# 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 this study, we first estimate the effect of import penetration on workers' future health, controlling for individual fixed effects. This empirical analysis complements existing studies that show workers exposed to trade shock experience higher frequencies in adverse medical events (sickness shocks) such as hospitalizations and emergency room visits. Given these empirical findings, we incorporate health into a quantitative dynamic model in which workers' future health is determined by sickness shocks and endogenous health investment. 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 mechanism of optimal health investment, and evaluate the efficacy of potential policy responses.

Our first goal is to estimate the effects of the trade shock on workers' future health. Following previous studies (e.g., Autor et al., 2013), we measure the magnitude of trade shock on workers 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). Using the panel data set allows us to control for individual fixed effects in estimating the China shock's effects on workers' future health statuses, complementing previous studies that utilized cross-sectional data sets. We find that the elasticity of future good health probability with respect to IPW is $-0.054$ for full-time manufacturing workers, and that the effect of the China shock is much stronger for workers with good initial health than for those with bad initial health.

Given the 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' health 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 and experience a sickness shock upon which they can choose health investment to improve their future health evolution. Unlike in previous studies, workers are able to partially or fully treat the sickness as well as invest more beyond the 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. Because workers' sickness shocks are distinct from their optimal health investment in our model, we face the following challenge to our calibration: how to relate the medical expenditures observed in the data to the model parameters of sickness shocks. Using the Medical Expenditure Panel Survey (MEPS) data, we observe that, after controlling for various individual characteristics, the probability of transitioning into a good health in the future is lower for the uninsured. Within insurance status, the transition probability to good health is decreasing in medical expenditures incurred in the current period. We thus interpret high medical expenditures as large sickness shocks, and assume that the insured always choose full treatment, and that the uninsured face the same distribution of sickness shocks as the insured. We can then use the observed medical expenditures and frequencies for the insured in the data to measure the magnitude and frequencies of the sickness shock in our model.

With these parameter values in hand, we specify a flexible Weibull function with baseline probabilities and minimum investments for the transition probability of good health, which we call the health production function, and apply the following procedures to calibrate the other parameters of the model. At the worker level, we target the transition probabilities by insurance status and sickness shocks; the shares of the population without medical utilizations by initial health, insurance, and employment statuses; and the average medical expenditures by the same groups. We then utilize labor market clearing conditions in the manufacturing sector and trade data to calibrate the sector-level parameters.

While our calibration procedure is standard, the flexibility of our health production function allows workers to optimally choose their health investment based on realized sickness shocks, income, insurance status as well as initial health status. The values of our calibrated parameters imply that workers with bad health face a much more concave health production function, relative to those with good initial health. This implies that for low levels of health investment, marginal benefit is higher, so they choose partial-treatment more often and zero investment less often. As a result, our model matches the targeted data moments well, including the group-specific shares of zero medical utilizations, the use of which is also novel to the literature. We further validate our model by confirming its performance on untargeted moments and comparing the model-implied elasticities of health with respect to income and spending with those from the empirical literature.

Given the calibrated parameter values, our model suggests that the China shock reduces the wage of U.S. manufacturing workers by 5.75%. The model predicted wage drop is within Autor et al. (2014)'s estimate ranges of 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 very concave health production function implies low marginal benefits for the high 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 1.5 times 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 health investment 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 over 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 reduce partial treatment of sickness, relative to the pre-China economy, and induce all workers to seek (some levels of) treatment when facing a sickness shock. As a result, universal health insurance would remedy over 80%, of the overall adverse health effects of the China shock.

Our counterfactual also demonstrates substantial heterogeneity in the efficacy of universal insurance across commuting zones and across sickness shocks. For the commuting zones with large increases in import penetration, the empirically estimated wage declines are large, and so our model predicts large declines in net health investment, the portion of health investment above and beyond sickness shocks. Because health insurance does not cover net investment, universal insurance would provide limited overall remedy for these commuting zones. For the individuals with the most severe sickness shocks, however, universal 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 due to various medical conditions including drug overdoses. 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.

In additional to empirical studies of health, there has been a growing literature that use structural models to evaluate how healthcare policies and technology affect health and welfare. Among them are Aizawa and Fang (2020), Hosseini et al. (2021), and De Nardi et al. (2023), all of which use micro-level data to guide their structural models to analyze the importance of health and health insurance on understanding welfare and aggregate outcomes and evaluating policies. While these papers abstract from endogenous health evolutions, Cole et al. (2019), Fonseca et al. (2021), and Lukas and Yum (2023) are among a few that endogenize health investment decisions and health dynamics. Cole et al. (2019) and Lukas and Yum (2023) incorporate health investment through efforts (e.g., exercise) for analysis of social insurance policies and wealth-health gaps in Germany, respectively, and Fonseca et al. (2021) studies the long-term trends in health spending and longevity in a model with endogenous medical spending. While our model shares common elements with these studies, our unique modeling of sickness shocks and the health production function implies that workers may optimally choose their investment based on severity of sickness shocks, and that their good-health probabilities may respond in a non-linear way to economic shocks.

Lastly, the studies investigating the role of health insurance on health outcomes have generated inconclusive findings. For example, 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. On the other hand, Goldin et al. (2021) uses randomized outreach program inducing insurance enrollment to conclude that insurance coverage decreases mortality for middle-aged adults.[1] 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.

[1]Finkelstein et al. (2012) and Weathers and Stegman (2012) report similar results to Baicker et al. (2013), while Card et al. (2009), Borgschulte and Vogler (2020) and Miller et al. (2021) have similar findings to Goldin et al. (2021).

# 2 Empirical Motivation

We use Panel Study of Income Dynamics (PSID) data to measure the impact of import penetration on individuals' probabilities of being in good health one year later.

## 2.1 Data

We first outline our data and the construction of our main variables.

**Panel Study of Income Dynamics** For worker-level data, we use the PSID. As we focus on the effects of import penetration on workers, we restrict our sample to those between the ages of 16 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. In PSID, each respondent is asked to rate his health into five categories (1 through 5). We combine the top two categories into a single category of *good* health, and combine the lower three into *bad* health. Under this choice of categorization, the shares of workers in each health category are equalized in our sample of full-time workers. The use of self-reported health 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] We obtain the restricted commuting-zone identifiers from the PSID to combine the individual-level outcomes with a measure of import penetration in his associated commuting zone. The data contains samples from 508 unique commuting zones for which we construct import penetration per worker that we describe next.

[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.

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

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

In this expression, $M_{j,t}^{\text{CHN}}$ and $L_{j,t}$ are, respectively, the US imports from China and employment in industry $j$ in year $t$, $L_{cz,j,t}$ is the employment in commuting zone $cz$ in industry $j$ and year $t$, and $L_{cz,t}$ is the employment in commuting zone $cz$ in year $t$. Intuitively, $\text{IPW}_{cz,t}$ 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 $t$.[3] In order to control for potential endogeneity in US imports, we follow Autor et al. (2013) and use the following instrument for $\text{IPW}_{cz,t}$:

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

As compared with the IPW measure, its instrument uses U.S. imports from eight other high-income countries (Australia, Denmark, Switzerland, Finland, Japan, Germany, New Zealand, and Spain) $M_{j,t}^{\text{OTH}}$ 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.

**Descriptive Statistics of the Merged IPW-PSID Data** Table 1 reports the summary statistics from our combined data set for all workers and by IPW quartiles. We also plot in Figure 1 the IPW distribution in the sample from year- and commuting-zone variations. We see that the IPW measure has large variations providing a useful variations for estimating its effects on workers. In order to illustrate the raw correlation patterns between workers' health and import penetration, we graph the mean values of the share of workers in Good health by quartile in Figure 2 (also reported in Table 1). Figure 2 shows that the share of workers in Good health monotonically decreases across IPW quartiles. In the next, we use the dataset to estimate the causal effects of IPW on workers' health.

[3]Autor et al. (2014) show that the IPW measure can also be constructed by industry by year, and that this measure provides useful variation if the industries are disaggregated. While PSID has worker affiliation by disaggregated industries, many of these industries have very small numbers of workers.

