Online Appendix

(Not Intended for Publication)

Interaction of the Labor Market and the Health Insurance System: Employer-Sponsored, Individual, and Public Insurance

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B A Simple Model for Illustration

In this section, we describe the detail of a simple model outlined in Section 3. Consider an economy with a competitive labor market and two competitive insurance markets (ESHI and HIX): There is a continuum of workers with the same skill and concave preference over consumption $U(\cdot)$, but different health status $x \in (0, \overline{x})$ and disutility of work $d \in \left(0, \overline{d}\right)$, drawn from $F(x, d)$. We consider that people with higher x have worse health status and thus unhealthier. If $x > x'$, the distribution of medical cost $G\left(c^{med}|x\right)$ first-order-stochastically dominates $G\left(c^{med}|x'\right)$. A worker's labor supply choice is $(h, z_1) \in \{(0,0), (1,0), (1,1)\}$, where h denotes whether or not one works, and z_1 denotes whether or not the job has ESHI. If $z_1 = 0$, one can choose whether or not to enroll in HIX $z_2 \in \{0, 1\}$. A worker is uninsured if $z_1 = z_2 = 0$. There is a continuum of firms with homogeneous production technologies, which decide whether to offer ESHI z_1 and how many workers to hire. Health insurance is available only via ESHI or HIX. Both markets offer an identical product that fully insures medical expenditure risks; neither market can price discriminate.

Equilibrium prices include the premium on HIX (r), the premium on ESHI (q) and the wage rate for each type of jobs $(w = [w_0, w_1])$. The premiums r and q are equal to the average medical cost among enrollees on HIX and that on ESHI, respectively (*risk pool segregation*).

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B.1 Worker's Problem

Given (r, w), a worker chooses (h, z_1, z_2) to maximize her expected utility, accounting for the uncertain medical cost:

$$\begin{aligned} \max_{h,z_1,z_2} \int U\left(C(h, z_1, z_2)\right) dG\left(c^{med}|x\right) - dh \quad \text{(B1)} \\ s.t.\ C(h, z_1, z_2) \;=\; (1-h)\,b + hw_{z_1} - z_2 r - (1-z_1)(1-z_2)\,c^{med}, \end{aligned}$$

where $C(\cdot)$ is one's net consumption. In the constraint, one's income is b if not employed and w_{z_1} if employed with z_1. If insured via HIX ($z_2 = 1$), one pays the HIX premium r. If uninsured $((1-z_1)(1-z_2) = 1)$, one pays a random medical cost c^{med}. Given that working involves disutility and that workers value insurance, in equilibrium, the following must be true: $w_0 > b$ and $w_0 > w_1$.

A worker's optimal choice of (h, z_1, z_2) can be solved via backward induction.

1. HIX Choice (z_2)*:* Consider a worker with $z_1 = 0$. He would enroll in HIX if $U(y-r) \geq E[U(y - c^{med})|x]$, where $y = (1-h)\,b + hw_0$. There is a unique threshold $x^*(y; r)$ defined by

$$U(y-r) = E[U(y - c^{med})|x^*(y; r)], \quad \text{(B2)}$$

such that $z_2 = 1$ if $x > x^*(y; r)$, i.e., workers with worse health status tend to enroll in HIX (adverse selection). The property of $x^*(\cdot; r)$ depends on $U(\cdot)$, e.g., $x^*(y; r)$ increases with y (the income effect) if $U(\cdot)$ is CRRA and is independent of y if $U(\cdot)$ is CARA. We consider $x^*(w_0; r) \geq x^*(b; r)$.

2. Employment Choice (h, z_1)*:* A worker solves the following

$$\begin{aligned} &\max\{U(b-r), U(w_1) - d, U(w_0 - r) - d\} \text{ if } x > x^*(w_0; r), \\ &\max\left\{U(b-r), U(w_1) - d, E[U(w_0 - c^{med})|x] - d\right\} \text{ if } x \in [x^*(b; r), x^*(w_0; r)], \\ &\max\left\{E[U(b - c^{med})|x], U(w_1) - d, E[U(w_0 - c^{med})|x] - d\right\} \text{ if } x < x^*(b; r). \end{aligned}$$

For each x, there is a $d^*(x; w)$ such that one would work if $d \leq d^*(x; w)$; the cutoff is given by
$d^*(x; w) =$

$$\begin{cases} \min\{U(w_1), U(w_0 - r)\} - U(b-r) \text{ if } x > x^*(w_0; r), \\ \min\left\{U(w_1), E[U(w_0 - c^{med})|x]\right\} - U(b-r) \text{ if } x \in [x^*(b; r), x^*(w_0; r)], \\ \min\left\{U(w_1), E[U(w_0 - c^{med})|x]\right\} - E[U(b - c^{med})|x] \text{ if } x < x^*(b; r). \end{cases} \quad \text{(B3)}$$

In the first case, $d^*(x; w) = d^*(x'; w)$, i.e., the cutoff is the same for all workers with $x > x^*(w_0; r)$. For workers with $d \leq d^*(x; w)$, their choices of job types are given by $z_1 = 1$ if $w_1 > w_0 - r$; $z_1 = 0$ if $w_1 < w_0 - r$; a fraction ϱ of workers choose $z_1 = 1$ if $w_1 = w_0 + r$. In the other two cases, $d^*(x; w)$

varies with x. Moreover, there is an $x^{**}(w_0 - w_1)$ defined by

$$U(w_1) = E[U(w_0 - c^{med})|x^{**}(w_0 - w_1)], \tag{B4}$$

such that $z_1 = 1$ if $x > x^{**}(w_0 - w_1)$ and $d \leq d^*(x; w)$.[1]

B.2 Firm's Problem

A firm solves the following

$$\max_{z_1, n} f(n) - z_1(w_1 + q)n + (1 - z_1)w_0 n.$$

Optimality requires that $f'(n^*) = w_1 + q$ if $z_1 = 1$ and $f'(n^*) = w_0$ if $z_1 = 0$.

B.3 Equilibrium

We focus on the equilibriums when both types of jobs exist, as is the case in the U.S. Such an equilibrium requires that $w_0 - w_1 = q$, so that firms are indifferent about $z_1 \in \{0, 1\}$. Moreover, it must be that $w_0 - w_1 \leq r$; otherwise, ESHI jobs are inferior to non-ESHI jobs for all workers and the supply for ESHI jobs would be zero. There are two cases to consider:
Case A: $w_0 - w_1 = r$, which implies: A1: $x^{**}(w_0 - w_1) = x^*(w_0; r) \geq x^*(b; r)$ (see $(B2)$ and $(B4)$). A fraction ϱ of workers with $x > x^*(w_0; r)$ and $d \leq d^*(x; w)$ will be enrolled in ESHI.[2] A2: $q = w_0 - w_1 = r$, i.e., the average cost on ESHI and that on HIX are the same.
Case B: $w_0 - w_1 < r$, which implies: B1**:** $x^{**}(w_0 - w_1) < x^*(w_0; r)$, all employed workers who are insured are enrolled in ESHI, and all HIX enrollees are non-employed. B2: $q = w_0 - w_1 < r$, which holds if and only if the risk pool on ESHI is healthier than that on HIX.

Existence Whether or not an equilibrium with both types of jobs is plausible depends on the primitives. Since the argument for both Case A and that for Case B are similar, we discuss Case B for an example.
Case B: $w_0 - w_1 < r$, which implies:
B1**:** $x^{**}(w_0 - w_1) < x^*(w_0)$, all employed workers who are insured are on ESHI market, and all enrollees on HIX market are non-employed.
B2: $q = w_0 - w_1 < r$, the equilibrium premium on ESHI is lower than that on HIX, which is possible if and only if the risk pool on ESHI is healthier than that on HIX.

[1] Whether or not $x > x^{**}(w_0 - w_1)$ is relevant for $x \leq x^*(w_0; r)$ depends on w_0 and w_1.
[2] In Case A, $x > x^{**}(w_0 - w_1)$ is irrelevant for those with $x < x^*(w_0)$.

Under B1, the total enrollment in ESHI (total labor supply for ESHI jobs) is given by

$$L_{ESHI} = \int_{x^{**}(w_0-w_1)}^{\overline{x}} \int_{d=0}^{d^*(x;w)} 1 dF_{d|x}(d|x)\, dF_x(x), \tag{B5}$$

and the total enrollment in HIX is given by

$$L_{HIX} = \int_{x^*(b)}^{\overline{x}} \int_{d^*(x;w)}^{\overline{d}} 1 dF_{d|x}(d|x)\, dF_x(x). \tag{B6}$$

The corresponding equilibrium premium for each market is given by

$$q = \frac{1}{L_{ESHI}} \int_{x^{**}(w_0-w_1)}^{\overline{x}} \int_{d=0}^{d^*(x;w)} C^{med}(x)\, dF_{d|x}(d|x)\, dF_x(x) \tag{B7}$$

$$r = \frac{1}{L_{HIX}} \int_{x^*(b)}^{\overline{x}} \int_{d^*(x;w)}^{\overline{d}} C^{med} dF_{d|x}(d|x)\, dF_x(x). \tag{B8}$$

The overall insured rate (R^{ins}) is the sum of the two:

$$R^{ins} = L_{ESHI} + L_{HIX}.$$

If x and d are uncorrelated, B2 requires that $x^{**}(w_0 - w_1) < x^*(b)$, which is more likely to hold if household preference $U(\cdot)$ does not feature strong income effect. For example, in the case of a CARA utility function, B2 holds because $x^{**}(w_0 - w_1) < x^*(w_0)$ and $x^*(b) = x^*(w_0)$. More realistically, one might expect that $corr(x, d) > 0$, i.e., those with poor health have higher disutility of working, ceteris paribus. In such a case, B2 holds automatically if $x^{**}(w_0 - w_1) \leq x^*(b)$. If $x^{**}(w_0 - w_1) > x^*(b)$, we can rewrite $(B6)$ as

$$L_{HIX} = \int_{x^*(b)}^{x^{**}(w_0-w_1)} \int_{d^*(x;w)}^{\overline{d}} 1 dF_{d|x}(d|x)\, dF_x(x) + \int_{x^{**}(w_0-w_1)}^{\overline{x}} \int_{d^*(x;w)}^{\overline{d}} 1 dF_{d|x}(d|x)\, dF_x(x). \tag{B9}$$

The HIX enrollees described by the second term in $(B9)$ are unhealthier than those in $(B5)$ when $corr(x, d) > 0$. The HIX enrollees described by the first term in $(B9)$ are a higher-d (unhealthier) subset of workers among those with $x \in (x^*(b), x^{**}(w_0 - w_1))$, who are nevertheless healthier than ESHI enrollees. If the savings from these enrollees are not large enough to offset the higher cost among the other HIX enrollees, B2 would still hold.

Implications When both ESHI and non-ESHI jobs exist in the equilibrium, the model implies:

1. For both HIX and ESHI, workers with worse health status tend to enroll (adverse selection); the severity of adverse selection may differ across the two markets in the equilibrium.

2. The risk pool on ESHI will be (weakly) less adversely-selected than that on HIX; the ESHI premium q will be (weakly) lower than the HIX premium r. If workers with poorer health incur higher disutility of work and/or workers' preferences do not feature a very strong income effect, then it is more likely that $q < r$.

3. In equilibriums with $q < r$, all employed workers who are insured are enrolled in ESHI and all HIX enrollees are non-employed. As a result, the risk segregation policy distorts labor market allocation because optimality requires independence of employment from insurance status; it also creates a regressive welfare effect in that lower-income households (the non-employed in this example) face higher premiums than higher-income households.

