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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A A Simple Model for Illustration

Worker's Problem Given (r, w_0, w_1), a worker's problem is

$$\max_{h,z_1,z_2} E[U(C(h,z_1,z_2))\,|x] - dh \tag{1}$$
$$s.t.\ C(h,z_1,z_2) = (1-h)\,b + hw_{z_1} - z_2 r - (1-z_1)(1-z_2)\,c^{med},$$

where $C(\cdot)$ is one's net consumption, and the expectation is taken over $c^{med}|x$. One's income is b (w_{z_1}) when non-employed (employed with z_1). If $z_2 = 1$, one pays the HIX premium r. If uninsured $((1-z_1)(1-z_2)=1)$, one pays a random medical cost c^{med}. 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

$$U(y-r) = E[U(y-c^{med})|x^*(y;r)], \tag{2}$$

such that $z_2 = 1$ if $x > x^*(y;r)$, i.e., workers with higher health risks 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

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effect) if $U(\cdot)$ is CRRA, and is independent of y if $U(\cdot)$ is CARA. We consider $x^*(w_0; r) \geq x^*(b; r)$.[1]
2. *Employment Choice* (h, z_1)*:* For each x, there is a $d^*(x; w)$, such that one would work if $d \leq d^*(x; w)$.
Case 1: $x > x^*(w_0; r)$, the worker solves the following

$$\max \{U(b-r), U(w_1) - d, U(w_0 - r) - d\}.$$

Here, $d^*(x; w)$ solves $U(b-r) = \min\{U(w_1) - d^*(x; w), U(w_0 - r) - d^*(x; w)\}$ and it is independent of x. For workers with $d \leq d^*(x; w)$, $z_1 = 1$ if $w_1 > w_0 - r$, and $z_1 = 0$ if $w_1 < w_0 - r$. If $w_1 = w_0 + r$, a fraction θ of workers choose $z_1 = 1$.
Case 2: $x \leq x^*(w_0; r)$, the worker solves the following

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

One can characterize $d^*(x; w)$ by a threshold condition again. Here, $d^*(x; w)$ varies with x. There is an $x^{**}(w_0 - w_1)$ defined by

$$U(w_1) = E[U(w_0 - c^{med})|x^{**}(w_0 - w_1)], \tag{3}$$

such that $z_1 = 1$ if $x > x^{**}(w_0 - w_1)$ and $d \leq d^*(x; w)$.[2]

Firm's Problem Firms solve 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 $z_1 = 0$.

Equilibrium with both ESHI and Non-ESHI Jobs We focus on 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. *Case A:* $w_0 - w_1 = r$, which implies: A1: $x^{**}(w_0 - w_1) = x^*(w_0; r) \geq x^*(b; r)$ (see (2) and (3)). A fraction θ of workers with $x > x^*(w_0; r)$ and $d \leq d^*(x; w)$ will be enrolled in ESHI.[3] A2: $q = w_0 - w_1 = r$, i.e., the average cost on ESHI and that on HIX are the same.

[1] Given that working involves disutility for workers and that workers value insurance, in equilibrium, the following must be true: $w_0 > b$ and $w_0 > w_1$.
[2] Whether or not $x > x^{**}(w_0 - w_1)$ is relevant for $x \leq x^*(w_0)$ depends on w_0 and w_1.
[3] In Case A, $x > x^{**}(w_0 - w_1)$ is irrelevant for those with $x < x^*(w_0)$.

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.

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

$$L_{ESHI} = \int_{x^{**}(w_0-w_1)}^{\overline{x}} \int_{d=0}^{d^*(x;w)} 1 dF_{d|x}(d|x)\, dF_x(x), \tag{4}$$

and the total enrollment in HIX is given by

$$L_{HIX} = \int_{x^*(b)}^{\overline{x}} \int_{d^*(x;w)}^{\overline{d}} 1 dF_{d|x}(d|x)\, dF_x(x). \tag{5}$$

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 (5) as

$$L_{HIX} = \int_{x^*(b)}^{x^{**}(w_0-w_1)} \int_{d^*(x;w)}^{\overline{d}} 1 dF_{d|x}(d|x)\, dF_x(x) + \int_{x^{**}(w_0-w_1)}^{\overline{x}} \int_{d^*(x;w)}^{\overline{d}} 1 dF_{d|x}(d|x)\, dF_x(x). \tag{6}$$

The HIX enrollees described by the second term in (6) are of higher health risks than those in (4) when $corr(x, d) > 0$. The HIX enrollees described by the first term in (6) the higher-d and hence riskier subset of workers among those with $x \in (x^*(b), x^{**}(w_0 - w_1))$, who are nevertheless less risky 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.