Table 1: Descriptive Statistics

| Variable | All | by IPW Quartile | | | |
|---|---|---|---|---|---|
| | | Q1 | Q2 | Q3 | Q4 |
| 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 categories) | 3.82 | 3.89 | 3.87 | 3.83 | 3.72 |
| | (0.92) | (0.90) | (0.90) | (0.92) | (0.95) |
| Health status (2 categories) | 0.65 | 0.68 | 0.67 | 0.65 | 0.61 |
| | (0.48) | (0.47) | (0.47) | (0.48) | (0.49) |
| Manufacturing | 0.20 | 0.18 | 0.22 | 0.19 | 0.21 |
| | (0.40) | (0.38) | (0.41) | (0.40) | (0.40) |
| IPW ($,000/Worker) | 1.44 | 0.22 | 0.54 | 1.17 | 3.43 |
| | (1.68) | (0.09) | (0.12) | (0.28) | (2.05) |

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 categories assigns a value between 1 and 5 with 1 being in excellent health. Similarly, Health status in two categories assigns a value of one to "Good" health (the top two statuses in five-category health status) and zero to "Bad" health.

Figure 1: Distribution of IPW

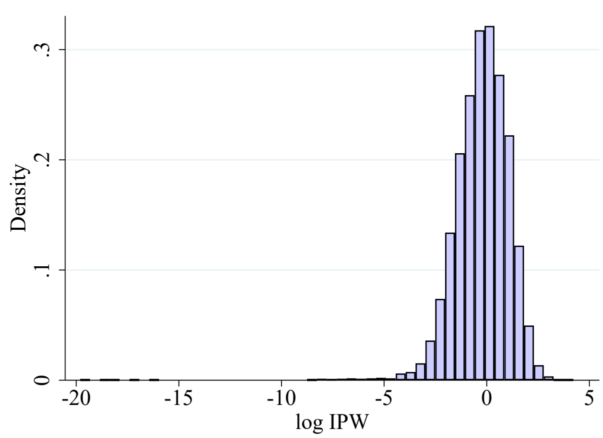
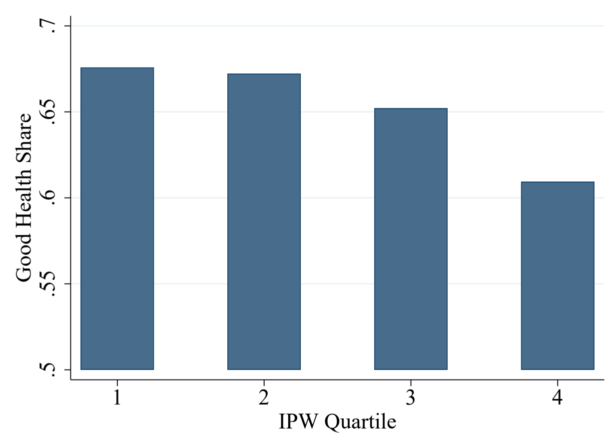



Figure 2: Health Status and IPW




## 2.2 The Causal Effects of Import Penetration on Future Health

Our econometric specification is as follows:

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

In Equation (1), the indicator variable $\text{GH}_{i,cz,t}$ takes the value of 1 if worker $i$, living in commuting zone $cz$, has Good Health in year $t$. The coefficients $\beta_i$ and $\beta_t$ are, respectively, worker- and year-fixed effects, and $Z_{i,t}$ is a vector of time-varying worker-characteristic controls (e.g., education). The coefficient of interest are $\gamma_k$, 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 $\gamma_k$ 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 (1) allow us to interpret $\gamma_k$ 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, $\beta_i$, 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 (e.g. Adda and Fawaz, 2020), the use of worker fixed effects is novel. It implies that regression (1) 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 2 reports the estimation results. The odd-numbered columns correspond to results using year fixed effects, and the even-numbered columns, using manufacturing-by-year fixed effects further controlling for manufacturing-specific trends. In columns (1) and (2), we place all workers in the same group. While the coefficients on import penetration are negative, this effect is not statistically significant. In columns (3) through (8), we divide the workers into their initial-year-characteristics subgroups, and report the coefficient estimates by subgroup.

Columns (3) and (4) show 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

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

Table 2: Import Penetration and Future Health

| $\gamma_k$ | Dependent variable: Probability of good health | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| All | -0.019 | -0.0192 | | | | | | |
| | (-1.64) | (-1.60) | | | | | | |
| Mfg. | | | -0.025*** | -0.027*** | | | | |
| | | | (-2.10) | (-2.12) | | | | |
| Non-Mfg | | | -0.012 | -0.012 | | | | |
| | | | (-1.13) | (-1.11) | | | | |
| Income Q1 | | | | | -0.050*** | -0.051*** | | |
| | | | | | (-2.81) | (-2.87) | | |
| Income Q2 | | | | | -0.026 | -0.025 | | |
| | | | | | (-1.44) | (-1.36) | | |
| Income Q3 | | | | | -0.023* | -0.022* | | |
| | | | | | (-1.84) | (-1.75) | | |
| Income Q4 | | | | | -0.012 | -0.012 | | |
| | | | | | (-0.98) | (-0.98) | | |
| Initial Good | | | | | | | -0.031** | -0.031** |
| | | | | | | | (-2.51) | (-2.42) |
| Initial Bad | | | | | | | 0.019 | 0.018 |
| | | | | | | | (1.62) | (1.54) |
| Worker FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | ✓ | | ✓ | | ✓ | |
| Mfg.$\times$Year | | ✓ | | ✓ | | ✓ | | ✓ |
| First-Stage $F$ | 12.92 | 12.65 | 52.71 | 40.41 | 15.10 | 15.24 | 58.06 | 55.31 |
| Obs. No. | 33,376 | | | | | | | |

Note: The table reports regression coefficients $\gamma_k$ from Equation (1). The standard errors are clustered by commuting zone and $t$-statistics are in parentheses. All regressions include the vector of time-varying worker characteristics, $Z_{i,t}$, as controls. Columns (3)-(6) report the coefficient estimates by subgroup ($\gamma_k$); year fixed effects are used for columns (1), (3), and (5); and as a robustness analysis, manufacturing-year effects are used for columns (2), (4), and (6). 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. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$

the China shock, import penetration primarily impacted the U.S. manufacturing sector. Further the estimates are robust to controlling for heterogeneous trends in manufacturing sector workers as seen in Column (4). Columns (5) and (6) show that the effect of import penetration is especially strong for the workers whose initial-year income is in the first quartile. This result is consistent with the reports from previous studies (e.g. Autor et al., 2014) that find stronger IPW effects on low-income workers, potentially leading to a larger deterioration in their health statuses. Lastly, in Columns (7) and (8), we see that the IPW had more adverse health effects on workers who initially had Good Health.

Table 3: Elasticity of IPW on Future Good Health

| | Status in Initial Year | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | All | Industry | | Income Quartile | | | | Health Status | |
| | | Mfg. | Non-Mfg. | Q1 | Q2 | Q3 | Q4 | Good | Bad |
| Elasticity | -0.042 | -0.054*** | -0.026 | -0.110*** | -0.056 | -0.050* | -0.026 | -0.068** | 0.042 |
| $\Delta$75-25% (*pp*) | -2.8 | -3.7 | -1.8 | -7.3 | -3.7 | -3.3 | -1.8 | -4.6 | 2.8 |

Note: The $\Delta$75-25% 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. All statistics are computed from the coefficients reported in Table 2 with $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

In Table 3, we use our coefficients reported in Table 2 to measure the elasticity of IPW on Good health probability and the differences in Good health probability between workers in commuting zones at 75-percentile and 25-percentile in the IPW distribution. These elasticities range between -0.054 to -0.110 for those who experienced a significant effect (e.g., manufacturing, initially good health, and low income workers), implying around 3*pp* to 7*pp* lower probabilities when comparing the exposures at 75-percentile and 25-percentile of the IPW distribution. These results corroborate previous studies, such as Adda and Fawaz (2020) and Pierce and Schott (2020) whose dependent variables are different (e.g. incidences of hospitalization and mortality), and provide additional empirical evidence and causal link between China shock and future health of workers.

In summary, the empirical analyses and results show that the import penetration caused an economically significant impact on the future health probability of workers. While these results are broadly reminiscent of previous applied-micro studies about the effects of the China shock on health, they raise the following new questions. 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.

## 3.1 Production

We start with the production 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 $\phi_m$ denote the manufacturing sector's share in final good production and thus,

$$x_m = \frac{\phi_m Y}{P_m}. \tag{2}$$

Equation (2) 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

$$x_{mS} = A\left[\omega_m^{\frac{1}{\sigma}} z_m{}^{\frac{\sigma-1}{\sigma}} + (1-\omega_m)^{\frac{1}{\sigma}} \left(z_m^*\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where $A$ is the TFP, $\omega_m$ 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

[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 3.5, we impose equilibrium conditions in the manufacturing sector, endogenizing the equilibrium wage effect in the manufacturing sector in response to the China shock.