C Model: Firm's Problem with Employer Mandates

With ESHI mandates, a firm with more than n_{cut} full-time equivalent workers has to either provide ESHI to full time workers or pay a penalty $T^{em}(\mathbf{n})$, which is a function of the firm's worker composition $\mathbf{n} = \{n_{sh}\}$. Let $\mathbf{n}_f^*(\mathbf{z})$ be the optimal labor input for a firm given the choice of ESHI provision $\mathbf{z} \in Z$.[3] The mandate will be binding if the unconstrained choice under $\mathbf{z} = \mathbf{0}$, $\mathbf{n}_f^*(\mathbf{0})$, contains over n_{cut} full-time equivalent employees. In this case and only in this case, the solution to the firm's problem needs to be modified: such a firm needs to compare the profit $\pi_f^*(\mathbf{0})$ net of penalty $T^{em}\left(\mathbf{n}_f^*(\mathbf{0})\right)$ with that from the following constrained optimization problem

$$\begin{aligned} \pi_f^c = & \max_{\{n_{sh}\}_{s,h}} \left\{ F(\mathbf{n}; \Upsilon_f) - \sum_{h \in \{P,F\}} \sum_{s=1}^{S} n_{sh} w_{shz}^m \right\} \\ & s.t. \sum_s n_{sF} + \iota \sum_s n_{sP} < n_{cut}, \end{aligned} \tag{B10}$$

where ι is the full-time equivalent of a part-time worker. Let $\mathbf{n}_f^c$ be the optimal solution to (B10). The probability of ESHI choices is as follows

Case 1: $\pi_f^c > \pi_f^*(\mathbf{0}) - T^{em}\left(\mathbf{n}_f^*(\mathbf{0})\right)$

$$\Pr(\mathbf{z}_f = \mathbf{z}') = \begin{cases} \dfrac{\exp\left(\frac{\pi_f^*(\mathbf{z}')}{\sigma\eta}\right)}{\exp\left(\frac{\pi_f^c}{\sigma\eta}\right) + \sum_{\mathbf{z} \in Z} \exp\left(\frac{\pi_f^*(\mathbf{z})}{\sigma\eta}\right)} & \text{for } \mathbf{z}' \neq \mathbf{0} \\ \dfrac{\exp\left(\frac{\pi_f^c}{\sigma\eta}\right)}{\exp\left(\frac{\pi_f^c}{\sigma\eta}\right) + \sum_{\mathbf{z} \in Z} \exp\left(\frac{\pi_f^*(\mathbf{z})}{\sigma\eta}\right)} & \text{for } \mathbf{z}' = \mathbf{0} \end{cases}.$$

[3]Note that Z contains three vectors: $\mathbf{z} = \mathbf{0}, \mathbf{z} = \mathbf{1}$, and $\mathbf{z}: z_{\cdot P} = 0, z_{\cdot F} = 1$.

Case 2: $\pi_f^c \leq \pi_f^* (\mathbf{0}) - T^{em} \left(n_f^* (\mathbf{0})\right)$

$$\Pr(\mathbf{z}_f = \mathbf{z}') = \frac{\exp\left(\frac{\pi_f^*(z') - I(\mathbf{z}=\mathbf{0}) T^{em}\left(n_f^*(\mathbf{z}')\right)}{\sigma_\eta}\right)}{\sum_{\mathbf{z}\in Z} \exp\left(\frac{\pi_f^*(\mathbf{z}) - I(\mathbf{z}=\mathbf{0}) T^{em}\left(n_f^*(\mathbf{z})\right)}{\sigma_\eta}\right)}.$$

D Data Details

D.1 Household Data

D.1.1 Sample Selection

States We use the restricted MEPS data with geocode, which identifies 30 states with the remaining states encrypted. The 30 identified states account for 89% of households in the U.S., from which we exclude Massachusetts and Hawaii, the two states that already implemented state-wide (nearly) universal coverage before the ACA. We restrict attention to the 28 remaining states, which includes Alabama, Arizona, California, Colorado, Connecticut, Florida, Georgia, Illinois, Indiana, Kentucky, Louisiana, Maryland, Michigan, Minnesota, Missouri, New Jersey, New York, North Carolina, Ohio, Oklahoma, Oregon, Pennsylvania, South Carolina, Tennessee, Texas, Virginia, Washington, and Wisconsin. Fifteen out of these 28 states are ACA Medicaid expansion compliers, including Arizona, California, Colorado, Connecticut, Illinois, Kentucky, Maryland, Michigan, Minnesota, New Jersey, New York, Ohio, Oregon, Pennsylvania, Washington.

We rank the 28 states by state-level poverty rates from low to high and group them into four groups:

1. Group 1 (the lowest poverty rate): Maryland, Connecticut, New Jersey, Minnesota, Virginia, Colorado, Wisconsin.
2. Group 2: Washington, Pennsylvania, Illinois, Indiana, Michigan, Oregon, Ohio
3. Group 3: Missouri, Florida, Oklahoma, California, New York, Alabama, North Carolina
4. Group 4 (the highest poverty rate): Texas, South Carolina, Georgia, Tennessee, Kentucky, Arizona, Louisiana

The pre-ACA data of all groups and the post-ACA data of Groups 2-4 are used for estimation, while the post-ACA data of Group 1 is held out for model validation.

Households For both 2012 and 2015 we utilize a 5% random sample of the ACS and the entire sample of the CPS. Within each sample, we restrict attention to the working-age (aged 22 to 64 in the survey year) population in the 28 states as described above, who were not enrolled in Medicare or receiving social security income. We exclude respondents working in the public administration sector or the military or attending schools. We also exclude respondents who report being covered by Medicaid but with household income above 300% of federal poverty line, i.e., obviously not eligible for Medicaid.[4] A coupled household is included in the sample only if both spouses meet the sample selection rule.

D.1.2 Empirical Definitions

1. Part-time/full-time status is defined based on whether or not one's weekly hours are at least 30 hours.

2. Household income refers to the sum of annual wage income of both spouses.

3. Age variable is categorical: we classify adults into four age groups, labeled as: (i) age 30 for those aged between 22 and 34; (ii) age 40 for those aged between 35 and 44; (iii) age 50 for those aged between 45 and 54; and (iv) age 60 for those aged between 55 and 64.

4. Education: individuals are categorized as having high education if they have a bachelor's degree or higher, low education if they do not have a high school degree, and middle education otherwise.

5. Insurance status: ACS collects insurance status information for each household member. In over 92% of households, the reported insurance statuses are the same across household members and belong to only one of the four cases: ESHI, Medicaid, individual insurance, and uninsured. The rest of the households report multiple statuses: one member reports multiple sources of insurance and/or the two spouses report different insurance statuses (e.g., a spouse reports being covered by Medicaid, while the other reports being uninsured). In these cases, we assign one out of their reported statuses to the entire household using the following priority order: ESHI (own employer or spouse employer), Medicaid, individual insurance, and uninsured. The assignment rule has little impact on auxiliary model statistics and hence our estimation results.[5]

D.2 Firm Data

Our main data on firms are from Kaiser. A firm in the Kaiser data is excluded from our sample if it belongs to the government sector or if it did not complete the survey (employer weight is missing). We

[4] In the most generous state, Medicaid eligibility rule has a cutoff on household income at 215% of FPL in 2012. About 0.4% of all households or 4.4% households reporting Medicaid coverage are dropped for violating this selection rule.

[5] For example, in 2012 (2015), the fraction of uninsured individuals is 24.9% (16.9%) in the raw data; and 22.1% (14.6%) after the adjustment.

supplement Kaiser with information from Statistics of U.S. Businesses (SUSB)[6] to calculate proper firm weights used in our auxiliary model calculation, as we describe in Section E.4.

D.3 Data Patterns: Income and Individual Health Insurance Take-up

As mentioned in Remark 1 in the paper, the CRRA utility function implies a negative relationship between the probability of purchasing individual insurance and income due to the income effects. This relationship is not supported by our data. For example, among the population who are either uninsured or insured via individual health insurance, we consider the following linear probability model

$$Ins_i = \alpha \ln(y_i) + \beta X_i + d_{s_i} + \epsilon_i, \tag{B11}$$

where Ins_i is a binary variable that takes 1 if i has individual insurance, 0 if i is uninsured; y_i is i's earning, X_i is observable characteristics, s_i is the state that i resides in and d_{s_i} is a state fixed effect. To include the zero-income population, we also run a regression using $\ln(y_i + 1)$ to replace $\ln(y_i)$.

$$Ins_i = \alpha \ln(y_i + 1) + \beta X_i + d_{s_i} + \epsilon_i. \tag{B12}$$

Notice that, these regressions serve only as a succinct way to summarize the data and do not bear any causal interpretation.

The results are reported in Table C1, where we find the coefficient of income α is significantly positive in both regressions, i.e., individuals with higher income are more likely to purchase health insurance.[7] This measured correlation runs opposite to the predictions implied by CRRA utility. Among others, one way to rationalize the data is to allow for a correlation between individual risk preferences and their skill levels.

E Two-Stage Estimation Details

E.1 Stage 1 Estimation: Household-Side Parameters

In Stage 1 estimation, we design auxiliary models to identify household-side parameters governing (i) the unobserved type distribution $\Pr((\mathrm{s}, \boldsymbol{\chi})\,|x, state)$, (ii) the disutility of work, (iii) wage offers, and (iv) preference for health insurance. It should be noted that all four groups of parameters are identified jointly. However, to the extent that certain aspects of the data are more informative of certain groups of parameters, we discuss the identification in parts.

[6] https://www.census.gov/programs-surveys/susb.html

[7] Note that the net insurance premium is affected by the level of income after the ACA due to income-dependent premium subsidies. To avoid any effect from this indirect channel, we use the pre-ACA data for our main analysis; however, we also show that results still hold when we use both pre- and post-ACA data.

Preference for Health Insurance First, we discuss how we can use insurance enrollment patterns to identify parameters governing households' preference for health insurance, given the rest of model primitives. To be concrete, consider the case where, given its labor supply decisions and net income y, neither ESHI nor Medicaid is available to the household with observables x on market m and it chooses whether or not to buy individual insurance (IHI). For the ease of notation, assume that the household size is 1. Equation (8) in the main text implies that the probability that such a household chooses $INS = 4$ (IHI) over $INS = 0$ (uninsured) is

$\Pr(INS = 4|x, m, y, INS \in \{0, 4\}) =$

$$\sum_{\chi} \Pr(\chi|x, m, y, INS \in \{0, 4\}) \Phi\left(\frac{1}{\sigma_{\varepsilon_{IHI}}}\left(\begin{array}{c} \int \frac{(y-OOP)^{\gamma_\chi}}{1-\gamma_\chi} dF_{OOP}(x, INS = 4) + \varpi_{\mathbf{IHI}} \\ -\int \frac{(\max\{y-OOP, \underline{c}\})^{1-\gamma_\chi}}{1-\gamma_\chi} dF_{OOP}(x, INS = 0) \end{array}\right)\right), \tag{B13}$$

where $\Pr(\chi|x, m, y, INS \in \{0, 4\})$ is the endogenous type distribution conditional on x, m, and the fact that the household's labor supply decision is such that its net income is y and that neither ESHI nor Medicaid is available. The distribution of households' out-of-pocket expenditure OOP varies with x and insurance statuses.

The type distribution $\Pr(\chi|x, m, y, INS \in \{0, 4\})$ reflects households' self selection in terms of their labor supply decisions; for now, we take it as given and will discuss its identification in the next step. Given $\Pr(\chi|x, m, y, INS \in \{0, 4\})$, it is clear that we can identify unknown parameters in Equation $(B13)$: risk aversion coefficients $\{\gamma_\chi\}_\chi$, the consumption floor $\underline{c}$, the preference for IHI $\varpi_{\mathbf{IHI}}$, and the standard deviation of preference shocks $\sigma_{\varepsilon_{IHI}}$. For example, before and after the ACA, the same household faces exogenously different $F_{OOP}(x, INS = 4)$ because the ACA made IHI much more generous. This known variation in the OOP distribution is associated with a change in the IHI take-up rate; we observe this correlation for each x group of households. Because $\varpi_{\mathbf{IHI}}$ enters the utility function as an additively separable parameter, these correlations are used to identify $\{\gamma_\chi\}$, $\underline{c}$, and $\sigma_{\varepsilon_{IHI}}$, while the level of the IHI take-up rate identifies $\varpi_{\mathbf{IHI}}$. A similar argument can be used to identify Medicaid-specific preference parameters $\sigma_{\varepsilon_{MC}}$ and $\varpi_{\mathbf{MC}}$.

Other Parameters Now, we discuss how we use (mainly) labor market outcomes before and after the ACA to identify the rest of household-side parameters, which are in turn used to derive the endogenous $\Pr(\chi|x, m, y, INS \in \{0, 4\})$ in the previous discussion. First of all, our identification relies on the assumption that the primitive distribution $\Pr((\mathbf{s}, \boldsymbol{\chi})|x, state)$ is policy invariant. This assumption allows us to identify state-level unobservables using within-state variation in labor market outcomes before and after the ACA. As we will show later, this argument is reflected in our auxiliary models.

