Penn Institute for Economic Research
Department of Economics
University of Pennsylvania
3718 Locust Walk
Philadelphia, PA 19104-6297
pier@econ.upenn.edu
http://economics.sas.upenn.edu/pier

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"The Determinants of Rising Inequality in Health Insurance and Wages: An Equilibrium Model of Workers' Compensation and Health Care Policies"

by

Rong Hai

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The Determinants of Rising Inequality in Health Insurance and Wages:

An Equilibrium Model of Workers' Compensation and Health Care Policies*

Rong Hai†

University of Pennsylvania

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Abstract

I develop and structurally estimate a non-stationary overlapping generations equilibrium model of employment and workers' health insurance and wage compensation, to investigate the determinants of rising inequality in health insurance and wages in the U.S. over the last 30 years. I find that skill-biased technological change and the rising cost of medical care services are the two most important determinants, while the impact of Medicaid eligibility expansion is quantitatively small. I conduct counterfactual policy experiments to analyze key features of the 2010 Patient Protection and Affordable Care Act, including employer mandates and further Medicaid eligibility expansion. I find that (i) an employer mandate reduces both wage and health insurance coverage inequality, but also lowers the employment rate of less educated individuals; and (ii) further Medicaid eligibility expansion increases employment rate of less educated individuals, reduces health insurance coverage disparity, but also causes larger wage inequality.

JEL Classification: J2, J3, I1, I24

Keywords: Labor Market, Health Insurance, Health Care Policies, Inequality

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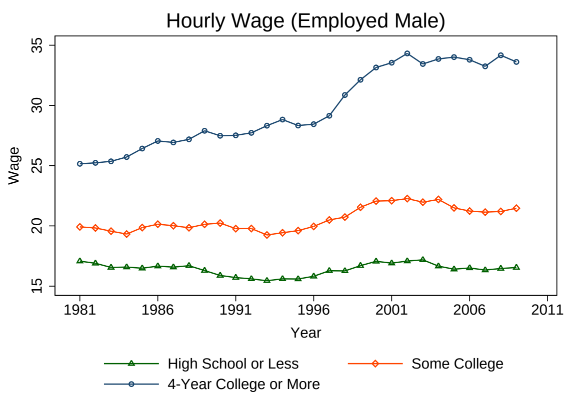
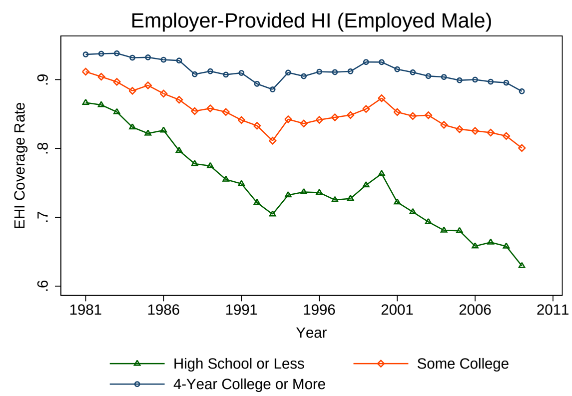
†ronghai@sas.upenn.edu

1 Introduction

A large literature documents rising wage differentials by education in the U.S. over the last 30 years (Katz and Murphy (1992), Katz and Autor (1999), Heckman et al. (1998), Autor et al. (2008), Lee and Wolpin (2010)). As seen in Figure 1(a), more educated workers experienced a relatively rapid increase in wages, and the college wage premium grew from 39 percent in 1981 to 71 percent in 2009.[1] Less often noted is the accompanying rising disparity in health insurance coverage, mainly due to a sharp decline in employer-provided health insurance among less educated workers.[2] As seen in Figure 1(b), employer-provided health insurance coverage among employed male workers with at most a high school degree fell from 87% in 1981 to only 63% in 2009, while coverage among those with a 4-year college degree or more was relatively stable. The gap in employer-provided health insurance coverage between college graduates and those with no college rose from 7 percentage points in 1981 to 25 percentage points in 2009.[3]



(a) Wage Inequality



(b) Health Insurance Coverage Inequality

Figure 1: Wage and Employer Provided Health Insurance Coverage Inequality

As noted, an extensive literature focuses on measuring and explaining the source of wage and earnings inequality. A key finding is that much of the rise in wage inequality since the 1980s can be explained by skill-biased technological change favoring skilled workers. A number of papers also document the rising inequality in the distribution of health insurance benefits, but existing research

[1]The college wage premium is measured as the log of the wage ratio between male workers with a 4-year college degree or more and male workers with at most a high school degree.