$\tau^* \geq 1$ represents the trade cost of manufacturing inputs. It is straightforward to show that

$$z_m = \omega_m \left(p_m\right)^{-\sigma} X_{mS} P_m^{\sigma-1}, \qquad z_m^* = \left(1-\omega_m\right)\left(\tau_m^* p_m^*\right)^{-\sigma} X_{mS} P_m^{\sigma-1}, \tag{4}$$

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

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

relates the prices of the manufacturing good to the prices of its domestic and imported inputs. Equation 4 is the demand for these inputs of 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 $\psi_m$ is productivity, and $L_m$ is the labor supply (in efficiency equivalent units) of the manufacturing sector. We assume that manufacturing labor is immobile to the rest of the economy. The price of the domestic input is thus proportional to the wage rate $w_m$:

$$p_m = \frac{w_m}{\psi_m}. \tag{5}$$

The domestic input is tradable. When it is exported, it faces the foreign demand of $D_m^*\left(p_m\right) \equiv D_m^* \cdot \left(p_m\right)^{-\sigma}$, 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.

## 3.2 Workers

**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 $\varepsilon\left(x\right)$ with probability $f\left(\varepsilon; x\right)$, and draws his labor endowment $z$, from an AR(1) distribution in logs with persistence $\rho_z$ and standard deviation $\sigma_z$. The productivity effect of health is captured by $\nu\left(x\right)$, 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 $\varepsilon$,and health investment $H$. As we have two health statuses, $Pr(x' = B) = 1 - Pr(x' = G)$. In particular, we assume that $Pr(x' = G)$ is increasing and concave in health investment $H$. 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 $\pi$ 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 $\pi$ and pay the insured at copay rate of $\chi(\varepsilon; x)$ up to $\varepsilon$ (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 Worker Problems

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

$$
\begin{aligned}
V^l(\mathbf{s}) \quad = \quad & \max_{c \geq 0, a' \geq 0, H \geq 0} U(c + tr, l; x) && (6) \\
& +\beta \sum_{x'} Pr(x') \delta(l, x') \mathbb{E}_{in', \varepsilon'} V^0(x', a', in', \varepsilon') + \\
& +\beta \sum_{x'} Pr(x') (1 - \delta(l, x')) \mathbb{E}_{in', \varepsilon', z'} V^1(x', a', in', \varepsilon', z') \\
\text{s.t.} \qquad & c + a' + \tilde{H} = I(l, x) + (1 + r) a + tr && (7) \\
& tr = \max\{0, \underline{c} - (I(l, x) + (1 + r) a)\} && (8) \\
& \tilde{H} = \begin{cases} H & \text{if uninsured} \\ \pi + (1 - \chi(\varepsilon; x)) \min\{\varepsilon, H\} + \max\{H - \varepsilon, 0\} & \text{if insured} \end{cases} && (9) \\
& Pr(x' = G) = F(H; x, \varepsilon), \quad Pr(x' = B) = 1 - F(H; x, \varepsilon) && (10) \\
& I(l, x) = \begin{cases} w\nu(x) z - T(w\nu(x) z) & \text{if } l = 1 \\ b & \text{if } l = 0. \end{cases} && (11)
\end{aligned}
$$

The worker maximizes his utility (6), 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 (7), his expenditures are consumption $c$, asset $a'$,and out-of-pocket health investment expenditures $\tilde{H}$, and government transfers (8) that guarantee a minimum

[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.

consumption floor of amount $\underline{c}$. The term $\tilde{H}$ is further elaborated in (9). Uninsured individuals incur all investment amounts out of pocket. Insured individuals pay premium $\pi$ and $1-\chi(\varepsilon;x)$ share of expenditures used to treat the sickness shock ($\min\{\varepsilon, H\}$). If they choose to invest beyond treating their sickness shock, they pay the full cost as shown in $\max\{H-\varepsilon, 0\}$. The investment, together with $x$ and $\varepsilon$ determines the worker's health status for tomorrow as shown in (10). The worker's resource on the right hand side of the budget constraint (7) is his income $I(l,x)$—after-tax labor income if employed and unemployment insurance if unemployed as expressed in (11)—and assets $(1+r)\,a$.

Intuitively, the choice of health investment, $H$, in the maximization problem of (6) involves the trade-off between the future benefits of good health and today's cost in terms of consumption, given today's health status, $x$. The cost for consumption depends on both the insurance status and whether $H$ is above or below the sickness shock, $\varepsilon$, for those with insurance, according to equation (9). On the other hand, relative to bad health tomorrow, $x'=B$, the state of good health ($x'=G$) may enjoy higher utility, higher labor income, less severe sickness shocks, lower job destruction rates if employed, and higher job finding rates if unemployed.

## 3.5 Competitive Equilibrium of the Manufacturing Sector

Let the 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

$$L_m = \sum_{\mathbf{s}} \nu(x) \cdot z \cdot \mathbb{I}_{l=1} \mu(\mathbf{s}), \tag{12}$$

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

$$z_{mS} = z_m + D_m^* \cdot (p_m)^{-\sigma}, \tag{13}$$

and the market clearing condition for the manufactured good is simply

$$x_{mS} = x_m. \tag{14}$$

**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 (6).

2. Prices follow (2), (3), (4), and (5).

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

$$\begin{aligned}\sum_{\mathbf{s}} b \cdot \mathbb{I}_{l=0}\mu(\mathbf{s}) + \sum_{\mathbf{s}} tr(\mathbf{s}) \cdot \mu(\mathbf{s}) \\ + \sum_{\mathbf{s}} [\chi(\varepsilon, x) \min\{H, \varepsilon\} - \pi] \cdot \mathbb{I}_{in=1}\mu(\mathbf{s}) + \mathcal{G} = \sum_{\mathbf{s}} T(y(\mathbf{s}))\mu(\mathbf{s})\end{aligned} \tag{15}$$

4. Markets clear; i.e., (12), (13), and (14) hold.

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

# 4 Calibration Procedure

Our goal is to 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).

In this section, we first lay out the parameters whose values we treat as determined (Section 4.1). We then discuss how we calibrate the parameters of the health production function and utility function in Section 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 Section 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 $\rho$, discount factor $\beta$, 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, average labor income of a worker with health type $x$ is $w_m \cdot \nu(x)$. We normalize $\nu(x = G) = 1$, to obtain $w_m$ from average income of workers with good health, then obtain $\nu(x = B) = 0.81$ from the income gradient of 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) preferences $\{\iota(x, l)\}$.

As we discussed in the Introduction, a feature of our health production function is its dependence on sickness shock $\varepsilon$ and endogenously chosen health investment $H$. The key

[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 | | |
| $\sigma$ | Risk aversion | 1.5 |
| $\beta$ | 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 |
| $(\rho_z, \sigma_z)$ | 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 |
| $\tau$ | Income tax rate | 20% |
| Production | | |
| $\omega_m$ | Home bias | 0.5 |
| $\sigma - 1$ | Trade elasticity | 3 |
| $\phi_m$ | Cobb-Douglas share of manufacturing | 0.17 |
| $\pi^D_{m,pre/post}$ | Domestic share of manufacturing: Pre; Post | 0.85; 0.71 |

challenge in parametrizing and calibrating the health production is that the sickness shock and health investment in our model may differ from medical expenditures that we observe in the data. For example, an uninsured worker may choose partial treatment in the event of a severe sickness shock. In this case, the total amount of health investment $H$ is smaller than the sickness shock $\varepsilon$ (that is, $H < \varepsilon$). On the other hand, an insured and employed worker with a minor sickness shock may choose full treatment and additional spending on gym membership and exercise equipment that improves his health in the future. In this case, health investment $H$ is larger than the sickness shock $\varepsilon$ that is fully treated through medical expenditures in the data (that is, $H > \varepsilon$). To make progress, we use the micro panel data of Medical Expenditure Panel Survey (MEPS) to establish three stylized facts about observed medical expenditures, current health status, insurance status, and health transition probabilities.[8] Then, we use these facts to guide us through the calibration process.[9]

[8] MEPS contains individual-level medical expenditures (as opposed to family-level expenditures reported in the PSID) and health measures consistent with the PSID data that are necessary for our analysis.