Second, notice that our labor supply model is essentially a generalized Roy model (Heckman and Vytlacil, 2007). As discussed in French and Taber (2011), identifying this class of models requires exclusion restrictions that affect the payoff in the relevant sector, but not payoffs in other sectors. To supplement policy variation, we allow the distribution of types and skills (and thus wage offers) to vary by education, age, gender, and marital status, but not by the presence of children or health status. By itself, either excluded variable increases the disutility of work and, via medical expenses, increases the value of ESHI jobs relative to non-ESHI jobs. More importantly, both excluded variables interact with policy changes. For example, although the ACA-induced change in equilibrium wages equally affects households of the same skill type within a state, ACA individual insurance premium subsidies, for which ESHI-covered workers are not eligible, interact with the size of the households. Similarly, because the dependence of insurance premiums on health was allowed before the ACA and disallowed after the ACA, the ACA led to differential changes in $F_{OOP}\left(x,INS=4\right)$ in $(B13)$ for households with different health statuses. As such, the ACA directly changed the value of non-ESHI jobs and differentially so for households depending on the presence of children and/or health status; this creates policy variation within the same unobservable type of households, given our exclusion restriction.

Third, to identify the correlation between skills and preference types, we exploit the fact that for the *same* household, we observe not only their labor market outcomes but also their choice of whether or not to get individual insurance/Medicaid if not covered by ESHI. Conditional on (x, state, year), the correlation between insurance takeup and income is informative of how skill and preferences are correlated. For example, all else being equal, the CRRA utility function implies a negative correlation between income and insurance takeup. This is violated in the data, which suggests a positive correlation between skills and risk aversion.

So far, we have used only a subset of policy variations in our identification argument. In our auxiliary models, we fully exploit ACA policy variation, such as the targeted nature of many ACA policy components, to inform us of model primitives. For example, premium subsidies and individual mandates are income-dependent. Although income itself is endogenous, we can still exploit how responses to the ACA vary by education.

E.2 Stage 2 Estimation: Firm-Side Parameters

Firm-side parameters include those governing i) the production function (A4), ii) the distribution of firm-specific technology $\mathbf{\Upsilon}=(T,A)$ (TFP and skill-biasedness), iii) the fixed cost of ESHI, and iv) the distribution of the random shocks associated with ESHI choice. Borrowing from the literature (e.g., Garicano et al., 2016), we pre-set the parameter θ in (A4) at 0.75 because it is neither the focus of our paper nor clearly identified. We estimate the rest of firm-side parameters for each Census region separately.

To see how these parameters are identified, it is useful to re-write firm's problem ((6) in the main text) as

$$\pi_{\mathbf{\Upsilon}}^{*}\left(w^{m},q^{m}\right)=\max_{\mathbf{z}\in Z}\left\{\pi_{\mathbf{\Upsilon}}^{*}\left(\mathbf{z}|w^{m},q^{m}\right)-I\left(\mathbf{z}\neq\mathbf{0}\right)\delta+\eta_{\mathbf{z}}\right\}, \tag{B14}$$

where we make it explicit that firm's profit is a function of prices (w^m, q^m). $\pi^*_{\boldsymbol{\Upsilon}}(\mathbf{z}|w^m, q^m)$ is the highest profit conditional on the ESHI choice $\mathbf{z}$, given by

$$\pi^*_{\boldsymbol{\Upsilon}}(\mathbf{z}|w^m, q^m) = \max_{\mathbf{n}} \left\{ F(\mathbf{n}; \boldsymbol{\Upsilon}) - \sum_{s,h} n_{sh} \left(w^m_{shz} \left(1 + \tau^m_w\right) + q^m z_{sh} \kappa^m_{sh} \right) \right\}. \tag{B15}$$

First, consider firms' problem in $(B15)$. Given $\mathbf{z}$, firm's input vector $\{n_{sh}\}$ satisfies the following set of first order conditions:

$$w^m_{shz}\left(1 + \tau^m_w\right) + q^m z_{sh} \kappa^m_{sh} = \begin{cases} TL^{\frac{\theta}{\rho}-1} AB_{sh} k^\rho_s \left(n_{sh}\right)^{\rho-1} \text{ if } s \geq s^* \text{ and } h = F, \\ TL^{\frac{\theta}{\rho}-1} \left(1 - A\right) B_{sh} k^\rho_s \left(n_{sh}\right)^{\rho-1} \text{ otherwise,} \end{cases} \tag{B16}$$

$$\text{where } L = A \sum_{s \geq s^*} B_{sF} l^\rho_{sF} + (1 - A) \left(\sum_{s<s^*} B_{sF} l^\rho_{sF} + \sum_s B_{sP} l^\rho_{sP} \right) \text{ and } l_{sh} = k_s n_{sh}.$$

The marginal cost of labor (the LHS of $(B16)$) consists of wage and the expected cost of ESHI, both of which are known given estimates from Stage 1: Wages $\{w^m_{shz}\}$ are Stage-1 parameter estimates, premium q^m is data, and household expected demand for ESHI (κ^m_{sh}) is derived from household preference parameters. More importantly, these costs vary across markets m (state$\times$policy era). Given skill levels $\{k_s\}$ implied by the skill distribution parameters estimated in Stage 1, the marginal productivity of labor (the RHS of $(B16)$) is known up to parameters (B, ρ, T, A); recall that (B, ρ) are common across firms and (T, A) are drawn from a parametric distribution. Via $(B16)$, these parameters govern firms' size and labor composition for a given ESHI choice.

Given the knowledge from Stage 1 estimation about the marginal costs of various types of labor inputs in each market, it is relatively easy to see from the system of first order conditions $(B16)$ how the associated variation in employee composition can be used to identify parameters B and ρ that are *common* across firms (recall that $\sum B_{sh} = 1$ is a normalization). The identification of the distribution of (T, A) needs to account for the fact that ESHI is an endogenous choice. For that, we exploit the following observations. First, Equation $(B15)$ and the associated first order condition $(B16)$ shown above are for the case before the ACA. The ACA employer mandate introduced a penalty into $(B15)$ for non-ESHI firms, where the penalty is a known function of the number of full-time equivalent employees. As detailed in Online Appendix C, the mandate changed the optimal choice of labor inputs given $\mathbf{z}$ and the relative values of $\{\pi^*_{\boldsymbol{\Upsilon}}(\mathbf{z}|w^m, q^m)\}_{\mathbf{z}}$ in a way that is known to us up to firm-side parameters. Second, as implied by $(B16)$, given ESHI choice, the ratio of different types of labor depends on A but not T. However, T directly affects the size of a firm. As such, given ESHI choice, the correlation between labor ratio and firm size is directly informative of the correlation between T and A.

Finally, the identification benefits from the assumption that idiosyncratic shocks $\{\eta_{\mathbf{z}}\}$ to firms' ESHI decisions are independent of (T, A). Under this assumption, the fixed cost of ESHI is identified from the relationship between firm size and ESHI offer rate (e.g., Aizawa and Fang, 2020).

E.3 Auxiliary Models for Stage 1 Estimation: Household-Side Parameters

Motivated by the identification argument, we target the following auxiliary models (Aux^h, superscript h for households), all of which are based on the estimation sample only.

Aux^h 1. Targets from the ACS

a. Regressions of the following form

$$y_{ist} = x_{ist}\alpha_1 + d_s + I(t = 2015)x_{ist}\left[MEP_s\alpha_2 + (1 - MEP_s)\,\alpha_3\right] + \epsilon_{ist},$$

where y_{ist} is an indicator of a given insurance/work status for individual i, with characteristics x_{ist} in state s and year t; d_s is a state fixed effect; and $MEP_s \in \{0, 1\}$ indicates whether or not State s expanded Medicaid under the ACA. The vector α_2 reflects (2015 versus 2012) changes in outcomes among different demographic groups (x) in Medicaid expansion states; α_3 reflects these changes in non-expansion states; ϵ_{ist} is an error term. Among our targeted coefficients, α_2 and α_3 differ by MEP_s and x (including the presence of children, our excluded variable) because many ACA policy doses vary across households with different earnings potentials and because Medicaid expansion induced significant changes in households' choice sets. How outcomes covary with these policy doses provides information to identify our model.[8]

b. Individuals' earnings regression of the following form:

$$\ln\left(w_{ist}\right) = x_{ist}\alpha_1^w + d_s^w + I(t = 2015)\alpha_2^w + I\left(h_{ist} = \text{full}\right)\alpha_3^w + \text{ESHI}_{ist}\alpha_4^w + \text{IND}_{ist}\alpha_5^w + \epsilon_{ist}^w,$$

where d_s^w is a state dummy, and coefficients α_3^w to α_5^w capture the *correlation* between earnings and full/part time status (h), ESHI status, and individual insurance purchase.

c. $E\left[\left(\ln\left(w_{ist}\right)\right)^2\right]$.

d. Fractions of individuals in each of the following categories, both for all individuals and by one-way demographics (marital status, presence of children, education, age groups):

· Uninsured, insured via ESHI, insured via Medicaid.

· Non-employed, employed full time.

· Uninsured and employed part time, uninsured and non-employed, Medicaid-covered and employed part time, Medicaid-covered and non-employed, and ESHI-covered and employed full time.

Aux^h 2. Moments from CPS that are informative of health-related utility parameters: by pre/post-

[8]Table B2 present the regression results from the entire samples (both estimation and validation samples) and Table E.3 presents the results from the estimation samples. Notice that the most important criterion for ACA policy doses is income, a fact that has been exploited in previous studies on the ACA, e.g., Frean et al. (2017) and Lurie et al. (2019).

ACA×Medicaid expansion/non-expansion states, the fraction of individuals who are

a. healthy and uninsured, healthy with ESHI, healthy with Medicaid.

b. healthy and non-employed, healthy and working full time.

Aux^h 3. Moments of joint outcomes between couples from the ACS that are informative of the correlation of types between spouses:

a. Covariance of log earnings between two spouses.

b. Fractions of couples who both work and who both work full time.

E.4 Auxiliary Models for Stage 2 Estimation: Firm-Side Parameters

For each Census region, we target the following auxiliary models (Aux^f, superscript f for firms):

Aux^f 1. Moments from Kaiser: (by policy era)

a. Mean and variance of firm size, fraction(full time employees), fraction(employees earning low/high wages).

b. Cov(firm size, fraction of full time employees), Cov(firm size, fraction of employees earning low/high wages).

c. Fraction of firms offering ESHI.

d. Cov($ESHI$, firm size), Cov($ESHI$, fraction of employees earning high wages), Cov($ESHI$, fraction of full time).

Aux^f 2. The aggregate supply of labor for each (s, h, z) category derived from Stage 1 estimates (by policy era).

Aux^f 3. Moments from SUSB (by policy era): Fraction of small firms.[9]

Guided by our identification argument, targets under Aux^f 1 are meant to capture the joint distribution of firm size, employee composition and ESHI provision, before and after the ACA. Targets under Aux^f 2 serve two purposes. First, they discipline the estimation algorithm to favor parameters that guarantee equilibrium consistency, which we deem as important for equilibrium counterfactual analyses. Second, Kaiser only includes crude measures of wages; skill-specific labor supply from Stage 1 supplements Aux^f 1 in pinning down the production technology parameters. Similarly, to overcome the limitation that only firms with more than 3 workers are represented in Kaiser, we target the fraction of small firms (Aux^f 3) from SUSB, which, together with Aux^f 1, provide a more complete picture of the distribution of firms.[10]

[9] Firm size is known up to size groups in SUSB, with the first category being size $\in [1, 4]$. We target the fraction of firms belonging to this group.

[10] Our model-simulated firms can be of any size. In calculating Aux^f 1 from our simulated data, we only use simulated firms with at least 3 workers and top code their sizes at 500, as is the case in the data. For Aux^f 2 and 3, all simulated firms are included in the calculation, and their sizes are not top coded. Details are in Online Appendix F.3.

F Further Technical Details for the Estimation

F.1 Total Medical Expenditure and Out of Pocket Medical Expenditure (OOP)

We estimate the distribution of medical expenditures, health insurance premiums, and the distribution of OOP based on the restricted MEPS data that includes geocodes. For a reasonable sample size, we pool MEPS data between 2009-2013 to estimate these objects for the pre-ACA economy and pool the data between 2014-2016 to estimate those for the post-ACA economy. All medical expenditures are adjusted to real dollar terms with the CPS medical price deflator.