B 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 $G(n_j)$, which is a function of the firm's worker composition $n_j = \{n_{jsh}\}$. The mandate will be binding if the unconstrained choice under $z = (0,0)$, $n_j^*(0,0)$, 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 $\pi_j^*(0,0)$ net of penalty $G\left(n_j^*(0,0)\right)$ with that from the following constrained optimization problem

$$\pi_j^c = \max_{\{n_{jsh}\}_{s,h}} \left\{ Y_j - \sum_{h\in\{P,F\}} \sum_{s=1}^{S} n_{jsh} w_{shz}^m \right\} \tag{7}$$
$$s.t. \sum_s n_{jsF} + \iota \sum_s n_{jsP} < n_{cut},$$

where ι is the full-time equivalent of a part-time worker. Let n_j^c be the optimal solution to (7). The probability of ESHI choices is as follows

Case 1: $\pi_j^c > \pi_j^*(0,0) - G\left(n_j^*(0,0)\right)$

$$\Pr(z_j = z') = \begin{cases} \dfrac{\exp\left(\frac{\pi_j^*(z')}{\sigma\eta}\right)}{\exp\left(\frac{\pi_j^c}{\sigma\eta}\right) + \sum_{z\in\{(1,0),(1,1)\}} \exp\left(\frac{\pi_j^*(z)}{\sigma\eta}\right)} & \text{for } z' \in \{(1,0),(1,1)\} \\ \dfrac{\exp\left(\frac{\pi_j^c}{\sigma\eta}\right)}{\exp\left(\frac{\pi_j^c}{\sigma\eta}\right) + \sum_{z\in\{(1,0),(1,1)\}} \exp\left(\frac{\pi_j^*(z)}{\sigma\eta}\right)} & \text{for } z' = (0,0) \end{cases}.$$

Case 2: $\pi_j^c \leq \pi_j^*(0,0) - G\left(n_j^*(0,0)\right)$

$$\Pr(z_j = z') = \frac{\exp\left(\frac{\pi_j^*(z') - I(z=(0,0))G\left(n_j^*(z')\right)}{\sigma\eta}\right)}{\sum_{z\in\{(0,0),(1,0),(1,1)\}} \exp\left(\frac{\pi_j^*(z) - I(z=(0,0))G\left(n_j^*(z)\right)}{\sigma\eta}\right)}.$$

C Data Details

C.1 Household Data

C.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.

C.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.

[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.

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]

C.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 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 D.3.

C.3 Data Pattern: 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

$$Ins_i = \alpha \ln(y_i) + \beta X_i + d_{s_i} + \epsilon_i, \quad (8)$$

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.

[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.

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

To include the zero-income population, we also run a regression using $\ln(y_i + 1)$ to replace $\ln(y_i)$.

$$Ins_i = \alpha \ln(y_i + 1) + \beta X_i + d_{s_i} + \epsilon_i, \tag{9}$$

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

The results are reported in Table B1, 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.

D Estimation Details

D.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 geocode. 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.

D.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 (m_i) as a mixed distribution, allowing for a mass point at 0. For adults, the probability of positive expenditure is given by

$$\Pr(m > 0|\,(x, z, s)) = \Phi\left(x\alpha_0 + \beta_{z0} + d_{0s}\right),$$

where x includes the age, gender, health status, and their interactions, β_{z0} is an insurance-status-z fixed effect, and d_{0s} is a state fixed effect. For the distribution of positive medical expenditure, we assume the following log normal distribution

$$\ln(m|\,(x, z, s)) \sim N\left(M(x, z, s), \sigma^2(x, z, s)\right),$$

[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.

