding from Table 3 where the coefficient estimate for this group is statistically insignificant. These results are mainly driven by the drop in over-investment in health, because most employed workers have health insurance.

Table 10 also shows the model predicted effects by sickness shock and insurance status. As discussed in Subsection 5.3, the health effects of having insurance are significantly larger for severe sickness in our model. As a result, Table 10 shows that the insured and uninsured experience very similar health effects from the China shock when they face mild sickness shocks of ε_0 through ε_2, ranging between 1.3% and 1.9%, but the uninsured have much

[21]The percent change in IPW is equal to $\left(\left(1-\pi^D_{m,pre}\right)-\left(1-\pi^D_{m,post}\right)\right)/\left(1-\pi^D_{m,pre}\right) = \left((1-0.71)-(1-0.85)\right)/(1-0.85) \approx 0.93$ (93%). And thus, the elasticity with respect to IPW can be obtained by dividing 93 to the percent change in good health share.

larger effects (in magnitude) for the severe sickness of ε_3 and ε_4. Among uninsured workers experiencing ε_3 shocks, the probability of transitioning to good health decreases by 4.22%, almost twice as large in magnitude as the 2.34% drop among insured workers. Interestingly, the health effects among the uninsured with the most severe shock, ε_4, are smaller than those with ε_3. Intuitively, this is the under-investment mechanism at work. Under ε_4, a larger share of workers choose zero treatment in the pre-China economy than under ε_3, and so these workers' transition probability to good health cannot decrease further.

In summary, Table 10 shows rich and non-linear heterogeneity in the health effects of the China shock across worker characteristics. We now move on to the aggregate effects of the China shock on health status, in order to highlight the economic significance of our simulation results.

Aggregate Health Effects We first clarify that the aggregate health effects for the manufacturing sector are not the weighted averages of the group-specific effects in Table 10, because of compositional changes. Specifically, the change in population share of good health can be decomposed to the sum of $\sum_{\boldsymbol{s}} \Delta Pr\left(G;\boldsymbol{s}\right) \times \mu\left(\boldsymbol{s}\right)$, the effect from changes in probability transitions, and $\sum_{\boldsymbol{s}} \Delta\mu\left(\boldsymbol{s}\right) \times Pr\left(G;\boldsymbol{s}\right)$, the effect from changes in the stationary distribution. Thus, the aggregate change in the population share in good health encompasses both the intensive-margin effect from the group-specific elasticities, $\Delta Pr\left(G;\boldsymbol{s}\right)$, as well as the extensive-margin effect from compositional changes, $\Delta\mu\left(\boldsymbol{s}\right)$.

In the aggregate, the model predicted change in good health share in the manufacturing sector is -2.15%, and the aggregate health investment H drops 7.2%. The drop in H, in turn, is driven by the 12% decline in over-investment. Over-investment declines substantially regardless of initial health status or insurance status, because the health production function is relatively flat at the level of optimal over-investment, and because over-investment is not covered by health insurance. The other component of H, medical expenditure, however, is almost unchanged (-0.6%), despite the substantial decline in the good-health share, because sickness shocks are more severe for those with bad health and so tend to require higher medical expenditures.

In our simulation, the equilibrium wage is endogenously determined in the post-China economy, through the manufacturing-sector labor-market clearing condition (21). This implies that the decrease in the aggregate good-health share reduces the aggregate labor supply to the manufacturing sector, and so cushions the downward pressure of the China shock on the equilibrium wage.

Overall, the 2.15% decline in good health share implies that in the post-China economy, the share of workers with good health decreases from 54.25% to 53.03%. 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 average U.S. population of 251.6 million in 1990-1992. According to MEPS, individuals with bad health have more frequent visits to the emergency room (ER) relative to their good health counterparts—0.44 and 0.21 per person per year, respectively—and also longer hospital stays—0.67 and 0.26 inpatient days per person per year, respectively. As a result, our model predicts that, in response to the China shock, the U.S. manufacturing workers make 103,000 more ER visits and spend 189,000 more inpatient days in hospitals *per year*. These examples further illustrate the above-mentioned model prediction that following the China shock, the overall health is substantially worse but total medical expenditure remains almost unchanged.

6.2 Counterfactuals: Universal Health Insurance

In the previous subsection, we have quantified the substantial adverse effects of the China shock on health status. We now explore the efficacy of potential policy responses to the China shock by conducting counterfactuals. Specifically, we simulate a post-China economy in which all individuals are covered by health insurance with the premium and coinsurance rates specified in Table 6.

6.2.1 The Overall Effect for the Manufacturing Sector

We first simulate the manufacturing sector. As in the post-China economy simulation of the previous subsection, we fix Y and D_m^* to the pre-China economy, while allowing the wage rate to adjust to clear the labor market. We impose budget-neutrality, that is, all individuals are subject to lump-tum transfers so that the government's exogenous expenditures $\mathcal{G}$ in Equation (18) in the counterfactual economies are equivalent to those in the benchmark post-China economy.