[9] Our model focuses on manufacturing workers' decisions, and thus use wages of manufacturing workers. For parameters governing health production, we calculate moments using all workers in the sample, which provides a larger sample size. The underlying assumption is that all individuals face the same health production function regardless of the sector they are employed in.

**Motivating Empirical Patterns**

<u>*Fact 1.*</u> *Mean medical expenditures are higher for the insured but the share of individuals with zero medical utilizations are lower; and the heterogeneity across employment statuses is small, once insurance status is controlled for.*

First, we plot the distribution of log total medical expenditures by insurance status in Figure 3. The medical expenditure distribution of the insured is rightward shifted relative to that of the un-insured. Table 5 shows the mean MEPS medical expenditure by the eight groups of current health status (2) by employment status (2) by insurance status (2), as well as the shares of individuals with zero medical utilizations by group. We compute the latter by using the Household Component Event files (MEPS-HC) of the MEPS Medical Conditions data to identify the individuals who never reported medical events or utilizations, such as dental visits, outpatient visits, or prescribed medicine.[10] As can be seen from Table 5, uninsured individuals have lower mean medical expenditures than the insured but higher zero shares of medical events, which may be due to their lack of resources and access. However, conditional on insurance status, we see a smaller gradient in observed average medical expenditures and the share of workers who utilize medical care across employment statuses.

<u>*Fact 2.*</u> *Both high medical expenditures and lack of insurance are associated with low future probabilities of good health.*

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

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

where $\text{Health}_{i,t(t+1)}$ is 1 if Good health, 0 otherwise in year $t$ $(t+1)$; $D^{med}_{i,t,k}$ is a dummy indicating decile of medical expenditure $k$ among the insured (total of 11 groups including zero); and $X_{i,t}$ is a set of individual-level controls including the number of reported medical conditions, employment, and insurance status. In Figure 4 are predicted probability of being in good health in the future by this period's health status, medical expenditure decile, and

[10] We do not use zero medical expenditures because some individuals might receive medical treatment for free.

Figure 3: Expenditure Distribution

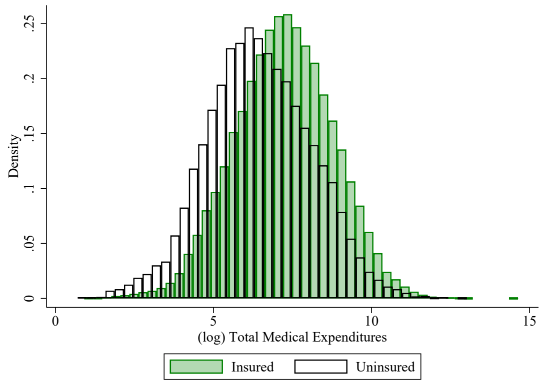



Table 5: Average Medical Expenditures

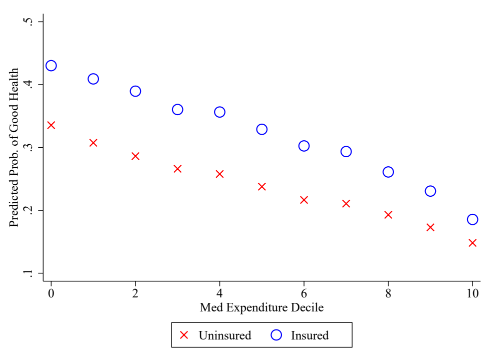
| | | | | |
|---|---|---|---|---|
| Average medical expenditures (positive only) | | | | |
| Bad | Emp/Ins | \$3,689 | Emp/Unins | \$2,412 |
| | Unemp/Ins | \$3,493 | Unemp/Unins | \$2,148 |
| Good | Emp/Ins | \$2,318 | Emp/Unins | \$1,625 |
| | Unemp/Ins | \$2,376 | Unemp/Unins | \$1,591 |
| Share of 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*: Figure 3 is from the MEPS data (1996-2014), where we plot distribution of log medical expenditures conditional on expenditures being positive. For medical expenditures in Table **??**, 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.

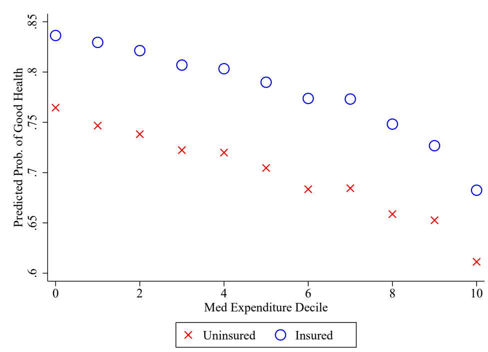
insurance status. The empirical patterns imply that, conditional on initial health, those with higher expenditures have lower probability of being in good health in the future. Further, conditional on being in the same expenditure decile, the uninsured individuals have lower probability of being in good health in the future.

Figure 4: Medical Expenditures, Insurance, and Future Health

(a) Bad Initial Health




(b) Good Initial Health




Fact 3. *Variation in today's health is associated with very large variations in mean medical expenditures, zero shares, and tomorrow's health.*

Finally, note that the vertical axis of the left panel of Figure 4 tops at 0.5, but that of the right panel bottoms at 0.6; i.e., the effect of today's health on tomorrow's health dwarfs those of both medical expenditure and insurance status. Table 5 also shows substantial differences between mean medical expenditures and zero shares across today's health status.

**Sickness Shocks and Health Insurance** Motivated by the stylized facts in Figure 4, we make the following assumptions about how our model parameters of sickness shock $\varepsilon$ relate to the observed medical expenditures in the data. First, the insured always choose full treatment; i.e. we interpret high medical expenditures as large sickness shocks, as consistent with Figure 4. Second, the uninsured face the same distribution of sickness shocks as the insured. These two assumptions allow us to use the observed medical expenditures and frequencies for the insured in the data to determine the magnitudes and frequencies of the sickness shocks in our model. We discretize the sickness shocks into five bins: $\varepsilon_0$ refers to those who do not face a sickness shock (no medical events), as measured in Table 5 above. Then we use the expenditure quartiles conditional on positive expenditures to construct $\varepsilon_1$ through $\varepsilon_4$ for each health status. 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, as is consistent with Fact 3.

Table 6: Predetermined Parameters Regarding Sickness Shocks and Health Insurance

| Parameter | Description | | Values | | | | |
|---|---|---|---|---|---|---|---|
| | | | $\varepsilon_0$ | $\varepsilon_1$ | $\varepsilon_2$ | $\varepsilon_3$ | $\varepsilon_4$ |
| $\varepsilon(x)$ | 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 |
| $\chi(\varepsilon; x)$ | Copay 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 | | |
| $\pi$ | 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 $\varepsilon_1$–$\varepsilon_4$ 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. Copay 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 copay rate by sickness shock, $\chi(\varepsilon; x)$, the insurance coverage rates by employment status, $\zeta(l)$, and the average health insurance premium, $\pi$. We summarize these values in Table 6, and make the following observations about them. First, although we use a simple copay structure, we use expenditure-dependent copay rates. This helps us capture other 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 copay rate decreases, and so health insurance is more useful for severe sickness shocks than for mild ones in our model. We revisit how these empirical features of health insurance impacts workers differentially in Section 6.

**Health Production Function** We need a flexible health production function, so that workers may potentially choose to partially (or fully) treat their sickness, or invest above and beyond the treatment of sickness through additional non-medical, monetary means. We use the flexible Weibull function to describe how the probability of future good health $Pr(x' = G)$, relates to today's health $x$, sickness shock $\varepsilon$, and health investment $H$:

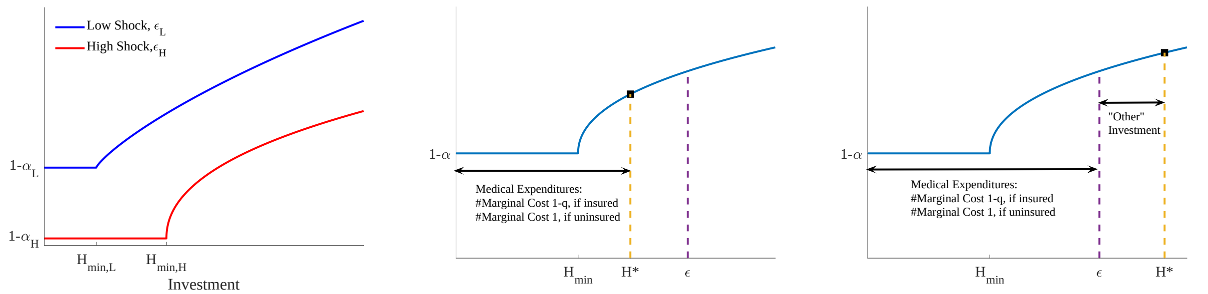
$$F(x' = G; x, \varepsilon, H) = \begin{cases} 1 - \alpha(x, \varepsilon) & \text{if } H \leq H_{min}(x, \varepsilon) \\ 1 - \alpha(x, \varepsilon)\exp\left[-\frac{(H - H_{min}(x,\varepsilon))^{\gamma(x)}}{\lambda(x)}\right] & \text{if } H > H_{min}(x, \varepsilon). \end{cases} \tag{16}$$

Motivated by Fact 3 above, we let all the parameters of the health production function (16), 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.