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

$$\begin{aligned} M(x,z,s) &= x\alpha_1 + \beta_{z1} + d_{1s}, \\ \sigma(x,z,s) &= \exp\left(x\alpha_2 + \beta_{z2} + d_{2s}\right). \end{aligned}$$

We estimate the parameters $\{\alpha_n, \{\beta_{zn}\}_z, d_{ns}\}_{n=0}^2$ via maximum likelihood, where individual i's contribution to the likelihood is given by

$$\begin{aligned} f(m_i|x_i,z_i,s_i) &= \left[1-\Phi\left(x_i\alpha_0+\beta_{z_i0}+d_{0s_i}\right)\right]^{1(m_i=0)} \times \\ &\quad \left[\Phi\left(x_i\alpha_0+\beta_{z_i0}+d_{0s_i}\right)\phi\left(\frac{\ln(m_i)-M(x_i,z_i,s_i)}{\sigma(x_i,z_i,s_i)}\right)\right]^{1(m_i>0)}. \end{aligned}$$

We specify the distribution of medical expenditures for children in a similar fashion, with the exception that the parameter counterpart of $\{\alpha_n\}_{n=0}^2$ 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 B3 and B4. Consistent with the data patterns as shown in Table B2, 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 (M). 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.*[8]

D.1.2 Insurance Premium

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

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

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_{s_i} is a state dummy. For the estimation, we

[8]To save space, Tables B3 and B4 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).

use the restricted MEPS data that includes geocode. Table B5 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.

D.1.3 Out of Pocket Medical Expenditure

Given a realization of the medical expenditure shock, a household's OOP is determined based on its health 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 OOP 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%.[9] Second, individuals with silver plans tend to receive a sizable income-based coinsurance subsidies, bringing the coinsurance rate of silver plans close to 15%.

D.2 Policy Functions

D.2.1 Net Government Transfer

We model the net government transfer to a household as

$$b\left(x, m, r, w^m_{shz} + w^m_{s'h'z'}, \mathbf{INS}\right) =$$

$$I\left(ACA\right)\begin{bmatrix} Sub(r, w^m_{shz} + w^m_{s'h'z'}, state) I\left(\mathbf{INS} = [0,0,0,1]^2\right) \\ -PE(x,r, w^m_{shz} + w^m_{s'h'z'}) I\left(\mathbf{INS} = [0,0,0,0]^2\right) \end{bmatrix}$$
$$-T(m, w^m_{shz} + w^m_{s'h'z'}) + WB(x, m, w^m_{shz} + w^m_{s'h'z'})$$

where $Sub(\cdot)$ is HIX premium subsidy function that applies when households participate in HIX $(INS = [0,0,0,1]^2)$ after ACA, and PE is the tax penalty that applies if individuals are uninsured when individual mandates are implemented, $T(\cdot)$ is the total income tax function, $WB(\cdot)$ is welfare benefit function.

[9] 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.

Premium Subsidy We model $Sub(\cdot)$ based on the actual formula of ACA premium subsidies, which depends on three factors (i) household income; (ii) the total premium; (iii) whether Medicaid is expanded in the state (MEP_{state}). 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). Specifically, we model $Sub(\cdot)$ as

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

We calibrate these subsidy parameters such that the premium contribution $(r - Sub(r,y,state))$ 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

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

where y denotes the household income. 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) in HIX.

Income Tax and Welfare Following Kaplan (2012), we specify the income tax function as

$$T(m,y) = y - \tau_{m0} - \tau_{m1}\frac{y^{1+\tau_{m2}}}{1+\tau_{m2}},$$

where the state-specific tax parameter vectors $\{\tau_m\}_m$ are estimated using NBER TAXSIM program.[10]

Following Chan (2013) and Gayle and Shephard (2019), we include and parameterize the following major welfare programs in our welfare function $WB(x,m,y)$:

1. The Supplemental Nutrition Assistance Program (SNAP): households with income below 138% of

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

FPL are eligible for SNAP, and the benefit varies by demographics x (marital status and the presence of children).

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.[11]

D.2.2 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.[12] We obtain the specific Medicaid eligibility rules via the Kaiser Family Foundation.[13] 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.[14]

[11]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)).

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

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

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

D.3 Firm-Side Estimation Details

D.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; while 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.[15]

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 auxiliary model for aggregate labor demand.

D.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}.