F.1.1 Total Medical Expenditure

We estimate the distribution of medical expenditures separately for adults and for children. In the data, the annual medical expenditure has a mass point at 0. As such, we specify the distribution of medical expenditures (C_{med}) as a mixed distribution, allowing for a mass point at 0 and estimate separately pre- and post-ACA. For the sake of exposition, we abstract the index of pre- and post-ACA in the rest of this section. For adults, the probability of positive expenditure is given by

$$\Pr(C_{med} > 0|\left(x, ins, state\right)) = \Phi\left(x\alpha_0 + \beta_{ins0} + d_{0state}\right),$$

where x includes the age, gender, health status, and their interactions, β_{ins0} is an insurance-status-ins fixed effect, and d_{0state} is a state fixed effect. For the distribution of positive medical expenditure, we assume the following log normal distribution

$$\ln\left(C_{med}|\left(x, ins, state\right)\right) \sim N\left(M_{med}\left(x, ins, state\right), \sigma^2_{med}\left(x, ins, state\right)\right),$$

where the mean and the standard deviation both vary with x, insurance status, and states:

$$\begin{aligned} M_{med}\left(x, ins, s\right) &= x\alpha_1 + \beta_{ins1} + d_{1state}, \\ \sigma_{med}\left(x, ins, state\right) &= \exp\left(x\alpha_2 + \beta_{ins2} + d_{2state}\right). \end{aligned}$$

We estimate the parameters $\{\boldsymbol{\alpha}, \{\boldsymbol{\beta}_{\mathbf{ins}}\}_{ins}, \mathbf{d_s}\}$ via maximum likelihood, where individual i's contribution to the likelihood is given by

$$\begin{aligned} f(C_{med,i}|x_i, ins_i, state_i) &= \left[1 - \Phi\left(x_i\alpha_0 + \beta_{ins_i0} + d_{0state_i}\right)\right]^{1(C_{med,i}=0)} \times \\ &\quad \left[\Phi\left(x_i\alpha_0 + \beta_{ins_i0} + d_{0state_i}\right)\phi\left(\frac{\ln\left(C_{med,i}\right) - M(x_i, ins_i, state_i)}{\sigma\left(x_i, ins_i, state_i\right)}\right)\right]^{1(C_{med,i}>0)}. \end{aligned}$$

We specify the distribution of medical expenditures for children in a similar fashion, with the exception that the parameter counterpart of $\{\boldsymbol{\alpha}\}$ are set to 0 for children, due to the lack of information on child-specific characteristics. That is, we assume that the distribution of medical expenditures for children differ only by insurance statuses and states.

The estimates of medical expenditure distribution are reported in Tables C3 and C4. Consistent with the data patterns as shown in Table C2, our estimates indicate that being insured, regardless of the source of coverage, is positively correlated with the probability of positive medical spending and the level of spending (C_{med}). For adults, being unhealthy and/or older are also positively correlated with medical spending.

Remark 1 *Different from the existing studies (e.g., Aizawa and Fang (2020) and French et al. (2018)) that focus on national level outcomes, we allow the distributions of medical expenditures to differ across states by including state fixed effects in our estimation equations. These state-specific effects serve as as one source of observable cross-state variation, which needs to be accounted for in our study.*[11]

F.1.2 Insurance Premium

We estimate pre-ACA individual insurance premiums via the following OLS regression

$$\ln\left(r_i^{pre}\right) = x_i\alpha_3 + d_{state_i} + \epsilon_i,$$

where r_i^{pre} is the premium faced by individual i in state s_i, x_i is a vector of characteristics including the age, gender, health status, and their interactions, and d_{state_i} is a state dummy. For the estimation, we use the restricted MEPS data that includes geocode. Table C5 reports the estimates.

In estimating the baseline model, for post-ACA individual health insurance premiums across states we use the actual premium observed in health insurance marketplaces. We set the premium to be the benchmark premium of the second lowest silver plan offered in each state reported by Center of Medicare and Medicaid Services (CMS). Then, we adjust the age-specific premium based on the default standard age curve set by the federal government: relative to the premium for the age-30 group, the premium is 12.5% higher for the age-40 group, 57.3% higher for the age-50 group, 139% higher for the age-60 group, and 44.1 % lower for children. This corresponds to $\Gamma(\cdot)$ in our model.

F.1.3 Out of Pocket Medical Expenditure

The out of pocket expenditure OOP is calculated as the sum of out of pocket medical expense and the individual health insurance premium if a household chooses $\mathbf{INS} = (4, 4)$. Given a realization of the medical expenditure shock, a household's out of pocket medical expense is determined based on its health

[11]To save space, Tables C3 and C4 do not report the estimated state fixed effects, but many of the estimates are economically and statistically significant. For example, the estimated state fixed effects on $\Pr(m > 0)$ range between -0.11 and 0.36 (for comparison, the coefficient for being unhealthy is 0.495).

insurance status. For tractability, we consider a simple coinsurance contract for each insurance status. Specifically, we calibrate the following objects to match the actual ratio of out of pocket medical expense to total medical expenditure in our MEPS data: the coinsurance rate of ESHI (15%), the coinsurance rate of Medicaid (0%) and the coinsurance rate of individual insurance pre-ACA (40%). Finally, we set the coinsurance rate of the post-ACA individual insurance at 15% based on the following facts. First, the actuarial value of the silver plan, the most popular plan, is 70%.[12] Second, individuals with silver plans tend to receive a sizable income-based coinsurance subsidies, bringing the coinsurance rate of silver plans close to 15%.

F.2 Policy Functions

F.2.1 Government Transfer on Health Insurance

We model the government transfer on health insurance, denoted by T^{ins} as

$$T^{ins}\left(w^m_{shz}+w^m_{s'h'z'},\mathbf{INS},x,m\right)=$$

$$I\left(ACA\right)\begin{bmatrix} Sub(w^m_{shz}+w^m_{s'h'z'},x,m)I\left(\mathbf{INS}=(4,4)\right) \\ -PE(w^m_{shz}+w^m_{s'h'z'},x,m)I\left(\mathbf{INS}=(4,4)\right), \end{bmatrix}$$

where $Sub\left(\cdot\right)$ is HIX premium subsidy function that applies when households participate in HIX ($INS = (4,4)$) after ACA, and $PE\left(\cdot\right)$ is the tax penalty that applies if individuals are uninsured when individual mandates are implemented. Each of them is specified as below.

Premium Subsidy We model $Sub\left(\cdot\right)$ based on the actual formula of ACA premium subsidies, which depends on three factors (i) household income; (ii) the total premium of household, denoted by $r^m(x)$; (iii) whether Medicaid is expanded in the states (m) (MEP_m). In ACA Medicaid expansion states, subsidies are available if household income is between 133% and 400% of federal poverty level (FPL); in non-expansion states, subsidies are available if household income is between 100% and 400% of FPL. Among subsidy-eligible population, the amount of subsidies decreases with household income (y) and increases with the total premium $(r^m(x))$. Specifically, we model $Sub\left(\cdot\right)$ as

[12]Recall that in the model, we assume a single plan on the post-ACA individual health insurance market, i.e., the silver plan from the marketplace.

$$Sub(y,x,m) = \begin{cases} \max\{r^m(x) - 0.02y, 0\} \text{ if } y \in (FPL, 1.33FPL] \text{ and } MEP_{state} = 0 \\ \max\{r^m(x) - 0.025y, 0\} \text{ if } y \in (1.33FPL, 1.5FPL] \\ \max\{r^m(x) - 0.0515y, 0\} \text{ if } y \in (1.5FPL, 2FPL] \\ \max\{r^m(x) - 0.07175y, 0\} \text{ if } y \in (2FPL, 2.5FPL] \\ \max\{r^m(x) - 0.08775y, 0\} \text{ if } y \in (2.5FPL, 3FPL] \\ \max\{r^m(x) - 0.095y, 0\} \text{ if } y \in (3FPL, 4FPL] \\ 0 \text{ otherwise} \end{cases}.$$

We calibrate these subsidy parameters such that the premium contribution $(r^m(x) - Sub(y,x,m))$ in each income group is equal to the within-group median contribution under the actual ACA subsidies formula.

Individual Mandate We model the individual mandate penalty (in \$) as follows:

$$PE(y,x,m) = \min\{r^m(x), \max\{0.02y, 600 \times \#adults + I(have\ children) \times 480\}\},$$

where y denotes the household income and $r^m(x)$ is the HIX premium. That is, the individual mandate is calculated based on the maximum of 2% of household income and minimum penalty ($600 \times \#adults + I(have\ children) \times 480$), capped at the total premium ($r^m(x)$) in HIX.

F.2.2 Government Transfer on Income Tax and Welfare

We model the government transfer on health insurance, denoted by T^{tax} as

$$T^{tax}\left(w^m_{shz} + w^m_{s'h'z'}, x, m\right) = -T^y\left(w^m_{shz} + w^m_{s'h'z'}, x, m\right) + WB\left(w^m_{shz} + w^m_{s'h'z'}, x, m\right),$$

where $T^y(\cdot)$ is income tax and $WB(\cdot)$ is the welfare benefit. Following Kaplan (2012), we specify the income tax function for an household with income y as

$$T^y(y,x,m) = y - \tau_0^{mx} - \tau_1^{mx}\frac{y^{1+\tau_2^{mx}}}{1+\tau_2^{mx}},$$

where tax parameter vectors $\{\boldsymbol{\tau}\}_{mx}$ are estimated using NBER TAXSIM program.[13] Income taxes account for both federal and state income (and worker's contribution of payroll) taxes. We allow that each tax parameter depends on both household demographic size and state where a household lives in.

Following Chan (2013) and Gayle and Shephard (2019), we include and parameterize the following

[13]Also using TAXSIM, Aizawa and Fang (2020) estimate the tax parameters at the national level.

major welfare programs in our welfare function $WB(y, x, m)$:

1. The Supplemental Nutrition Assistance Program (SNAP): households with income below 138% of FPL are eligible for SNAP, and the benefit varies by demographics x (marital status and the presence of children) and whether the time is pre- or post-ACA.

2. Temporary Assistance for Needy Families (TANF): we calibrate the policy parameters using the Welfare Rules Database (WRD) from the Urban Institute. Following WRD notations, TANF benefit is modeled as

$$TANF\left(y, x, state\right) =$$

$$\begin{cases} \max \left\{ \begin{array}{l} \min \left\{ \begin{array}{c} M\left(x, state\right), \\ \left[G\left(x, state\right) - \left(y - D\left(state\right)\right)\left(1 - r_B\left(state\right)\right)\right] r_C\left(state\right) \end{array} \right\} \\ , 0 \end{array} \right\} & \text{if } y < e\left(x, state\right) r_A\left(state\right) \\ 0 \text{ otherwise.} & \end{cases}$$

Households with income $y < e\left(x, state\right) r_C\left(state\right)$ are eligible for TANF, where $e\left(x, state\right)$ is the need standard that varies with x (especially marital status) and across states, r_C is the ratio used for adjusting the standard. $M\left(x, state\right)$ is the maximum TANF benefit, $G\left(x, state\right)$ is the payment standard, both of which vary with x and states. There are also state-specific dollar disregards $D\left(state\right)$ and percent disregards $r_B\left(state\right)$. The benefit level is further adjusted by $r_C(state)$, which is 1 in many states.[14]

F.2.3 Medicaid Eligibility

Medicaid eligibility depends on household demographic characteristics, following rules that vary across states and policy eras. For tractability, we only model the income-testing part of Medicaid eligibility rules and abstract from asset testing requirement.[15] We obtain the specific Medicaid eligibility rules via the Kaiser Family Foundation.[16] In particular, eligibility-defining income thresholds vary with household characteristics (e.g., the presence of dependents) and across states. In modeling these rules, we account for the substantial variation in pre-ACA Medicaid eligibility rules across states and household characteristics. After ACA, we model Medicaid eligibility rules as defined by the federal government in Medicaid expansion states. In non-expansion states, we explicitly account for state-specific programs that provide Medicaid to the low-income population.[17]

[14] Similar to Gayle and Shephard (2019), because our model is static, we do not incorporate certain features of the TANF program (e.g., the time limits in benefit eligibility, Chan (2013)).

[15] See French et al. (2019) for an analysis of the role of asset testing under ACA.

[16] https://www.kff.org/state-category/medicaid-chip/

[17] For example, Wisconsin did not comply with ACA Medicaid expansion, however, it has its own Medicaid program called BadgerCare.