The health production function in Equation (16) has the following properties. First, in the absence of health investment, $H = 0$, the probability of good health is $1 - \alpha(x, \varepsilon)$. This can be interpreted as a baseline probability. Intuitively, $\alpha(x, \varepsilon)$ increases with $\varepsilon$, given health status $x$ (as illustrated in Figure 5(a)), because a large sickness shock (e.g., cancer) may lower one's baseline probability. Second, $H_{min}(x, \varepsilon)$ represents the minimum investment needed to improve the probability of good health (e.g., when one has cancer, small amount of investment is not effective). The flat portion of the health production function in Figure

Figure 5: Health Production and Investment

(a) Health Production (b) Partial-Treatment (c) Treatment Beyond Sickness




5(a) helps visualize $H_{min}(x, \varepsilon)$. 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 $\varepsilon$ increases, but its share relative to $\varepsilon$ 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). As a result, the optimal health investment is $H^* = 0$, $H_{min}(x, \varepsilon) < H^* \leq \varepsilon$ (under-investment), or $H^* > \varepsilon$ (over-investment), but never $H^* \in (0, H_{min}(x, \varepsilon))$. Figures 5(b) and (c) show cases of under- and over-investment. We refer to the investment less than or equal to the shock $\varepsilon$ as medical expenditures, and that above $\varepsilon$ as non-medical expenditures (which are implicitly perfect substitutes). Below, we 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

$$U(c, l; x) = \frac{[c \cdot \exp \iota(x, l)]^{1-\rho}}{1-\rho}, \tag{17}$$

in which $c$ denotes consumption and $\rho$ 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 so provides stronger incentives for health investment.

**Properties of the Value Function** Because the health production function (16), and utility function (17) are both well-behaved, the value function of workers' optimization problem (6) is also well-behaved, increasing in income and concave in assets (among others). As a result, given the positive health gradients of wage, job continuation rate, and job finding rate in Table 4, $V^l(G, \cdot) > V^l(B, \cdot)$, ceteris paribus. These higher valuations incentivize 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 4 but with five sickness shocks, 20 moments); (ii) the share of population with zero medical events (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 health, zero shares, and mean medical expenditures. First, from Figure 5(a), we see that an increase in $\alpha(x, \varepsilon)$ lowers the baseline probability of good health and are identified from the variation of the good health probabilities across sickness sock $\varepsilon$ 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 medical expenditures and zero shares across labor market status and insurance status within a given $\varepsilon$ shock. Lastly, an increase in the minimum share, $s(x) = H_{min}(x, \varepsilon)/\varepsilon$, directly impacts the share of workers who choose zero expenditures. It also decreases the probabilities of future good health for large sickness shocks, like $\varepsilon_3$ and $\varepsilon_4$, 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 $\iota(B, U)$ increases the zero shares for the uninsured. Overall, $s(x)$ and $\iota(x,l)$ (particularly $\iota(B,U)$) are identified from the share of workers with zero medical expenditures and the variation in the probabilities of future good health between large and small sickness shocks.

## 4.3 Production Parameters and the China Shock

In the previous section, we described how we calibrate the parameters of the health production function (16), and utility function (17), and solve the workers' optimization problem (6), 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 (13)—(14), 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 $\psi_m$ and the final goods price $P$ to one. The sectoral home bias, $\omega_m$, 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 (13)—(14) imply that

$$w_m L_m = \pi_m^D \phi_m Y + D_m^* p_m^{1-\sigma}, \quad \pi_m^D = \frac{\omega_m (p_m)^{1-\sigma}}{\omega_m (p_m)^{1-\sigma} + (1-\omega_m)(\tau_m^* p_m^*)^{1-\sigma}}, \tag{18}$$

where $\pi_m^D$ is the domestic share of the manufacturing sector. Equation (18) is the labor market clearing condition for the manufacturing sector. On its left-hand side, $w_m$, the equilibrium wage, has its value set as $w_m$ 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 (12). 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 ($\nu(x = B) = 0.81$ in Table 4). Our remaining task, then, is to ensure that the right-hand side of Equation (18) 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, $\phi_m$ 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 (18).

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

$$\frac{\text{Manufacturing Export}}{GNE} = \frac{D^*_m \cdot {p_m}^{1-\sigma}}{Y}. \tag{19}$$

From STAN, we obtain that this ratio is 0.057 (the average for 1990-1992). We then use equations (18) and (19) 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 $\pi^D_m$ 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 $\tau^*_m$, 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, $Y$.[11] 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).[12] 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 (18), 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 (18) allows us to solve for the post-China-shock equilibrium wage, $w_m$, because the inner loop

[11] 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.

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

pins down the aggregate labor supply, $L_m$, as a function of $w_m$, via Equation (12), and that $p_m = w_m$, by equation (5). In the second approach, we allow both $w_m$ and job continuation rates to change. In order to contrast with the first approach, we set the wage decline to be 2.3%, the lower end of the estimates from Autor et al. (2014), and search for the change in $1-\delta(E,x)$ that balances equation (18). For both approaches, we compare the model predictions of the export-GNE ratios with data.

# 5 Calibration Results

Now, we report parameter values and model fit, validate our model, and discuss the key mechanisms.

## 5.1 Parameter Values and Model Fit

In Table 7, we report the values of parameters calibrated in the model. Table 8 compares the model predicted mean medical expenditures and shares of zero medical events with data targets and Figure 7 plots the model predicted probabilities of future good health with data.

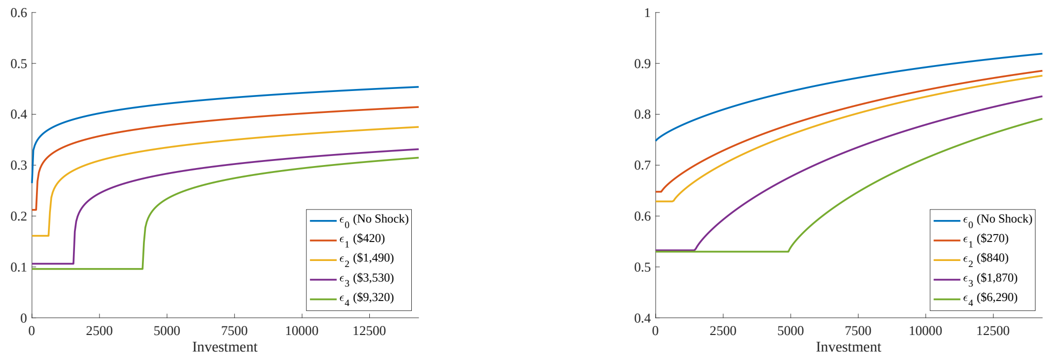
Table 7: Parameters Calibrated in the Model

| Parameter | Description | | Values | | | | |
|---|---|---|---|---|---|---|---|
| Health production | | | | | | | |
| | | | $\varepsilon_0$ | $\varepsilon_1$ | $\varepsilon_2$ | $\varepsilon_3$ | $\varepsilon_4$ |
| $1-\alpha(x,\varepsilon)$ | 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 | | | | |

We first discuss the health production function, plotted in Figure (6) from parameters presented in Tables 6 and 7. The first salient feature is that good health probability $F(\cdot)$ shifts down as the sickness shock $\varepsilon$ becomes more severe or health status $x$ becomes worse, as the calibrated baseline probability $1-\alpha(x,\varepsilon)$ decreases with $\varepsilon$ and increases with $x$. Second, there is a large difference in curvature of $F(\cdot)$ for $H > H_{min}$ between bad and good initial

Figure 6: Calibrated Health Production

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




health, determined jointly by $\gamma(x)$ and $\lambda(x)$. In particular, the marginal benefit of an extra dollar above $H_{min}$ is larger for initial bad health than it is for initial good health. However, this marginal benefit decreases more rapidly as $H$ increases for bad health, whereas for good health, there is considerable marginal benefits for health investment for a wide range of $H$ values. Given these features, those with good health are more likely to choose either $H^* = 0$ or $H^* > \varepsilon \geq H_{min}$. On the other hand, underinvestment ($H^* < \varepsilon$) is more common among the bad health given the sharp decrease in their marginal benefit as $H$ increases. Lastly, given our assumption on the minimum health investment required $H_{min} = s(x) \cdot \varepsilon$, a worker with a severe shock has to incur a large amount of investment for it to help improve his health in the future, potentially forcing them to forego any treatment ($H^* = 0$) in the absence of sufficient amount of resources. These choices of workers are further governed by $\iota(x, l)$, implying a negative marginal utility of consumption among those with bad health and the unemployed, consistent with Low and Pistaferri (2015).