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

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

E Counterfactual Policy: CEV Calculation

Household baseline ex ante welfare is given by

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

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

Solve for Δ such that

$\mathbf{V}^{new}(x,m,\boldsymbol{\chi},\mathbf{s}) - \mathbf{V}(x,m,\boldsymbol{\chi},\mathbf{s}) =$

$$\begin{aligned}
&\left\{ \begin{array}{l} \sum_{(\mathbf{h},\mathbf{z})} \Pr(\mathbf{h},\mathbf{z}|x,m,\boldsymbol{\chi},\mathbf{s})\, Eu((1+\Delta)\, C(\mathbf{h},\mathbf{z}), \mathbf{h}, \mathbf{INS}(\mathbf{h},\mathbf{z}); x, \boldsymbol{\chi}) \\ \quad - \sum_{(\mathbf{h},\mathbf{z})} \Pr(\mathbf{h},\mathbf{z}|x,m,\boldsymbol{\chi},\mathbf{s})\, Eu(C(\mathbf{h},\mathbf{z}), \mathbf{h}, \mathbf{INS}(\mathbf{h},\mathbf{z}); x, \boldsymbol{\chi}) \end{array} \right. \\
= & \sum_{(\mathbf{h},\mathbf{z})} \Pr(\mathbf{h},\mathbf{z}|\cdot) \left[E\left(\frac{(1+\Delta)\left(\frac{C(\mathbf{h},\mathbf{z})}{n_x}\right)^{1-\gamma}}{1-\gamma} \right) - E\left(\frac{\left(\frac{C(\mathbf{h},\mathbf{z})}{n_x}\right)^{1-\gamma}}{1-\gamma} \right) \right] \\
= & \sum_{(\mathbf{h},\mathbf{z})} \Pr(\mathbf{h},\mathbf{z}|\cdot) \left[\left((1+\Delta)^{1-\gamma} - 1\right) E\left(\frac{\left(\frac{C(\mathbf{h},\mathbf{z})}{n_x}\right)^{1-\gamma}}{1-\gamma} \right) \right].
\end{aligned}$$

So that,

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

i.e.,

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

We obtain CEV for each household as

$$CEV(x,m,\boldsymbol{\chi},\mathbf{s}) = \Delta \sum_{(\mathbf{h},\mathbf{z})} \Pr(\mathbf{h},\mathbf{z}|\cdot)\, E\left(\frac{C(\mathbf{h},\mathbf{z})}{n_x} \right).$$