F.3 Firm-Side Estimation Details

F.3.1 Auxiliary Models: Kaiser Data

Two factors need to be accounted for in order to guarantee the consistency between auxiliary models from Kaiser data and those from model-simulated data. First, in our model, each state is an economy, and firms in different states face different equilibrium prices. In Kaiser, firm locations are known up to the region level. Second, Kaiser data only contain firms with at least 3 employees, while firms in our model can choose any number of employees. The auxiliary models from Kaiser are subject to these data limitations, i.e., they are calculated at the region level and represent firms with at least 3 employees. To calculate the corresponding auxiliary models from our simulated data, we need to aggregate the simulated firm decisions using properly assigned firm weights. To do so, we use the following procedure.

1. From SUSB, calculate $p_s(x)$, the fraction of private-sector firms located in State s conditional on characteristics x, where x includes firm size group and region.[18]

2. Denoting w_i as the firm weight reported in Kaiser, which corresponds to how many firms are represented by firm i. Predict the fraction of Kaiser firms that are in state s as $P_s = \frac{\sum_i w_i p_s(x_i)}{\sum_i w_i}$.

3. Simulate N firms in region R, where for each state s in region R, the number of simulated firms is $N_s \approx N \frac{P_s}{\sum_{s \text{ in } R} P_s}$. Within these N_s firms, calculate the number of firms that are predicted to have size $n \geq 3$, $\tilde{N}_s$.

4. To calculate region-level auxiliary models corresponding to those from Kaiser, a simulated firm i with size n_i in state s is assigned the weight ω_s with

$$\omega_{si} = \begin{cases} \frac{\tilde{N}_s}{\sum_{s' \in R} \tilde{N}_{s'}} \text{ if } n_i \geq 3 \\ 0 \text{ if } n_i < 3 \end{cases}.$$

Note: Firm sizes are capped at 500 in Kaiser. In our simulated data, if the simulated $size$ is bigger than 500, we use 500 to calculate auxiliary statistics corresponding to Kaiser targets, and we use $size$ exactly to calculate the auxiliary model for aggregate labor demand.

F.3.2 Auxiliary Models: SUSB

Kaiser data do not contain small firms, and so in order to match the overall distribution of firms, we supplement the auxiliary models from Kaiser with additional moments from SUSB. Namely, the fraction of small firms by policy era and region, where small firms refer to those with size ≤ 4 (SUSB reports size in categories, and size below 4 is the first size group). Denote this fraction as f_{gt}^{small}.

[18] By construction, $p_s(x) = 0$ if a region does not contain s.

F.3.3 Auxiliary Models: Aggregate Labor Supply

In the model, each state is an independent economy with (working age) population size normalized to 1. To calculate region or country level statistics, we need to take into account that (working age) population sizes differ across states. To aggregate labor demand from simulated firm decisions to be matched with the aggregate labor supply from simulated household decisions, we use the following procedure (separately for year 2012 and year 2015):

1. To calculate region-level auxiliary models of aggregate labor demand, a simulated firm i with size n_i in state s is assigned the weight ω_s^a with

$$\omega_{si}^a = \frac{N_s}{\sum_{s' \in R} N_{s'}}.$$

2. Calculate the relevant population size in a geographic unit g (g refers to a state s or a region R) as

$$\mu_g = \frac{S_g N}{\text{Employment rate in } g},$$

where S_g is the average firm size of all firms in g from SUSB, so the numerator is the total employment represented by N firms. Dividing it by employment rate in g (from ACS) gives the total population size in our simulated economy in region g.

3. Let n_{ish} be the simulated number of type (s, h) workers firm i decides to hire, the labor demand for (s, h) type of worker, measured in terms of fraction of the population in g, is given by

$$\frac{\sum_i \omega_{s_i}^a n_{ish} I\left(s \text{ in } g\right)}{\mu_g}.$$

F.4 Out of Sample Validation Performance: Model vs Multinomial Logit

This section compares the model's out of sample validation performance with the one from a statistical, multinomial logit model. We specify the multinomial logit model following the specifications in our auxiliary model (except that our auxiliary models are linear):

$$y_{ist}^* = x_{ist}\alpha_1 + d_s + I(t = 2015)x_{ist}\left[MEP_s\alpha_2 + \left(1 - MEP_s\right)\alpha_3\right] + \epsilon_{ist},$$

where y_{ist}^* is the outcome variables: we run two set of the multinomial regressions separately: (i) the outcome is a combination of individual insurance status and employment status; (ii) two separate multinomial logit models where the the outcome in the first model is insurance status alone and the outcome in the second model is employment status alone.

As in our estimation, we estimate these multinomial logit models using only the estimation sample. Then, using the estimates from the multinomial logit models, we predict outcomes in the hold-out sample.

The predict outcomes among holdout samples from the multinomial logit models are reported in Table E6. We find that these logit models predict well in the proportion of ESHI coverage and full time workers. However, they fail to predict Medicaid status and part-time status, while our structural model well captures these patterns.

G Counterfactual Policy

G.1 CEV Calculation

Household baseline ex ante welfare is given by

$$\begin{aligned}\mathbf{V}(\mathbf{X},m) &\equiv E\max_{(\mathbf{h},\mathbf{z})}\{V(\mathbf{h},\mathbf{z},\mathbf{X},m)+\epsilon_{\mathbf{h},\mathbf{z}}\}\\ &= \sum_{(\mathbf{h},\mathbf{z})}\Pr(\mathbf{h},\mathbf{z}|\mathbf{X},m)\,Eu(C(\mathbf{h},\mathbf{z}),\mathbf{h},\mathbf{INS}(\mathbf{h},\mathbf{z});\mathbf{X}),\end{aligned}$$

where $\Pr(\mathbf{h},\mathbf{z}|\mathbf{X},m)$ is the baseline optimal choice probability and $C(\mathbf{h},\mathbf{z}),\mathbf{INS}(\mathbf{h},\mathbf{z})$ are the optimal consumption and insurance under $(\mathbf{h},\mathbf{z})$. Let the welfare in a given new equilibrium in the counterfactual environment be $\mathbf{V}^{new}(\mathbf{X},m)$.

Solve for Δ such that
$\mathbf{V}^{new}(\mathbf{X},m)-\mathbf{V}(\mathbf{X},m)=$

$$\begin{aligned}&\left\{\begin{array}{c}\sum_{(\mathbf{h},\mathbf{z})}\Pr(\mathbf{h},\mathbf{z}|\mathbf{X},m)\,Eu((1+\Delta)\,C(\mathbf{h},\mathbf{z}),\mathbf{h},\mathbf{INS}(\mathbf{h},\mathbf{z});\mathbf{X})\\ -\sum_{(\mathbf{h},\mathbf{z})}\Pr(\mathbf{h},\mathbf{z}|\mathbf{X},m)\,Eu(C(\mathbf{h},\mathbf{z}),\mathbf{h},\mathbf{INS}(\mathbf{h},\mathbf{z});\mathbf{X})\end{array}\right.\\ =&\sum_{(\mathbf{h},\mathbf{z})}\Pr(\mathbf{h},\mathbf{z}|\cdot)\left[E\left(\frac{(1+\Delta)\left(\frac{C(\mathbf{h},\mathbf{z})}{size_{\mathbf{X}}}\right)^{1-\gamma}}{1-\gamma}\right)-E\left(\frac{\left(\frac{C(\mathbf{h},\mathbf{z})}{size_{\mathbf{X}}}\right)^{1-\gamma}}{1-\gamma}\right)\right]\\ =&\sum_{(\mathbf{h},\mathbf{z})}\Pr(\mathbf{h},\mathbf{z}|\cdot)\left[\left((1+\Delta)^{1-\gamma}-1\right)E\left(\frac{\left(\frac{C(\mathbf{h},\mathbf{z})}{size_{\mathbf{X}}}\right)^{1-\gamma}}{1-\gamma}\right)\right].\end{aligned}$$

So that,

$$(1+\Delta)^{1-\gamma}=\frac{\mathbf{V}^{new}(\mathbf{X},m)-\mathbf{V}(\mathbf{X},m)}{\sum_{(\mathbf{h},\mathbf{z})}\Pr(\mathbf{h},\mathbf{z}|\cdot)\,E\left(\frac{\left(\frac{C(\mathbf{h},\mathbf{z})}{size_{\mathbf{X}}}\right)^{1-\gamma}}{1-\gamma}\right)}+1$$

i.e.,

$$\Delta = \left(\frac{\mathbf{V}^{new}\left(\mathbf{X}, m\right) - \mathbf{V}\left(\mathbf{X}, m\right)}{\sum_{(\mathbf{h},\mathbf{z})} \Pr\left(\mathbf{h}, \mathbf{z}|\cdot\right) E\left(\frac{\left(\frac{C(\mathbf{h},\mathbf{z})}{size_{\mathbf{X}}}\right)^{1-\gamma}}{1-\gamma}\right)} + 1 \right)^{\frac{1}{1-\gamma}} - 1.$$

We obtain CEV for each household as

$$CEV\left(\mathbf{X}, m\right) = \Delta \sum_{(\mathbf{h},\mathbf{z})} \Pr\left(\mathbf{h}, \mathbf{z}|\cdot\right) E\left(\frac{C\left(\mathbf{h}, \mathbf{z}\right)}{size_{\mathbf{X}}}\right).$$

G.2 Calibration of θ^0

We set θ^0 as $\theta^0 = \frac{g_{ESHI}}{g_{HIX}} \frac{ME_{ESHI}}{ME_{HIX}}$, where $\frac{g_{ESHI}}{g_{HIX}} = \frac{0.85}{0.7}$ is the ratio of generosity or actuarial values of ESHI relative to HIX, and $\frac{ME_{ESHI}}{ME_{HIX}}$ accounts for differences in the quality and amount of care as proxied by the population level medical spending on $k \in \{\text{HIX, ESHI}\}$: ME_k is the average medical expenditure if *everyone* (i.e., without selection) participates in k, where the expenditure is predicted by our estimated medical expenditure process on k.

H Sensitivity Analysis

H.1 The Impact of Changes in Parameter Values on Auxiliary Models

Following Cooper (2016) and Einav et al. (2018), we provide more evidence on the mapping between data and parameters via a perturbation exercise. We adjust each parameter one at a time and measure responses of the predicted auxiliary models we use for estimation. To be specific, letting $\left\{\widehat{\beta}_n\right\}_{n=1}^{N}$ be the vector of estimated structural parameters and $\left\{\widehat{\sigma}_{\beta_n}\right\}_{n=1}^{N}$ be the vector of their standard errors, we re-simulate our model N times. In the n^{th} simulation, we use the parameter vector $\left\{\widehat{\beta}_1, ..., \widehat{\beta}_n + \widehat{\sigma}_{\beta_n}, ..., \widehat{\beta}_N\right\}$, where the n^{th} parameter is perturbed by its standard error, and obtain new estimates of the auxiliary models. We then compute the percent change in absolute terms for each auxiliary model (regression coefficient or moment). This exercise produces a matrix of dimension (number of auxiliary models $\times$ number of parameters).

To ease exhibition, we group household-side auxiliary models (i.e., targets in the first-stage estimation) into 5 groups as specified in Section E.3: Aux^h 1a (work status and insurance status regression coefficients), Aux^h 1b (earnings regression coefficients), Aux^h 1c and 1d (cross-sectional moments of insurance and work statuses), Aux^h 2 (moments by health status), and Aux^h 3 (moments of joint outcomes between couples). We then summarize the average (absolute) percent change across auxiliary models within each group associated with a standard-error change of a parameter.

Table G1 reports the results for a subset of household-side parameters (the results for other parameters are available from the authors upon request). Rows 1-3 show how auxiliary models respond to changes in risk aversion parameters. These changes induce more significant responses in auxilary models that summarize insurance and employment status: how households respond to ACA-induced changes (Aux^h 1a) and the overall distribution of households across different statuses (Aux^h 1c and 1d).

We find similar patterns for the direct utility from health insurance options (ϖ_{INS}) and disutility from work: Aux^h 1a, 1c and 1d are more responsive. Noticeably, the preference for ESHI, the parameter that directly affects both one's labor supply and insurance decisons (work with ESHI or not), has a large impact on cross-sectional moments of employment and insurance statuses. This effect is larger than those from preferences for HIX and Medicaid, because the latter two would only indirectly affect one's labor supply decisions. Although somewhat subtle, preferences for health insurance options (ϖ_{INS}) induce larger changes in health-specific moments (Aux^h 2) than risk aversion and work disutility parameters. Finally, when we increase the fraction of Type-1 (more risk averse) households, more households choose to get insured (via ESHI, HIX, or Medicaid), leading to significant changes in all auxiliary models. Noticeably, auxiliary regression models that summarize how households respond to ACA-induced changes (Aux^h 1a and 1b) are more responsive to the type distribution parameter than to other parameters. Our identification relies on the assumption that type distribution is policy invariant; how households differentially respond to ACA (as summarized by Aux^h 1a and 1b) provides identifying information for the type distribution.