Under these parameters, the model generates reasonable fits on the share of individuals with zero medical expenditures and average medical expenditures conditional on positive expenditures, as summarized in Table 8. In the model, workers of bad (good) health face a 5% (8%) probability of not experiencing any sickness shocks, $f(\varepsilon_0; x)$ reported in Table 6. This, however, does not necessarily imply that 5% of bad health workers expend zero medical expenditures, because individuals endogenously choose their investment. Importantly, relative to their sickness shocks $\varepsilon$, they may under-invest ($H < \varepsilon$) or over-invest ($H > \varepsilon$) in their health. In Table 8, the model predicted zero expenditure shares are equivalent to the share of workers not facing sickness shocks $f(\varepsilon_0; x)$ for those who are employed and

Table 8: Model Fit on Targeted Moments

| Moments | Model | Data | Moments | Model | Data |
|---|---|---|---|---|---|
| Share of individuals with zero medical expenditures (health investment) | | | | | |
| 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.

insured. However, even though all workers of bad health experience the same sickness shock probabilities, higher share of unemployed and uninsured individuals have zero medical expenditures: 19% (26%) of unemployed and uninsured workers of bad (good) health have zero medical expenditures, and their shares are close to those in the data. In our model, the reason these workers do not incur any medical expenditures despite experiencing a sickness shock is because these workers may have less resources (e.g., income, insurance access) coupled with the fact that our health production function features a minimum investment. The discrepancies in the zero expenditure shares are more stark across insurance statuses than across employment statuses, thanks to a generous copay rate of insurance that lower effective marginal cost of medical expenditures. These mechanisms further translate into lower average medical expenditures among the unemployed and uninsured compared to the employed and insured workers in the model. Overall, our model is successful in generating both the qualitative and quantitative heterogeneity in medical expenditure patterns of workers of different characteristics.[13]

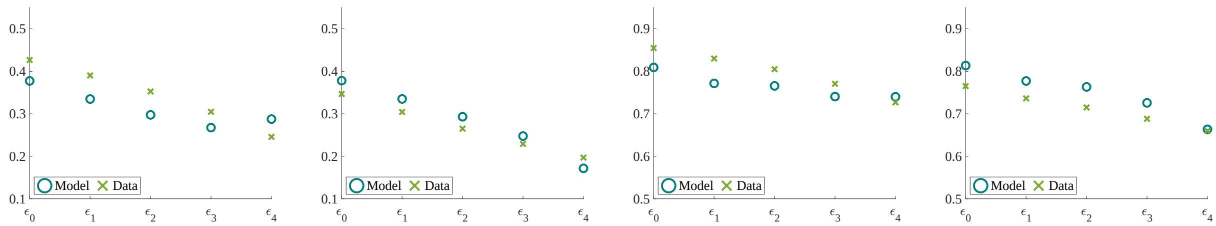
The resulting future good health probabilities are plotted in Figure 7 for the four targeted groups. Generally, conditional on worker's health and insurance statuses, workers with a large sickness shock have a lower probability of being healthy, consistent with data. Importantly, experiencing a large sickness shock has more detrimental effects on future health

[13]Given the workers' choice of health investment and copay 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 (15)).

Figure 7: Model Fit on Good Health Probability

Bad Initial Health | Good Initial Health

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




transitions of uninsured workers than it has on insured workers. This feature arises in the model endogenously due to the under-treatment of sickness shocks among the uninsured. In the model, while employed and insured workers fully treat their sickness shocks (that is, choose $H^* \geq \varepsilon$), 53% (20%) of uninsured workers of bad (good) health under-treat their sicknesses (that is, $H^* < \varepsilon$).

## 5.2 Validation of the Model

In this section, we provide validation of the model by comparing model predictions with untargeted moments in the data.

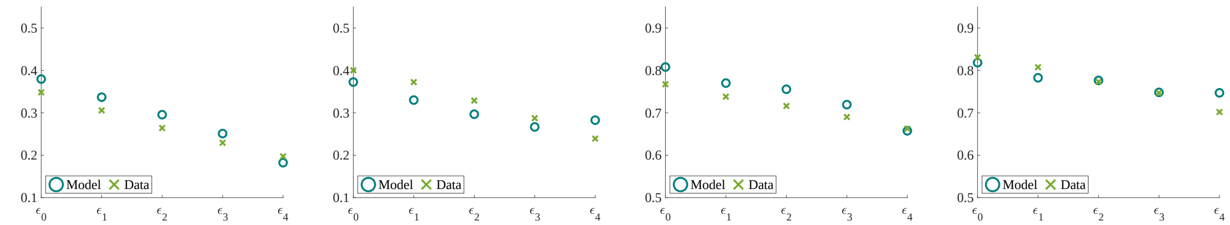
First, Figure 8 plots the model predicted future probabilities of good health by sickness shocks with data by more disaggregated demographic group—initial health, employment and insurance statuses—relative to our target moments—initial health and insurance statuses. In Figures 8(a) and (c) are good health probabilities of the employed and uninsured workers with initially bad and good health respectively; whereas in Figures 8(b) and (d) are those of the unemployed and insured workers. These moments are not directly targeted in our calibration, yet produce good fits with the data moments. In particular, the model is able to generate the high good health probability even among those who are unemployed as long as they are insured (see, for example, Figure 8(d)). In the model, with a high utility cost of bad health and unemployment $\iota(x = B, l = 0)$, the unemployed has high incentives to invest in health, above and beyond the treatment of their sicknesses. This novel feature of ours allows the model to generate patterns consistent with empirical data.

Second, we check whether health investment in the model is in line with the data. In calibrating parameters for the health production function, we target medical expenditures and probability of being in good health by various worker characteristics. The model further

Figure 8: Good Health Probability by Employment/Insurance

Bad Initial Health | Good Initial Health

(a) Emp. & Uninsured (b) Unemp. & Insured (c) Emp. & Uninsured (d) Unemp. & Insured




allows for investment above and beyond the sickness shocks, that is investment $H$ may be larger (or smaller) than the size of the sickness shock $\varepsilon$. We do not directly target the total health investment $H$ as it is very difficult to find data that measures total health investment. In the model, however, we can calculate non-medical consumption as $c+\min\{0, H-\varepsilon\}$ where $\min\{0, H-\varepsilon\}$ is the *net* investment in health (beyond medical expenditures used to treat sickness shocks). As a way of validating the total health investment in the model, we utilize the recent surveys of the PSID (years 1999-2013) that include detailed consumption data. We construct non-medical consumption to income ratio among the employed, that is equal to 70% for those with bad health and 60% for those with good health.[14] An analogous measures in our model are 68% and 71%. That is, despite not being directly targeted, the model generates a reasonable non-medical consumption to income ratio, relieving concerns about the validity of the size of total inputs into health.

Third, we compare the model-predicted income elasticity of health investment with the estimates from the 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 empirical estimates from various papers including Acemoglu et al. (2013) of between 0.3 and 1.1.[15]

Lastly, we evaluate whether the model makes sensible predictions about the impacts of

[14] 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.

[15] 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.

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% |

the China shock on the aggregate variables of the manufacturing sector. In Table 9, we summarize the model-implied effects of the China shock. In the first experiment in which only wage adjusts and the job-destruction rate remains fixed, we observe that the model predicts a 5.75% drop in the wage rate of manufacturing workers, and the export-GNE ratio of 0.068 for the U.S. manufacturing sector in the post-China equilibrium. Note that employment rate also changes, due to the deterioration of health status among the workforce that impacts their labor market transition rates. The former is consistent with the upper end of the estimates from Autor et al. (2014), 7.2%, and the latter 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 the labor market equilibrium condition (18) is reached by a uniform increase in job destruction rates $\delta(E, x)$ of workers. Our model predicts a 1.12*pp* increase in the job destruction rate that leads to a 3.4 *pp* drop in the employment rate of the manufacturing sector. 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).