Table 11 summarizes our key results. In the post-China economy with universal insurance, the wage drops by 6%, similar in magnitude to the 5.8% drop in the benchmark

Table 11: Effects in Post-China Economies under Benchmark and Universal Insurance

	Pre-China Economy	Change from Pre-China Economy: Post-China with Benchmark Insurance	Change from Pre-China Economy: Post-China with Universal Insurance
Wage	\$50,211	-5.8%	-6.0%
Health investment, H	\$5,666	-7.2%	-1.4%
Medical expenditure, $\min\{H, \varepsilon\}$	\$2,400	-0.6%	13.7%
Over-investment, $\max\{H - \varepsilon, 0\}$	\$3,267	-12.0%	-12.5%
Partial treatment ($H < \varepsilon$) share	12.1%	+0.9*pp*	-0.9*pp*
Zero treatment ($H = 0$) share	4.6%	+0.9*pp*	-4.6*pp*
Good health share	54.3%	-1.2*pp*	-0.2*pp*

post-China economy. The small difference arises because other things equal, an improvement in overall health increases aggregate labor supply and so reduces the equilibrium wage.

The similar wage decline implies a similar decline in over-investment under universal health insurance (12.5%), as compared with the benchmark post-China economy (12%). Medical expenditure, however, increases by 13.7% under universal health insurance, in contrast to its 0.6% decline in the benchmark. As a result, despite the similar wage effects, the drop in health investment, H, is much smaller in magnitude with universal health insurance (1.4%) than with the benchmark (7.2%).

In order to explore the mechanisms through which universal health insurance increases medical expenditure, we examine the share of individuals who choose partial treatment and zero treatment. While universal health insurance reduces the share of partial treatment, the effect is relatively small, because even insured individuals may optimally choose partial treatment if they have limited resources. In contrast, universal health insurance completely eliminates zero treatment. The resulting increase in medical expenditure is substantial because of the minimum investment, H_{min}.

Overall, in the presence of universal insurance, the population share of good health would only drop by 0.2*pp* relative to the pre-China economy. In comparison, this share drops by 1.2*pp* in the benchmark post-China economy. In other words, if universal health insurance had been implemented after the China shock, it would have remedied 83.3% of the adverse health effects of the China shock. This remedy happens primarily because under universal health insurance, everybody would invest at least the minimum amount for health when he is sick. On the other hand, our results also show that universal health insurance would not be 100% effective, because health insurance provides no protection against the decline in over-investment. We now further clarify this point by examining the heterogeneous effects of the counterfactual universal health insurance across commuting zones.

6.2.2 Heterogeneity Across Commuting Zones

In order to simulate heterogeneous effects across commuting zones, we first multiply the percentiles of the distribution of ΔIPW (e.g. $4,500 per worker, or 4.5 units, at the 75th percentile) by Autor et al. (2013)'s coefficient estimate,[22] to obtain the percentiles of the distribution of empirically estimated wage changes (e.g. 9.7% at the 75th percentile). We list these percentiles and wage changes in the first two columns of Table 12.

We then interpret each percentile as a single commuting zone, and simulate the effect of the China shock by feeding in the wage drops exogenously, without solving for the equilibrium wage using Equation (21). We report the results of these simulations in the third column of Table 12. We then perform the same counterfactual universal health insurance as in Subsection 6.2, imposing budget-neutrality within each commuting zone. We present the results of these counterfactuals in the last column of Table 12.

Table 12: Health Effects by IPW Exposure

		% of Population with Good Health (*pp* change from Pre-China)	
ΔIPW Percentile	Wage Drop (%)	Benchmark Insurance	Universal Insurance
5^{th}	0.2	54.2 (-0.05)	55.2 (+0.97)
10^{th}	0.4	54.1 (-0.10)	55.1 (+0.91)
25^{th}	2.0	53.8 (-0.40)	54.8 (+0.62)
50^{th}	5.5	53.1 (-1.11)	54.2 (-0.04)
Mean (53^{rd})	7.3	52.7 (-1.48)	53.8 (-0.40)
75^{th}	9.7	52.2 (-1.97)	53.4 (-0.85)
90^{th}	15.8	50.9 (-3.28)	52.2 (-2.02)
95^{th}	21.7	49.7 (-4.51)	51.0 (-3.18)

From Table 12, we see that, as expected, the commuting zones with large drops in wages experience large deterioration of health. For example, although the median commuting zone experiences a drop of 1.11*pp* in the population share of good health, the 95^{th} percentile commuting zone has the sharp decline of 4.5*pp*, more than 8%.