We conduct a similar exercise for firm-side parameters. We group firm-side auxiliary models (i.e., targets in the second-stage estimation) into 3 groups: moments related to the firm size distribution, moments related to the ESHI provision distribution, and moments related to a firm's employee composition (full time, high wage etc). We take the average (absolute) percent change across auxiliary models within each group associated with a standard error change of a parameter. Given that we allow all parameters to be region-specific, we also take the average across regions in order to ease the presentation.

Table G2 reports the results for a subset of firm-side parameters. As expected, TFP parameters (e.g., $\underline{T}$), which govern the overall productivity of a firm, affect firm-size moments more than other moments. Parameters governing the distribution of skill-biasedness (e.g., μ_A) and the relative weights of different skill types $\{B_{sh}\}$ affect employee composition the most, followed by ESHI provision decison.[19] The parameter that governs the correlation between TFP and skill-biasedness (ν) affects all three groups of moments by similar percentage terms. Finally, ESHI fixed costs' largest effects are on ESHI-related moments, as expected. Furthermore, by changing firms' ESHI offering decisions, these parameters also change how costly it is to attract different types of workers and hence affect employee composition moments.

[19] Notice that $\{B_{sh}\}$ is a vector, we report the average impact across (s, h) and across regions.

H.2 Sensitivity Analysis in Counterfactual Experiments

We conduct two sets of robustness checks.

H.2.1 The Impact of Changes in Parameter Values on Counterfactual Policy Implications

Following Taber and Vejlin (2020), we examine how our counterfacutal policy implications vary with our model parameters via a perturbation exercise. We focus on a set of parameters that are of key importance in our model: Risk aversion ($\gamma_{\boldsymbol{\chi}}$:), a constant parameter in the unobserved type distribution $\Pr(\chi)$, consumption floor, disutility of working, the effect of the unobserved type χ in the skill distribution $\Pr(s|x,\chi)$, a scale parameter of firm-side TFP $\underline{T}$, and the fixed cost of offering ESHI. We adjust each of these parameter one at a time and examine how our policy implications vary accordingly.

To be specific, for each $\widehat{\beta}_n$ that we examine, we change it twice: first to $\widehat{\beta}_n + \widehat{\sigma}_{\beta_n}$ and then to $\widehat{\beta}_n - \widehat{\sigma}_{\beta_n}$ while holding all the other parameters fixed at their estimated values. For each change, we re-simulate the baseline equilibrium and the equilibrium under the ESHI-HIX risk pooling counterfactual, leading to a new estimate of the policy impact. Table G3 report the results. The first row shows policy impacts of ESHI-HIX risk pooling under the original parameter estimates. In Row 2 onwards, each row labled with "+" ("-") shows the same policy impacts when the corresponding parameter in that row is increased (decreased) by its standard error. Overall, policy impacts under perturbed parameter values (one at a time) are very similar to our original results.

H.2.2 Different Utilities from Health Insurance by Health Status

In our model, households share the same direct utility from health insurance (ϖ_{INS}) regardless of their health statuses.[20] As a robustness check, we consider cases where healthy households derive 20% higher or lower direct utility from each insured option (ϖ_{INS}) than unhealthy households, while holding the mean ϖ_{INS} at its estimated value. Tables F3 to F6 show that, our policy implications persist and are comparable to the common-ϖ_{INS} case.

[20]Healthy households, who are more likely to have had insurance in the past, may have higher non-pecuniary utility from health insurance; a higher ϖ_{INS} for healthy households would capture this dynamic effect in a reduced-form way. We thank an anonymous referee for pointing this out.

I Additional Figures and Tables

I.1 Data

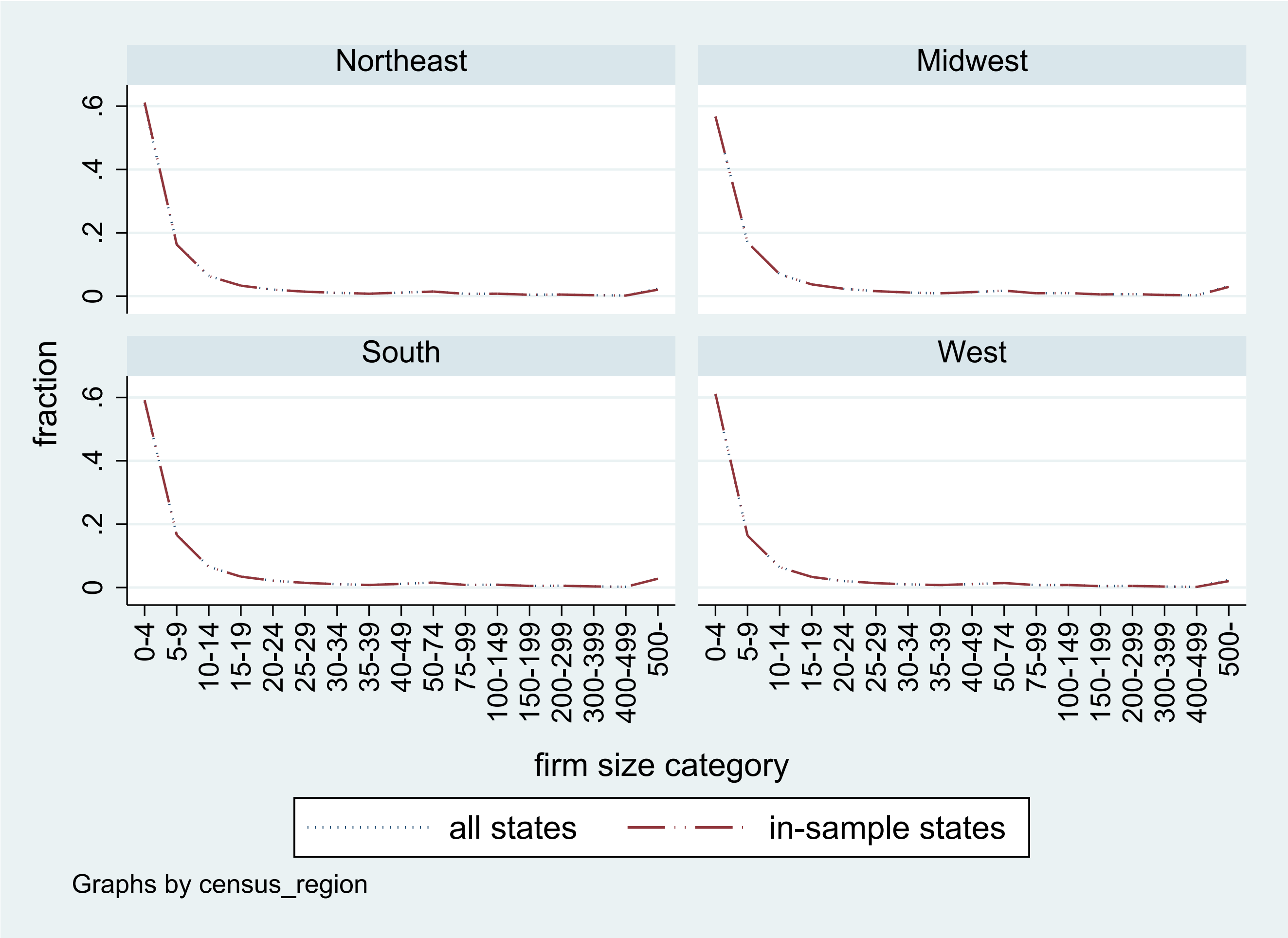

Figure A1: Firm Size Distribution in SUSB data: All States vs In-sample States

Table B1: Within-Couple Correlation

Medicaid	Expansion States		Non-Expansion States	
	2012	2015	2012	2015
Education: %				
(Low, Low)	6.00	6.46	6.26	6.81
(Mid, Mid)	37.17	35.90	39.71	38.73
(High, High)	27.33	27.40	22.63	24.68
Work Status: %				
(Full time, Full time)	52.86	53.49	53.04	54.12
(Full time, Part time)	10.82	10.17	9.68	8.84
(Full time, Nonemp)	31.20	32.42	32.97	32.64
(Part time, Part time)	0.44	0.40	0.31	0.24
(Part time, Nonemp)	1.71	1.37	1.42	1.57
Wage Correlation$\vert$both working	0.25	0.26	0.22	0.22
Number of Coupled Households	7,745	6,233	5,296	4,829

Note. The cross-sectional correlation is tabulated with our ACS samples.

Table B2: Insurance and Work Status Regressions

	Uninsured	Medicaid	ESHI	Nonemployed	Full time
ACA*Medicaid Expansion States (α_2)					
α_{20}	-0.059	0.049	0.007	-0.014	0.015
	(0.011)	(0.013)	(0.012)	(0.007)	(0.008)
Edu Low (α_{21})	-0.055	0.064	-0.006	-0.005	0.015
	(0.015)	(0.014)	(0.012)	(0.013)	(0.015)
Edu High (α_{22})	0.071	-0.059	-0.013	0.022	-0.010
	(0.011)	(0.010)	(0.012)	(0.005)	(0.009)
Childless (α_{23})	0.003	-0.012	-0.004	-0.003	0.001
	(0.012)	(0.010)	(0.011)	(0.008)	(0.009)
Single (α_{24})	-0.104	0.060	0.025	-0.026	0.020
	(0.013)	(0.012)	(0.017)	(0.010)	(0.011)
ACA*Non-Expansion States (α_3)					
α_{30}	-0.058	-0.001	0.045	-0.027	0.022
	(0.011)	(0.008)	(0.017)	(0.012)	(0.011)
Edu Low (α_{31})	0.019	-0.025	-0.003	0.033	-0.020
	(0.015)	(0.014)	(0.013)	(0.020)	(0.020)
Edu High (α_{32})	0.012	0.012	-0.015	0.010	-0.001
	(0.017)	(0.006)	(0.013)	(0.008)	(0.007)
Childless (α_{33})	-0.013	0.023	-0.017	0.027	-0.023
	(0.015)	(0.007)	(0.013)	(0.009)	(0.009)
Single (α_{34})	-0.019	-0.008	0.005	-0.026	0.017
	(0.015)	(0.007)	(0.013)	(0.009)	(0.009)

Note. See Section E.3 for the regresion specification. Other control variables include state dummies, education, gender, I(childless), marital status, age, and age-squared. The regression is based on both estimation and validation samples in our structural estimation. The regression coefficients based only on the estimation samples are reported in Table E3. Standard errors are clustered at the state level.

I.2 Parameters Estimated outside of the Model

Table C1. Individual Insurance and Income

	2012 only		2012 and 2015	
	Estimate	Std. Error	Estimate	Std. Error
Regression $(B11)^*$				
ln(earning)	0.058	(0.006)	0.060	(0.005)
State FE	Yes		Yes	
Year FE			Yes	
Sample Size	6,691		11,705	
Regression $(B12)^*$				
ln(earning+1)	0.009	(0.001)	0.013	(0.001)
State FE	Yes		Yes	
Year FE			Yes	
Sample Size	11,757		20,113	

* Both regressions control for education, marital status, I(childless), gender, age, age^2.

Note. See (B11) and (B12) in Section D.3 for the specification. Both regressions control for education, marital status, I(childless), gender, age, and age-squared.

Table C2. Summary Statistics: Medical Expenditure $(\$)$

Year	2012		2015	
	Mean	Std. Dev.	Mean	Std. Dev.
Adults				
Overall	3673.6	(12832.7)	3878.55	(12683.4)
Unhealthy	8759.6	(19514.3)	9261.73	(25743.8)
Uninsured	1650.3	(6024.2)	1857.97	(8934.8)
Uninsured×Unhealthy	3971.4	(10468.0)	3734.7	(10592.1)
ESHI	4450.5	(12282.0)	4536.06	(13606.5)
ESHI×Unhealthy	11892.6	(23292.5)	11864.1	(29050.0)
Individual Insurance	2982.6	(8451.7)	3834.93	(11966.0)
Individual Insurance×Unhealthy	12291.2	(22970.7)	15398.2	(33956.9)
Medicaid	5230.4	(30970.3)	4083.94	(13230.9)
Medicaid×Unhealthy	10207.3	(20587.4)	7809.3	(22844.5)
Medicaid expansion states	3861.4	(14581.5)	4129.72	(15544.7)
Non-expansion states	3470.5	(10617.0)	3749.37	(10921.8)
# Obs.	81,020		45,069	
Children				
Overall	1710.9	(8271.0)	1900.9	(8697.9)
# Obs.	47,258		26,701	

Note. Data source: MEPS. See Section F.1 for the detail.