F Additional Figures and Tables

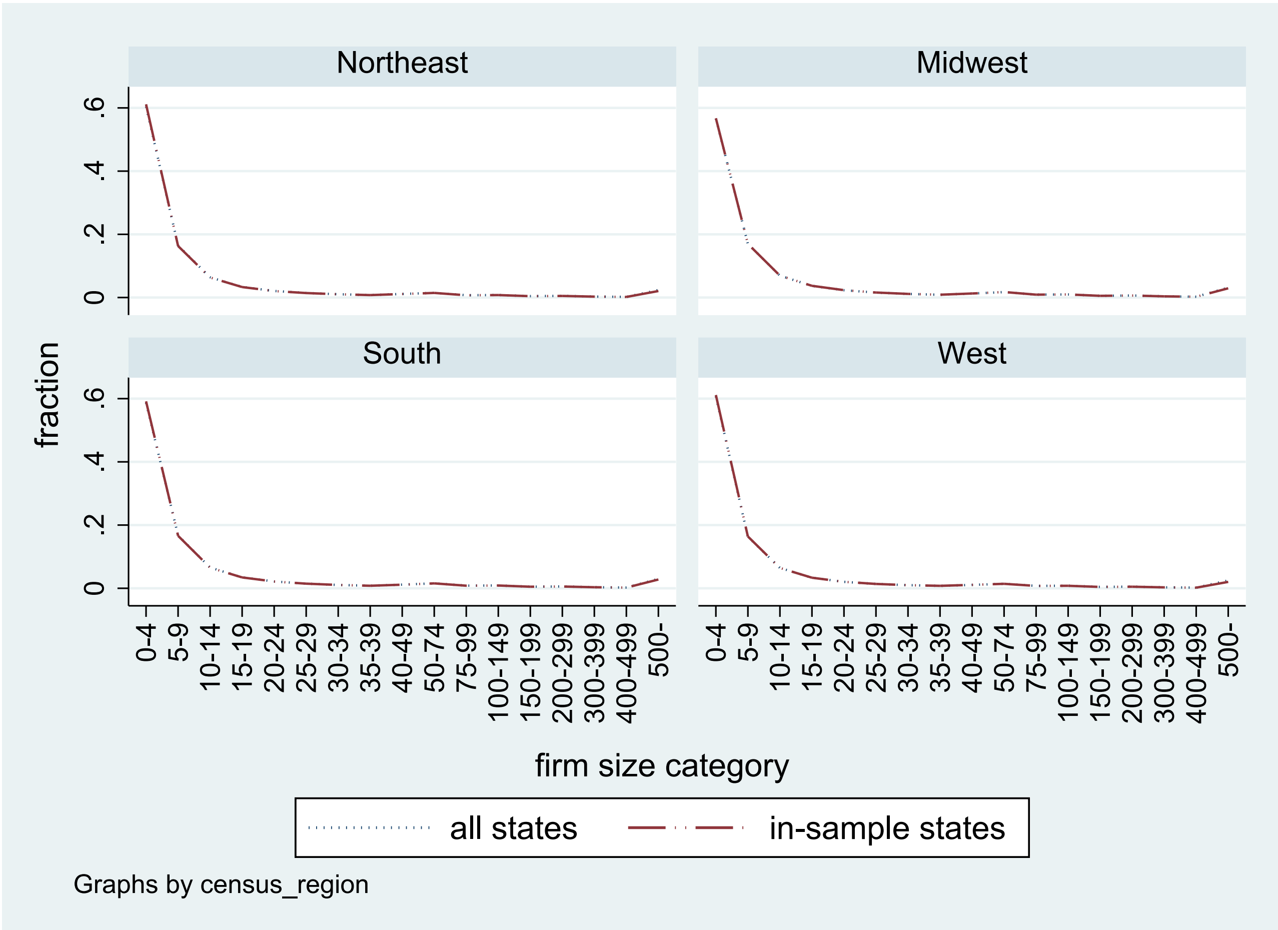

Figure A1: Firm Size Distribution in SUSB data: All States vs In-sample States

Table A1: 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|both working	0.25	0.26	0.22	0.22
Number of Coupled Households	7,745	6,233	5,296	4,829

Table A2: 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 %	20.81	21.17	15.68	17.84	21.22	19.45	15.63	16.24
Fr(HighWage Workers) %	46.86	61.15	55.29	59.85	49.06	53.25	51.76	51.25
Fr(FullTime Workers) %	20.37	22.34	25.20	25.04	29.03	19.17	27.01	32.52
Size*ESHI	66.39	70.82	80.38	76.01	75.76	67.22	72.16	76.55
ESHI*Fr(HighWage Workers) %	16.36	16.50	21.16	16.59	15.86	13.10	17.80	22.06
ESHI*Fr(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
Fr(HighWage Workers) %	31.71	36.67	33.79	32.96	34.08	37.35	36.80	35.10
Fr(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*Fr(HighWage Workers) %	19.18	24.73	23.60	22.28	18.14	24.81	23.55	21.94
ESHI*Fr(FullTime Workers) %	43.96	51.07	49.60	50.29	38.12	50.91	44.81	44.48

Table B1. Individual Insurance and Income

	2012 only		2012 and 2015	
	Estimate	Std. Error	Estimate	Std. Error
Regression $(8)^*$				
ln(earning)	0.061	(0.007)	0.061	(0.005)
State FE	Yes		Yes	
Year FE			Yes	
Sample Size	6,691		11,705	
Regression $(9)^*$				
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.

Table B2. 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	

Table B3. Medical Expenditure Process (Adults)

	2012		2015	
M	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)
$ln\,(\sigma)$				
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)
$\Pr\,(m > 0)$				
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. Expenditure is measured in $10,000, 2. State fixed effects are included throughout.

3. The default group is healthy uninsured males who are in the age 30 group and living in California.

Table B4. Medical Expenditure Process (Children)

	2012		2015	
M	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)
$\ln(\sigma)$				
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)
$\Pr(m > 0)$				
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. Expenditure is measured in \$10,000. 2. State fixed effects are included throughout. 3. The default group is uninsured children living in California.

Table B5. 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. r is measured in \$10,000. 2. State fixed effects are included. 3. The default group is age-30 healthy males living in California.

Table B6: Other Parameter Estimates: Household and Wages

A. Household Preferences					
Scale Parameter of Logit shocks (σ)			Disutility of Working		
Medicaid	0.807	(0.009)	Child (part time)	-0.911	(0.004)
Individual insurance	0.841	(0.036)	Child (full time)	-0.982	(0.004)
Labor supply	0.791	(0.002)	υ (scale in coupled hh)	0.478	(0.001)
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)			

* State-specific parameters are available upon request.

Table B7: 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)

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