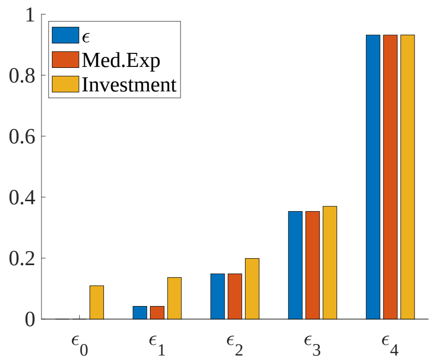
## 5.3 Key Model Features

In our model, the key determinant of the transition probabilities to future health is total health investment, $H$, which, in turn, consists of both medical expenditures—portion of investment up to the sickness shock, $\min\{H, \varepsilon\}$—and net investment—portion of investment beyond the sickness shock treatment, $\max\{H - \varepsilon, 0\}$. Figure 9 illustrates the sickness shock, $\varepsilon$, medical expenditure, and total health investment by health and insurance status of the employed.

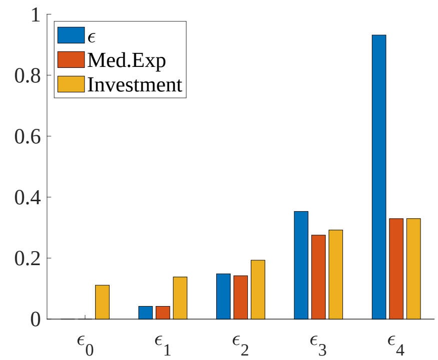
Figure 9: Health Investment

Bad Initial Health

(a) Employed & Insured

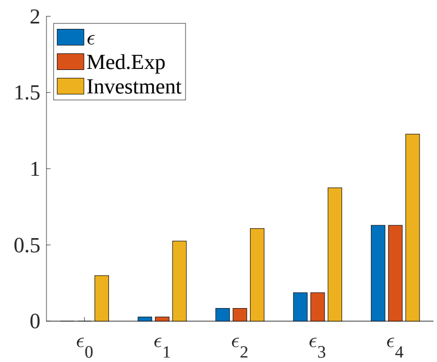



(b) Employed & Uninsured

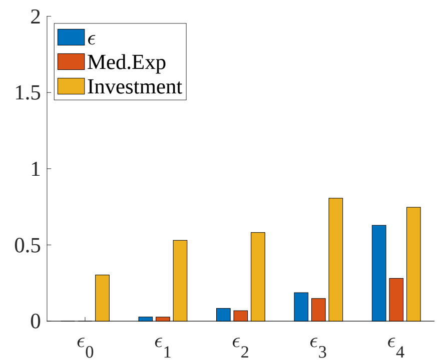



Good Initial Health

(c) Employed & Insured




(d) Employed & Uninsured




In Figure 9(a), we see that for the employed and insured workers with bad health, average medical expenditure matches the size of the sickness shock for all values of $\varepsilon$; i.e. they always choose full treatment of sickness. In addition, total health investment, $H$, exceeds the value of $\varepsilon$ for $\varepsilon_0$ (no medical events) through $\varepsilon_3$, implying that net investment is positive. For the most severe sickness of $\varepsilon_4$, however, $H = \varepsilon_4$ and so net investment drops to 0. .

In contrast, Figure 9(b) shows that for the employed but uninsured workers with bad health, partial treatment is common. To be specific, these workers choose full treatment and positive net investment for the mildest sickness, $\varepsilon_1$. For the mild sickness of $\varepsilon_2$, 35.5% choose partial treatment, where $H \geq H_{min}$ but $H < \varepsilon_2$, while the rest choose full treatment and positive net investment. The latter dominates, and so we see that overall, $H > \varepsilon_2$ in Figure 9(b). When it comes to the moderately severe sickness of $\varepsilon_3$, the vast majority, 82.3%, choose partial treatment, and so $H < \varepsilon_3$ in Figure 9(b). For the most severe sickness of $\varepsilon_4$, nearly half, or 45.1%, choose no treatment at all (i.e. $H = 0$), and on top of that, 54.6% choose partial treatment. As a result, both medical expenditure and $H$ are substantially below the size of the shock in Figure 9(b). Overall, for this group of workers, 15.7% choose no treatment and another 36.0% choose partial treatment, implying that full treatment is the exception.

Figures 9(c) and (d) are analogous plots for those with good initial health. In Figure 9(c), the insured always choose full treatment and positive net investment, because their good initial health implies high wages and high marginal productivity of the health production function, $F$, and they also have health insurance. This is the main difference between Figures 9(c) and 9(a).

In Figure 9(d), we see, as in 9(b), that the average medical expenditure is below the size of the sickness shock for $\varepsilon_2$ through $\varepsilon_4$. This pattern, however, is driven by no treatment, rather than partial treatment, as in Figure 9(b). The share of no investment is, respectively, 17.9%, 20.5% and 55.3%, for $\varepsilon_2$ through $\varepsilon_4$, while the share of partial treatment is 0. The rest choose full treatment and positive net investment. These choices are made partly because of the high marginal productivity of the health production function for the good-health workers, as shown in Figure 6(b). As a result, we see that overall, $H > \varepsilon$ for $\varepsilon_2$ through $\varepsilon_4$ in Figure 9(d), unlike in 9(b).

In summary, the heterogeneity in health investment that Figure 9 illustrates underlies the model predicted outcomes that we described in Sections 5.1 and 5.2. It also plays an important role in the way in which workers exposed to the China shock may experience negative health outcomes in the future.

# 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 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 how the China shock affects manufacturing workers' health dynamics (which we have not used as target moments). Our benchmark China shock experiment follows the first specification specified in Table 9; i.e. we assume that the China shock does not impact the job destruction rates. We start with the results by group, compare them with our empirical estimates from Table 3, and clarify their mechanisms and intuition. We then show the aggregate results for the manufacturing sector to draw out the economic significance.

**Heterogeneous Effects by Group** 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 only through workers' optimal choices of health investment, and all other mechanisms[16] have been assumed away. As a result, the comparisons below show the contributions of the single mechanism of optimal health investment.

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 |
| $\varepsilon_0$ (no shock) | -1.36 | -1.39 | -1.35 |
| $\varepsilon_1$ | -1.91 | -1.94 | -1.90 |
| $\varepsilon_2$ | -2.10 | -2.24 | -2.04 |
| $\varepsilon_3$ | -2.81 | -4.22 | -2.34 |
| $\varepsilon_4$ (severe shock) | -2.44 | -3.17 | -2.22 |

First, among the employed, the probability of being in good health decreases by 2.15%, which translates into good-health elasticity of IPW for the employed of -0.023.[17] In our

[16]See, e.g., Goldin et al. (2021), for a discussion of the potential mechanisms.

[17]The percent change in IPW is equal to $\left(\left(1-\pi^D_{m,pre}\right)-\left(1-\pi^D_{m,post}\right)\right)/\left(1-\pi^D_{m,pre}\right) \;=$

empirical analysis in Section 2, where we estimate the elasticity among initially employed workers, we find the elasticity of -0.054 as reported in Table 3. This implies that the optimal-health-investment mechanism accounts for over two-fifths of our empirical estimate. Next, for employed workers with good initial health, transition probability to good health drops by 1.36% (elasticity -0.0149), suggesting that 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 effect is -0.78% (elasticity -0.0052), very close to 0, consistent with the finding from Table 3 where the coefficient estimate for this group is statistically insignificant. Intuitively, the model predicted elasticity is much smaller (in magnitude) for those with bad health than for those with good health, because the health production function is much flatter for the former group as shown in Figure 6.

Table 10 also shows the model predicted effects by sickness shock and insurance status. While these health predictions do not have empirical counterparts in Table 3, they clarify that in our model, insurance status affects health through workers' health investment choices. Intuitively, insurance premium is the same for all sickness shocks, but the health effects of having insurance is way larger for severe sickness. As a result, Table 10 shows that the insured and uninsured have very similar health effects when they face mild sickness shocks of $\varepsilon_0$ through $\varepsilon_2$, ranging between 1.3% and 1.9%, but the uninsured have much larger effects (in magnitude) for the severe sickness of $\varepsilon_3$ and $\varepsilon_4$. Among uninsured workers experiencing $\varepsilon_3$ 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, $\varepsilon_4$, are smaller than those with $\varepsilon_3$. This is partially because under $\varepsilon_4$, a larger share of workers choose zero health investment in the pre-China economy than under $\varepsilon_3$, and these workers' transition probability to good health cannot decrease further. In our model, the choice of zero health investment may be optimal due to the existence of the flat region (minimum investment) in the health production function.