We also see that while universal insurance helps mitigate these negative health effects, the efficacy of the mitigation varies substantially across commuting zones. For a commuting zone

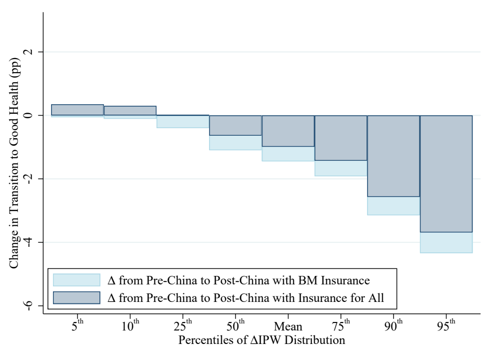
[22] We use the estimate in Table 9 of Autor et al. (2013), 2.14% per unit of ΔIPW.

with a small wage decline (e.g. those below the 25th percentile), universal health insurance 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 95th percentile, even with universal health insurance, the good health share would still drop by 3.18*pp* relative to the pre-China economy. This means that universal health insurance would only remedy around 30% ((4.51-3.18)/4.51) of the health deterioration from the China shock.

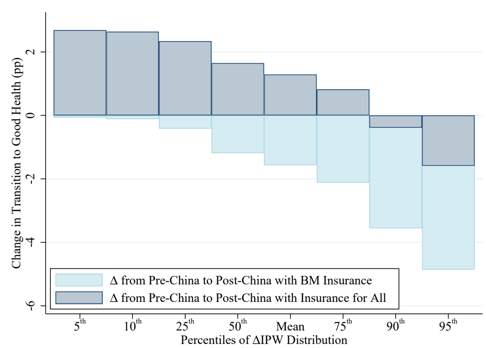
The intuition of these results is similar to that for Table 11. Relative to the benchmark post-China economy, universal health insurance has little effect on the change in over-investment, but increases medical expenditure substantially. When wage decline is small, so is the drop in over-investment, and so the increase in medical expenditure dominates. With large wage declines, however, the drop in over-investment dominates, and so the overall efficacy of universal health insurance would be limited.

Figure 8: Health Effects by IPW Exposure and Sickness Shocks

(a) Moderate Sickness Shocks



(b) Severe Sickness Shocks



In Figure 8, we further disaggregate the efficacy of universal health insurance by sickness shock. Specifically, Figure 8(a) plots the change in the transition probability to good health relative to the pre-China economy under benchmark insurance and under universal insurance by percentiles of ΔIPW among those with the moderate sickness shock of ε_2. Meanwhile, Figure 8(b) plots those for the severe sickness shock of ε_4.[23]

We first see, from Figure 8(a), that among those mildly sick, the efficacy of universal health insurance would be small across the ΔIPW distribution, as the change in the transition probability to good health, from pre-China to universal insurance, is similar to that from

[23]The graphs for ε_0 and ε_1 are similar to Figure 8 (a), and the graph for ε_3 is similar to Figure 8(b).

pre-China to the benchmark. However, as sickness becomes more severe, the gap between the two bars becomes much larger, as shown in Figure 8(b). For the commuting zone at the 5^{th} percentile, universal health insurance would increase the transition probability to good health by 2.76pp, much higher than the 0.41pp increase experienced by those with ε_2, shown in Figure 8(a). Even for the commuting zone at the 75^{th} percentile, experiencing a 9.7% wage drop, universal health insurance would still increase the transition probability to good health relative to the pre-China economy, more than fully offsetting the deterioration in health from the China shock. Overall, Figure 8(b) shows that for the severely sick individuals, universal health insurance would be very effective in mitigating the adverse health effects of the China shock.

7 Conclusion

In this paper, we study how the China shock affects workers' health through the mechanism of optimal health investment. We use micro-level panel data to show that exposure to the China shock reduces workers' probability of being in good health, with the elasticity of around -0.05. We then calibrate a quantitative model of health transition dynamics with a flexible health production function, where workers may optimally choose to under-invest or over-invest in health relative to the sickness shock. The model replicates key empirical moments in the micro data of health, including the shares of zero medical utilizations that have been overlooked in the previous literature. Our simulation shows that the health effects of the China shock have rich and non-linear heterogeneity across worker characteristics, and that the mechanism of optimal health investment is quantitatively important, capturing 40% of our empirical elasticity estimates, and economically significant, pushing nearly half a million manufacturing workers into bad health.

In our counterfactuals, we find that universal health insurance, implemented after the China shock, would remedy over 80% of the overall adverse health effects, primarily through the substantial reduction in the under-investment of health. However, since health insurance does not cover over-investment in health, the efficacy of universal health insurance would be fairly limited for the commuting zones with large exposure to the China shock, with the silver lining that it would still be highly effective for the individuals with the most severe sickness. 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).

While our model accommodates rich heterogeneity across initial health, employment, insurance, and sickness, it abstracts from the life-cycle effects of the China shock. It may be an interesting avenue for future research to explore whether the age at which a worker is exposed to the China shock may impact his employment and health investment decisions. In addition, although we focus on the China shock in this study, our model framework is general, and so could be applicable to answer other questions. For example, it may be interesting to explore whether under-investment and over-investment in health may contribute to the evolution of health inequalities and earnings, complementing recent works by Hosseini et al. (2021) and De Nardi et al. (2023).

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