[2]Reliance on employer-provided health insurance is a major feature of the U.S health insurance market stemming from wage controls during World War II (Stabilization Act of 1942) and tax-exempt treatment for employer-provided health benefits since 1954 (Internal Revenue Code of 1954). In 1981, 78% of men aged 25 to 64 were covered by employer-provided health insurance, and, though falling, this ratio was still 65% in 2009. Over this same period, the fraction of men aged 25 to 64 who did not have any form of insurance increased from 14% to 22%.

[3]A similar pattern in employer provided health insurance holds also for females.

has not yet investigated the causes of the observed changes in health insurance coverage or how these changes relate to wage changes (see for example Pierce (2001), Levy (2006)).

In this paper, I develop and structurally estimate an equilibrium model of the labor and health insurance markets, in which workers' compensation consists of wage and health insurance offers, and skill prices and health insurance premium are endogenously determined. I use the model to analyze the causes of rising inequality in health insurance along with wages. In particular, I address the following questions: what factors have contributed to these trends and what is their relative quantitative significance? and how do changes in health insurance inequality relate to changes in wage inequality? I also use the model to examine the effects of employer mandates and further Medicaid eligibility expansion, which were introduced in the Patient Protection and Affordable Care Act of 2010, on aggregate employment, health insurance, wage inequality, and welfare.[4]

My model incorporates three types of exogenous changes as possible determinants of the observed wage and health insurance coverage trends: skill-biased technological change, changes over time in the cost of medical care services, and expansion in Medicaid eligibility. The population of the economy at any calendar time consists of overlapping generations of males and females aged 25-64. There are three education levels: high school or less, some college, 4-year college or more. In addition to education, an individual's skill level is determined by health status and work experience.

In each period of the model (annually), an individual decides whether to work or not. If the individual works, the individual can further choose between two compensation packages. One compensation package consists of wages plus health insurance, whereas the other compensation package is just wages. Both the two compensation packages have the same total monetary value, which is equal to the workers marginal productivity in labor market.

Individuals are risk averse and have preferences over health, leisure and consumption. An individual's medical expenditure is equal to the per-unit cost of medical services times the amount purchased. The demand for medical services is modeled as a function of the individual's health, health insurance status and other characteristics (for example, age), and is subject to shocks. If covered by health insurance, the individual does not pay for medical services out-of-pocket.[5] Health status evolves stochastically as a function of current health status and health insurance coverage. Thus, an individual demands health insurance for two reasons. First, health insurance insures against medical expenditure risk. Second, it improves the individual's future health and hence

[4] Under employer mandates, employers are required to provide health insurance for its employee or pay a fine.

[5] I only consider full coverage and no coverage, although the framework can be extended to include partial insurance.

future productivity.

An individual's choices about work and about the compensation package are also affected by the implicit tax subsidy that employer-provided health insurance provides as well as the government social safety net programs. Specifically, the model incorporates two types of government programs. First, the government provides a means-tested public health insurance program, Medicaid. Medicaid is the largest public funded health insurance program for non-elderly adults in the U.S., and the fraction of the population covered by Medicaid has almost doubled over the last thirty years.[6] Second, the government provides other social safety net programs, such as Supplemental Security Income, uncompensated care, unemployment insurance and food stamps, that guarantee a minimum consumption floor for individuals.[7]

To close the model, I introduce an aggregate production function, which depends on the efficiency units of labor supplied by different educational groups and which determines the equilibrium prices of labor market skills. Similarly, the price of health insurance premium at each period is equal to the equilibrium average medical expenditure among covered workers.

In the model, the rising cost of medical services has a direct effect on the demand for health insurance and, through the labor and health insurance market equilibria, also affects the health insurance premium and thus the wage component of total compensation. The existence of a minimum consumption floor provided by the government induces changes in the demand for health insurance that vary by education groups. Expanding Medicaid eligibility reduces the demand for health insurance among the less educated. This demand reduction increases the incentive for the less educated to choose wage only compensation. Skill-biased technological change increases the relative demand for higher skilled (more educated) workers, which tends to increase both wage and health insurance coverage inequality. All three changes affect the equilibrium price of health insurance, as the health status distribution of those opting for health insurance in the compensation package changes.

The model is solved with an iterative algorithm by adopting a forecasting rule for skill prices and for the insurance premium that is consistent with agents' optimization behavior within the model. Model parameters are estimated by simulated method of moments, combining data from four sources: the 1982-2010 March Current Population Survey, the 1996 Survey of Income and Program

[6] It has increased from 8.4% in 1987 to 15.7% in 2009 (Income, Poverty, and Health Insurance Coverage in the United States: 2010. the U.S. Census Bureau. Issued September 2011).