Table C3. Medical Expenditure Process (Adults)

	2012		2015	
M_{med}	Estimate	Std. Error	Estimate	Std. Error
unhealthy	0.921	(0.027)	0.864	(0.036)
age40	0.099	(0.023)	0.149	(0.031)
age50	0.365	(0.023)	0.400	(0.031)
age60	0.773	(0.024)	0.821	(0.033)
female	0.435	(0.017)	0.467	(0.023)
ESHI	0.893	(0.021)	0.800	(0.031)
IHI	0.508	(0.052)	0.612	(0.083)
Medicaid	0.723	(0.036)	0.589	(0.042)
$ln\left(\sigma_{med}\right)$				
unhealthy	0.162	(0.024)	0.157	(0.031)
age40	-0.012	(0.020)	-0.012	(0.029)
age50	-0.022	(0.021)	-0.003	(0.030)
age60	-0.054	(0.023)	0.013	(0.032)
female	-0.061	(0.016)	-0.024	(0.022)
ESHI	-0.224	(0.019)	-0.188	(0.027)
IHI	-0.347	(0.051)	-0.258	(0.075)
Medicaid	0.022	(0.029)	-0.043	(0.037)
$\Pr\left(C_{med} > 0\right)$				
unhealthy	0.495	(0.023)	0.519	(0.030)
age40	0.144	(0.017)	0.168	(0.023)
age50	0.335	(0.018)	0.339	(0.025)
age60	0.606	(0.022)	0.568	(0.031)
female	0.529	(0.013)	0.495	(0.019)
ESHI	0.914	(0.014)	0.893	(0.020)
IHI	0.897	(0.051)	0.692	(0.079)
Medicaid	0.633	(0.025)	0.608	(0.029)

Note. 1. See Section F.1.1. about the specification of the medical expenditure process. The default group is healthy uninsured males who are in the age 30 group and living in California. The key parameter estimates are reported in the Table. State fixed effects are included throughout and their estimates are available per request.
2. Expenditure is measured in $10,000.

Table C4. Medical Expenditure Process (Children)

	2012		2015	
M_{med}	Estimate	Std. Error	Estimate	Std. Error
ESHI	0.650	(0.036)	0.629	(0.051)
IHI	0.444	(0.072)	0.124	(0.115)
Medicaid	0.110	(0.036)	0.078	(0.050)
$\ln(\sigma_{med})$				
ESHI	-0.140	(0.035)	-0.121	(0.054)
IHI	-0.410	(0.078)	-0.403	(0.182)
Medicaid	-0.006	(0.035)	0.022	(0.052)
$\Pr(C_{med} > 0)$				
ESHI	0.822	(0.027)	0.869	(0.041)
IHI	1.241	(0.083)	0.592	(0.158)
Medicaid	0.582	(0.025)	0.566	(0.038)

Note. 1. See Section F.1.1. about the specification of the medical expenditure process. The default group is uninsured children living in California. The key parameter estimates are reported in the Table. State fixed effects are included throughout and their estimates are available per request.
2. Expenditure is measured in \$10,000.

Table C5. Pre-ACA Individual Insurance Premium

$\ln(r_i^{pre})$	Estimate	Std. Error
unhealthy	0.100	(0.100)
age40	0.684	(0.075)
age50	0.780	(0.064)
age60	1.022	(0.062)
female	-0.127	(0.047)

Note. 1. See Section F.1.2. about the regression specification. The default group is age-30 healthy males living in California. The key parameter estimates are reported in the Table. State fixed effects are included throughout and their estimates are available per request.
2. r is measured in \$10,000.

I.3 Other Structural Parameter Estimates

Table D1: Other Parameter Estimates: Household and Wages

A. Household Preferences					
Scale Parameter of Logit shocks (σ)			Disutility of Working		
Medicaid	0.807	(0.009)	υ (scale in coupled hh)	0.478	(0.001)
Individual insurance	0.841	(0.036)			
Labor supply	0.791	(0.002)			
B. Type Distribution (CA is the default state)					
AL	0.096	(0.002)	NJ	-0.008	(0.002)
AZ	0.341	(0.002)	NY	-0.048	(0.002)
CO	-0.475	(0.003)	NC	0.161	(0.002)
CT	-0.440	(0.004)	OH	-0.969	(0.007)
FL	0.932	(0.002)	OK	0.180	(0.003)
GA	0.061	(0.002)	OR	-0.012	(0.003)
IL	-0.546	(0.004)	PA	-0.288	(0.002)
IN	0.079	(0.003)	SC	0.810	(0.002)
KY	0.266	(0.002)	TN	0.326	(0.001)
LA	0.107	(0.003)	TX	1.350	(0.003)
MD	-1.248	(0.009)	VA	-0.014	(0.002)
MI	-0.233	(0.003)	WA	-0.141	(0.003)
MN	-1.447	(0.021)	WI	-0.428	(0.005)
MO	-0.094	(0.004)	Constant	-0.884	(0.006)
C*.Wage Distribution $\ln\left(w^m_{sh0}\right) \sim N\left(\omega^0_h + \omega^0_{state} + \omega^0_{year}, \sigma^2_{wh}\right)$, $\frac{w^m_{sh1}}{w^m_{sh0}} = \frac{1}{1+\exp\left(\omega^1_0 + \omega^1_1 w^m_{sh0}\right)}$					
ω^0_P	-0.104	(0.001)	ω^0_{2015}	0.030	(0.0001)
σ_{wP}	-0.337	(0.002)	ω^1_0	-0.519	(0.002)
ω^0_F	1.281	(0.0003)	ω^1_1	0.190	(0.0004)
σ_{wF}	0.934	(0.0004)			

Note. * State-specific parameters in the wage distribution are available upon request.

Table D2: Other Firm-Side Parameters

CES labor input weights: $B_{sP} = B_{sF} \times \widehat{B_{SP}}, \sum_{s,h} B_{sh} = 1$								
Region	Northeast		Midwest		West		South	
B_{1F}	0.086	(0.028)	0.090	(0.057)	0.100	(0.015)	0.085	(0.029)
B_{2F}	0.142	(0.048)	0.140	(0.072)	0.143	(0.022)	0.137	(0.048)
B_{3F}	0.206	(0.042)	0.204	(0.039)	0.189	(0.016)	0.196	(0.044)
B_{4F}	0.121	(0.025)	0.127	(0.009)	0.119	(0.008)	0.123	(0.024)
B_{5F}	0.314	(0.046)	0.311	(0.019)	0.312	(0.012)	0.308	(0.018)
$\widehat{B_{1P}}$	0.243	(0.944)	0.243	(0.121)	0.237	(0.115)	0.242	(0.305)
$\widehat{B_{2P}}$	0.190	(0.592)	0.193	(0.313)	0.187	(0.105)	0.193	(0.397)
$\widehat{B_{3P}}$	0.185	(0.097)	0.187	(0.363)	0.170	(0.102)	0.186	(0.361)
$\widehat{B_{4P}}$	0.184	(0.268)	0.185	(0.914)	0.181	(0.085)	0.184	(0.274)

Note. See (A4) for the empirical specification of the production function. The standard errors of estimates are in parenthesis.

I.4 Model Fit

Table E1. Within-Sample Fit: Status and Earnings Moments

	Status (%)				ln(Earnings)			
	Data		Model		Data		Model	
Year	2012	2015	2012	2015	2012	2015	2012	2015
ESHI	66.30	67.06	67.91	67.49	8.14	8.13	8.44	8.44
Medicaid	6.41	10.03	5.46	9.39	6.94	6.88	6.80	6.70
Uninsured	22.11	15.20	21.94	15.37	7.25	7.26	7.56	7.79
Part time	6.58	6.53	6.81	6.70	6.66	6.58	6.30	6.29
Full time	71.08	72.18	73.20	73.42	8.05	8.04	8.41	8.41

Table E2.Within-Sample Fit: Status Regressions

	Uninsured		Medicaid		ESHI		Nonemployed		Full time	
Medi. Expand	Expand	No	Expand	No	Expand	No	Expand	No	Expand	No
					Data					
ACA	-0.067	-0.058	0.051	0.002	0.011	0.038	-0.014	-0.025	0.015	0.022
ACA*lowEdu	-0.061	0.023	0.066	-0.024	-0.004	-0.007	-0.001	0.035	0.015	-0.022
ACA*highEdu	0.073	0.006	-0.064	0.013	-0.015	-0.012	0.018	0.010	-0.003	-0.003
ACA*single	-0.101	-0.013	0.063	-0.010	0.019	0.003	-0.025	-0.028	0.018	0.017
ACA*childless	0.005	-0.016	-0.013	0.021	-0.002	-0.013	-0.004	0.026	0.001	-0.023
					Model					
ACA	-0.026	-0.087	0.026	0.008	-0.034	0.036	0.001	0.015	-0.002	-0.024
ACA*lowEdu	-0.131	-0.022	0.127	-0.047	-0.019	0.045	0.014	-0.014	-0.008	0.001
ACA*highEdu	0.097	0.015	-0.080	0.012	0.012	0.002	0.001	-0.008	-0.001	0.013
ACA*single	-0.145	0.024	0.105	0.010	0.016	-0.036	0.006	-0.002	-0.001	0.002
ACA*childless	-0.025	0.027	0.000	0.005	0.039	-0.024	-0.017	-0.014	0.013	0.025

Table E3: Model Fits: Firm-Side Moments

	Data		Model	
Year	2012	2015	2012	2015
Size	22.08	22.26	21.29	21.20
% ESHI	56.59	51.37	56.80	50.88
% HighWage Workers	23.57	27.55	33.77	35.79
% FullTime Workers	74.02	73.29	80.12	80.26
Size*ESHI	18.66	17.83	18.51	16.67
ESHI* % HighWage Workers	17.61	17.81	22.56	22.19
ESHI* % FullTime Workers	47.62	41.44	49.10	44.71

Table E4: Model Fits: Firm-Side Moments By Region

Year	2012				2015			
Region	NE	M	W	S	NE	M	W	S
	Data							
Size	24.73	24.21	19.47	20.99	25.26	24.53	19.70	20.72
% ESHI	46.86	61.15	55.29	59.85	49.06	53.25	51.76	51.25
% HighWage Workers	20.37	22.34	25.20	25.04	29.03	19.17	27.01	32.52
% FullTime Workers	66.39	70.82	80.38	76.01	75.76	67.22	72.16	76.55
Size*ESHI	20.81	21.17	15.68	17.84	21.22	19.45	15.63	16.24
ESHI* % HighWage Workers	16.36	16.50	21.16	16.59	15.86	13.10	17.80	22.06
ESHI* % FullTime Workers	40.25	46.84	49.53	50.92	36.92	41.78	39.56	45.14
	Model							
Size	24.50	22.35	20.16	19.59	23.67	22.62	21.38	18.70
% ESHI	51.48	57.14	56.83	59.50	43.98	56.75	50.17	51.57
% HighWage Workers	31.71	36.67	33.79	32.96	34.08	37.35	36.80	35.10
% FullTime Workers	79.49	83.07	80.85	78.00	79.68	83.38	81.41	77.78
Size*ESHI	21.09	20.02	16.22	17.64	18.25	18.45	14.57	16.00
ESHI* % HighWage Workers	19.18	24.73	23.60	22.28	18.14	24.81	23.55	21.94
ESHI* % FullTime Workers	43.96	51.07	49.60	50.29	38.12	50.91	44.81	44.48

Table E5: Holdout Sample Fit (Lowest Poverty States 2015)

%	Data		Model	
	All	MEP States	All	MEP. States
ESHI	74.44	72.72	72.58	72.21
Medicaid	8.92	10.19	8.32	10.09
Uninsured	10.18	10.51	10.57	10.19
Part time	6.80	6.69	7.29	7.38
Full time	76.81	76.55	74.33	73.25

Table E6: Holdout Sample Fit (Lowest Poverty States 2015) from Multinomial Logit Model

%	Model 1: joint outcome		Model 2: separate oucomes	
	All	MEP States	All	MEP. States
ESHI	73.37	72.94	72.3	72.83
Medicaid	5.88	6.57	5.96	6.7
Uninsured	11.97	10.7	12.14	10.98
Part time	5.05	4.78	5.19	5.07
Full time	74.72	75.7	73.77	74.26

I.5 Counterfactual Policies: Additional Results and Robustness Checks

Table F1: Changes in Net Premium and Government Savings in HIX Subsidies per Enrolled Household

		6.15% reduction in HIX premium		33.52% reduction in HIX premium	
Age 40	Income	ΔNet Premium (%)	Savings in Gov. Subsidy ($)	ΔNet Premium (%)	Savings in Gov. Subsidy ($)
Single	1.5 FPL	0.00	259.50	0.00	1414.03
	2 FPL	0.00	259.50	0.00	1414.03
	2.5 FPL	0.00	259.50	0.00	1414.03
	3 FPL	0.00	259.50	-11.90	1035.25
	3.5 FPL	0.00	259.50	-24.48	504.67
	>4 FPL	-6.15	0.0	-33.52	0.0
Couple	1.5 FPL	0.00	518.99	0.00	2828.05
	2 FPL	0.00	518.99	0.00	2828.05
	2.5 FPL	0.00	518.99	0.00	2828.05
	3 FPL	0.00	518.99	0.00	2828.05
	3.5 FPL	0.00	518.99	0.00	2828.05
	>4 FPL	-6.15	0.0	-33.52	0.0

Note. Upper (lower) panel: % change in the post-subsidy HIX premium for an age-40 childless single (coupled) household by income relative to FPL, and the associated savings in gov. HIX subsidy per enrolled household. HIX premium is calculated at the national average for these households.