In summary, Table 10 shows rich and non-linear heterogeneity in the health effects of the China shock across worker characteristics. In Section 6.2 below, we further elaborate on the heterogeneity with the characteristic of insurance status, when we discuss the results of our

$((1-0.71)-(1-0.85))\,/\,(1-0.85) \approx 0.93$ (93%). And thus, the elasticity with respect to IPW can be obtained by dividing 93 to the percent change in good health share.

counterfactuals.

**Aggregate 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 first component of $H$ in our model, net investment (see sub-section 5.3), drops by 12%, in response to the decline in wage income, partly because the health production function is relatively flat where net investment is positive and net investment is not covered by health insurance. The other component, medical expenditure, however, is almost unchanged (-0.6%), despite the substantial decline in the good-health share,as sickness shocks are more severe for those with bad health.

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 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. 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 copay 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 sub-section, 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 (15) in the counterfactual economies are equivalent to those in the benchmark post-China economy.

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

| | | Change from Pre-China Economy | |
|---|---|---|---|
| | Pre-China Economy | Post-China with Benchmark Insurance | 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% |
| Net investment, $\max\{H-\varepsilon, 0\}$ | \$3,267 | -12.0% | -12.5% |
| Partial treatment ($H < \varepsilon$) share | 12.1% | +0.9*pp* | -0.9*pp* |
| No treatment ($H = 0$) share | 4.6% | +0.9*pp* | -4.6*pp* |
| Good health share | 54.3% | -1.2*pp* | -0.2*pp* |

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 post-China economy. The small difference arises because wage is endogenously determined through the manufacturing-sector labor-market clearing condition of 18. 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 net 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 of their sickness ($H < \varepsilon$ but $H > 0$), and the share of those who choose no treatment at all ($H = 0$). 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 (see Section 5.3). In contrast, universal health insurance completely eliminates no treatment. The resulting increase in medical expenditure is substantial, because our health production function, 16, has 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.

### 6.2.2 Heterogeneity Across Commuting Zones

In the previous section, our analyses focus on the manufacturing sector, where the wage decline of 5.8% is close to the empirically estimated median across commuting zones. Because Autor et al. (2013) show large heterogeneity in the change in IPW ($\Delta$IPW) across commuting zones, we now study the heterogeneous effects of the counterfactual universal health insurance across commuting zones.

To do so, we multiply the percentiles of the distribution of $\Delta$IPW (e.g. $4,500 per worker, or 4.5 units, at the 75th percentile) by Autor et al. (2013)'s coefficient estimate,[18] 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.

[18] We use the estimate in Table 9 of Autor et al. (2013), 2.14% per unit of $\Delta$IPW.

We 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 (18). 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 Section 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 |
| $5^{\text{th}}$ | 0.2 | 54.2 (-0.05) | 55.2 (+0.97) |
| $10^{\text{th}}$ | 0.4 | 54.1 (-0.10) | 55.1 (+0.91) |
| $25^{\text{th}}$ | 2.0 | 53.8 (-0.40) | 54.8 (+0.62) |
| $50^{\text{th}}$ | 5.5 | 53.1 (-1.11) | 54.2 (-0.04) |
| Mean ($53^{\text{rd}}$) | 7.3 | 52.7 (-1.48) | 53.8 (-0.40) |
| $75^{\text{th}}$ | 9.7 | 52.2 (-1.97) | 53.4 (-0.85) |
| $90^{\text{th}}$ | 15.8 | 50.9 (-3.28) | 52.2 (-2.02) |
| $95^{\text{th}}$ | 21.7 | 49.7 (-4.51) | 51.0 (-3.18) |

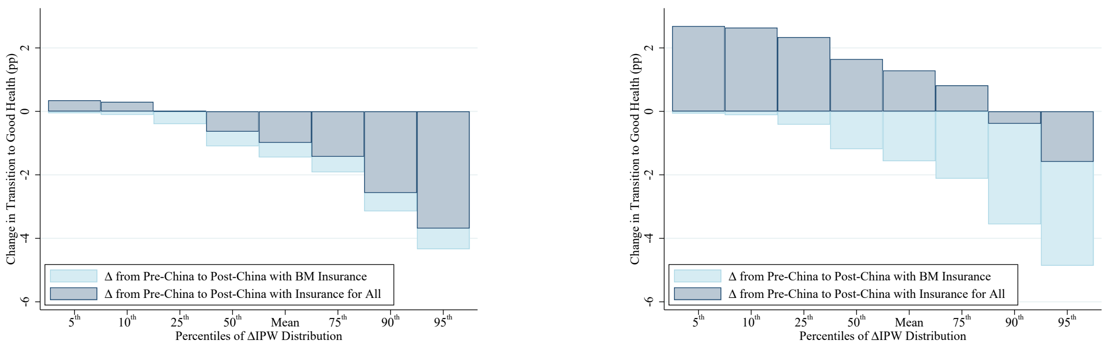
From Table 12, we see that, as expected, the commuting zones with large drops in wages experience large deterioration of health. For example, although the median commuting zone experiences a drop of 1.11$pp$ in the population share of good health, the $95^{\text{th}}$ percentile commuting zone has the 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 with a small wage decline (e.g. those below the $25^{\text{th}}$ 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 $95^{\text{th}}$ 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 net investment, but increases medical expenditure substantially. When wage decline is small, so is the drop in net investment, and so the increase in medical expenditure dominates. With large wage declines, however, the drop in net investment dominates, and so the overall efficacy of universal health insurance would be limited.

Figure 10: Health Effects by IPW Exposure and Sickness Shocks

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




In Figure 10, we further disaggregate the efficacy of universal health insurance by sickness shock. Specifically, Figure 10(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 $\varepsilon_2$. Meanwhile, Figure 10(b) plots those for the severe sickness shock of $\varepsilon_4$.[19]

We first see, from Figure 10(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 pre-China to the benchmark. However, as sickness becomes more severe, the gap between the two bars becomes much larger, as shown in Figure 10(b). For the commuting zone at the 5$^{\text{th}}$ percentile, universal health insurance would increase the transition probability to good health by 2.76$pp$, much higher than the 0.41$pp$ increase experienced by those with $\varepsilon_2$, shown in Figure 10(a). Even for the commuting zone at the 75$^{\text{th}}$ 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 10(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.

[19]The graphs for $\varepsilon_0$ and $\varepsilon_1$ are similar to Figure 10 (a), and the graph for $\varepsilon_3$ is similar to Figure 10(b).

# 7 Conclusion

In this paper, we calibrate a quantitative dynamic model and use it as a laboratory to study how the China shock affects workers' health through the mechanism of optimal health investment, and to evaluate the efficacy of potential policy responses. Using a micro-level panel data set, we estimate the elasticity of future good health probability with respect to IPW of -0.054, with larger effects among the workers in the manufacturing sector, with initial good health and low income. We then calibrate a quantitative model where transition probability of good health depends on workers' sickness shocks and their endogenously chosen health investment. The model is abled to replicate key empirical moments regarding health status transitions and medical expenditure patterns. Our quantitative evaluation of the health effect of the China shock delivers rich and non-linear heterogeneity across worker characteristics, and suggests that the mechanism of health investment captures 40% of our estimated health elasticity from IPW. 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 complete elimination of non-treatment of sickness. However, the efficacy of universal health insurance would be fairly limited for the commuting zones with large increases in IPW, with the silver lining that it would still be highly effective for the individuals with the most severe sickness shocks.

Our current model focuses on heterogeneity across employment, insurance, and sickness shocks, but abstracts from 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 can have varying effects on their responses related to employment and health investment. In addition, although we apply our model to study the China shock, our framework is more general, and so applicable to other topics in economics. For example, our health production function embeds and allows for rich heterogeneity in endogenous health evolution by worker characteristics. It can therefore be used to understand the evolution of health inequalities and how it relates to earnings, complementing recent works by Hosseini et al. (2021) and De Nardi et al. (2023). We leave these topics to future work.

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