Table F2: Cross-Subsidization between ESHI and HIX: Effects on Single and Childless Adults

	$\theta = \theta^0$		$\theta = 1.5\theta^0$	
A. Δ Status (ppt)				
	Single	Childless	Single	Childless
Uninsured	0.01	-0.03	-0.23	-0.26
HIX	0.10	0.12	0.52	0.57
ESHI	-0.09	-0.10	-0.32	-0.33
Nonwork	-0.01	0.00	-0.01	0.02
Fulltime	0.05	0.01	0.05	-0.01
B. Welfare				
	CEV ($)	Fr(Winners)	CEV ($)	Fr(Winners)
Single	69.4	0.70	130.6	0.78
Chidless	86.0	0.71	177.2	0.82

Note. This table reports equilibrium effects of ESHI-HIX cross subsidization when $\theta = \theta^0$ and $\theta = 1.5\theta^0$ on insurance and work status (A) and welfare (B) for single and childless adults.

Table F3: Cross-Subsidization between ESHI and HIX: Prices, Status, Earnings, and Productivity ($\theta = \theta^0$)

	Original Results[a]					Health-Status-Specific Utility from Insurance[b]				
A. Δ Prices (%)										
Premium	HIX			ESHI		HIX			ESHI	
	-6.15			0.56		-8.98			0.81	
Wage	Non-ESHI Jobs			ESHI Jobs		Non-ESHI Jobs			ESHI Jobs	
	-0.19			0.38		-0.16			0.55	
B. Δ Status (ppt)										
	Uninsured	HIX	ESHI	Nonwork	Fulltime	Uninsured	HIX	ESHI	Nonwork	Fulltime
All	-0.02	0.12	-0.09	-0.01	0.02	-0.02	0.20	-0.16	-0.01	0.03
Low Edu	-0.01	0.09	-0.08	-0.04	0.05	-0.01	0.20	-0.17	-0.05	0.08
High Edu	-0.03	0.11	-0.07	0.01	0.00	-0.04	0.17	-0.13	0.02	-0.01
Single	0.01	0.10	-0.09	-0.01	0.05	0.02	0.15	-0.15	-0.01	0.06
Childless	-0.03	0.12	-0.10	0.00	0.01	-0.03	0.22	-0.18	0.01	0.01
C. Δ Earnings |employed (%)			0.58					1.65		
Δ Total Output (%)			3.06					3.21		

Note. a. ESHI-HIX risk pooling policy effect in the original model (reported in Table 5 in the main text).
b. ESHI-HIX risk pooling policy effect in when the direct utility from health insurance ϖ_{INS} is higher for healthy individuals.

Table F4: Cross-Subsidization between ESHI and HIX: Household Welfare and Gov Spending ($\theta = \theta^0$)

	Original Results[a]		Health-Status-Specific Utility from Insurances[b]	
Welfare	CEV ($)	Fr(Winners)	CEV ($)	Fr(Winners)
Overall	75.2	0.70	136.67	0.70
Type 1 Singles or (Type 1, Type 1) Couples	90.3	0.73	162.26	0.73
Type 2 Singles or (Type 2, Type 2) Couples	9.7	0.54	21.57	0.55
Low Edu Singles or (Low, Low) Couples	40.4	0.63	59.61	0.64
High Edu Singles or (High, High) Couples	119.1	0.78	224.71	0.77
Single	69.4	0.70	134.42	0.69
Childless	86.0	0.71	157.79	0.71
Savings in Gov. expenditure per hh ($)	14.3		19.79	
Savings in HIX subsidies per enrolled hh ($)	204.6		269.68	

Note. a. ESHI-HIX risk pooling policy effect in the original model (reported in Table 6 in the main text).
b. ESHI-HIX risk pooling policy effect in when the direct utility from health insurance ϖ_{INS} is higher for healthy individuals.

Table F5: Cross-Subsidization between ESHI and HIX: Prices, Status, Earnings, and Productivity ($\theta = \theta^0$)

	Original Results[a]					Health-Status-Specific Utility from Insurance[b]				
A. Δ Prices (%)										
Premium	HIX			ESHI		HIX			ESHI	
	-6.15			0.56		-6.05			0.57	
Wage	Non-ESHI Jobs			ESHI Jobs		Non-ESHI Jobs			ESHI Jobs	
	-0.19			0.38		-0.16			0.57	
B. Δ Status (ppt)										
	Uninsured	HIX	ESHI	Nonwork	Fulltime	Uninsured	HIX	ESHI	Nonwork	Fulltime
All	-0.02	0.12	-0.09	-0.01	0.02	-0.01	0.14	-0.13	-0.01	0.03
Low Edu	-0.01	0.09	-0.08	-0.04	0.05	0.01	0.14	-0.13	-0.05	0.08
High Edu	-0.03	0.11	-0.07	0.01	0.00	-0.02	0.12	-0.10	0.02	-0.01
Single	0.03	0.11	-0.13	-0.01	0.06	0.02	0.15	-0.15	-0.01	0.06
Childless	-0.03	0.12	-0.10	0.00	0.01	-0.01	0.15	-0.14	0.00	0.01
C. Δ Earnings |employed (%)	0.58					1.61				
Δ Total Output (%)	3.06					3.14				

Note. a. ESHI-HIX risk pooling policy effect in the original model (reported in Table 5 in the main text).
b. ESHI-HIX risk pooling policy effect in when the direct utility from health insurance ϖ_{INS} is higher for unhealthy individuals.

Table F6: Cross-Subsidization between ESHI and HIX: Household Welfare and Gov Spending ($\theta = \theta^0$)

	Original Results[a]		Health-Status-Specific Utility from Insurances[b]	
Welfare	CEV ($)	Fr(Winners)	CEV ($)	Fr(Winners)
Overall	75.2	0.70	113.98	0.69
Type 1 Singles or (Type 1, Type 1) Couples	90.3	0.73	135.95	0.72
Type 2 Singles or (Type 2, Type 2) Couples	9.7	0.54	18.23	0.55
Low Edu Singles or (Low, Low) Couples	40.4	0.63	44.33	0.61
High Edu Singles or (High, High) Couples	119.1	0.78	190.97	0.78
Single	69.4	0.70	125.06	0.69
Childless	86.0	0.71	134.93	0.70
Savings in Gov. expenditure per hh ($)	14.3		19.8	
Savings in HIX subsidies per enrolled hh ($)	204.6		197.73	

Note. a. ESHI-HIX risk pooling policy effect in the original model (reported in Table 6 in the main text).
b. ESHI-HIX risk pooling policy effect in when the direct utility from health insurance ϖ_{INS} is higher for unhealthy individuals.

I.6 Sensitivity Analysis

Table G1: Impact of Changes in Parameter Values on Auxiliary Models (Stage 1 Estimation)

(% in absolute terms)	Aux^h 1a	Aux^h 1b	Aux^h 1c and 1d	Aux^h 2	Aux^h 3
γ_{χ} : Type 1	0.20	0.16	0.81	0.13	0.02
γ_{χ} : Type 2	0.34	0.17	1.08	0.16	0.01
γ_{χ} : (Types 1, 2) couples	0.27	0.09	0.29	0.10	0.02
ϖ_{INS}: ESHI	0.39	0.22	15.59	1.81	0.08
ϖ_{INS}: HIX	0.05	0.03	1.96	0.29	0.01
ϖ_{INS}: Medicaid	0.23	0.13	0.50	0.31	0.01
Disutility of Working: Full time job	0.37	0.04	2.73	0.12	0.16
Constant in $\Pr(\chi = 1)$	1.38	0.60	11.51	0.78	0.17

Note. Each cell shows, as the parameter estimate in the row increases by one standard error, the associated average % change (in absolute terms) in auxiliary models within each group in the column. The list of auxiliary models is reported in Appendix E.3.

Table G2: Impact of Changes in Parameter Values on Auxiliary Models (Stage 2 Estimation)

(% in absolute terms)	Firm Size	ESHI	Employee Composition
TFP: scale $\underline{T}$	7.22	2.78	2.29
Skill-biasedness: μ_A	2.12	10.63	16.30
Skill-specific parameters $\{B_{sh}\}$	3.74	8.94	63.66
Correlation between T and A: ν	1.31	1.57	1.78
Fixed cost of offering ESHI	0.46	11.21	5.03

Note. Each cell shows, as the parameter estimate in the row increases by one standard error, the associated average % change (in absolute terms) in auxiliary models within a group in the column and across regions. The list of auxiliary models is reported in Appendix E.3.

Table G3: Impact of Changes in Parameter Values on Counterfactual Policy Implications

		Uninsured	HIX	ESHI	Non-employed	Full-time	Average CEV	Saving in Gov.exp.
Original Parameter values		-0.024	0.118	-0.091	-0.007	0.023	75.240	14.207
$\gamma_{\boldsymbol{\chi}}$: Type 1	$+$	-0.024	0.118	-0.091	-0.007	0.023	75.916	14.296
	$-$	-0.023	0.115	-0.090	-0.007	0.023	74.627	14.381
Constant in $\Pr(\chi)$	$+$	-0.020	0.123	-0.100	-0.009	0.026	69.115	14.367
	$-$	-0.024	0.118	-0.091	-0.007	0.023	70.669	14.302
Consumption Floor	$+$	-0.024	0.118	-0.091	-0.007	0.023	72.089	14.288
	$-$	-0.024	0.118	-0.091	-0.007	0.023	74.741	14.300
Disutility of Working:	$+$	-0.024	0.118	-0.091	-0.007	0.023	71.372	14.291
Full time job (Type 1)	$-$	-0.023	0.115	-0.090	-0.007	0.023	75.644	14.384
Disutility of Working:	$+$	-0.024	0.118	-0.091	-0.007	0.023	72.597	14.276
Full time job (Bad Health)	$-$	-0.023	0.116	-0.090	-0.007	0.023	72.272	14.401
Effect of χ in $\Pr(s\|x,\chi)$	$+$	-0.020	0.120	-0.097	-0.009	0.026	68.230	14.511
	$-$	-0.024	0.118	-0.092	-0.007	0.024	73.229	14.305
TFP: scale $\underline{T}$ (post-ACA)	$+$	-0.024	0.118	-0.091	-0.007	0.023	77.1167	14.294
	$-$	-0.024	0.118	-0.091	-0.007	0.023	71.021	14.294
Fixed cost of offering ESHI	$+$	-0.080	0.094	-0.020	0.008	-0.008	97.705	14.966
	$-$	-0.020	0.129	-0.094	-0.002	0.019	124.373	14.885

Note. 1. Changes in insurance and employment status are in ppts. The unit of CEV and Saving in Gov.exp. are $.

2. Row 1 shows policy impacts of ESHI-HIX risk pooling under the original parameter values.

3. From Row 2 onwards, the row with "+" ("-") shows policy impacts of ESHI-HIX risk pooling when the corresponding parameter is increased (decreased) by a standard error.

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