[7] Uncompensated care is an overall measure of hospital care provided for which no payment was received from the patient or insurer. In 2004, 85% of uncompensated care was paid by the government (Kaiser Family Foundation, 2004).

Participation, the 2005 Medical Expenditure Panel Survey, and the 1981-2009 Employment Cost Index from the Bureau of Labor Statistics.

Using the estimated model, I find that, in the absence of skill-biased technological change, the employer-provided health insurance coverage gap between 4-year college male workers and high school male workers would have been 6 percentage points in comparison to the benchmark case (fitted model) of 24 percentage points in 2009. The wage inequality (measured as log wage ratio) between these two groups of workers would have been 25 percent in comparison to 68 percent. If the cost of medical services had remained at the 1981 level, then the employer-provided health insurance coverage gap would be 16 percentage points, compared to the benchmark gap of 24 percentage points; the log wage ratio between male workers with at least a 4-year college degree and male workers with at most a high school degree in 2009 would be 72 percent, compared to 68 percent. Last, simulations based on the model show that the impact of eliminating the Medicaid eligibility expansion on employer-provided health insurance coverage and wage inequality is quantitatively small.

I also use the model to analyze the impact of policies that were introduced in the 2010 Patient Protection and Affordable Care Act, and find that (i) the introduction of an employer mandate reduces both wage and health insurance coverage inequality but also lowers the employment rate by 3 percentage points for men with at most a high school degree; and (ii) further Medicaid eligibility expansion increases the employment rate by 5 percentage points for men with at most a high school degree, reduces health insurance coverage disparity, but also causes larger wage inequality.

The literature shows that access to health insurance has important effects on both labor force participation and job choice (see a survey by Gruber (2000)). Recent studies that investigate the relationship between health insurance and labor market include Dey and Flinn (2005), Blau and Gilleskie (2008), Manovskii and Bruegemann (2010), and Pashchenko and Porapakkarm (2012). In contrast to these studies, this paper analyzes the time series patterns of health insurance coverage and wages as well as the joint determination of both health insurance and wage inequality.

The rest of the paper is organized as follows. In Section 2, I develop an equilibrium overlapping generations model and discuss the model solution algorithm. Section 3 describes the data, and Section 4 discusses estimation strategy. Section 5 reports parameter estimates and model fit. Section 6 analyzes the relative quantitative significance of the determinants of rising inequality in health insurance and wages. Section 7 describes the results from counterfactual policy experiments, and Section 8 concludes.

2 The Model

2.1 Setup

The population of the economy at each calendar time t consists of both males and females aged 25 to 64. Each individual's education level belongs to one of three categories: less than high school (HS), some college (SC), and 4-year college or more (CG). Different education levels correspond to different skill types, which are imperfect substitutes in an aggregate production function. As further described below, technology is skill-augmenting, which, by complementing the productivity of education-specific skills in the aggregate production function, can generate demand shifts that favor higher educated workers.

2.1.1 Individuals' Choice Set and Skill Production

At the beginning of each model period, which corresponds to one year, an individual decides whether to work or not. If the individual decides to work, he can further choose between two compensation packages, one consists of wages plus health insurance and another is just wages. Both two compensation packages have the same total monetary value, determined by the worker's marginal productivity in labor market.

A worker's marginal productivity is the product of an education-specific competitively determined skill rental price (r) and the amount of education-specific skill units possessed by the individual (s). Therefore, the wages (w_a) and health insurance ($I_a^e \in \{0,1\}$) compensation for a worker of education-specific skill units s_a^j must satisfy

$$w_a + \lambda p_t \cdot I_a^e = r_t^j s_a^j \tag{1}$$

where $\lambda \in (0,1)$ is the share of health insurance premium paid by the employer if $I_a^e = 1$, and $p_t > 0$ is the equilibrium group health insurance premium at time t. Equation (1) is also the zero profit condition for employers, thus employers are indifferent between offering a compensation package that consists of just wages and a compensation package comprised of wages plus health insurance. λp_t is the wage differential between these two compensation packages.

An individual's education-specific skill units (s_a^j) depends on the individual's unobserved initial human capital endowment ($\kappa_{0,k,\text{sex}}^j$ for a type-k individual with education level j), health status that is predetermined at the end of previous period (h_a), work experience ($expr_a$), and an age-varying i.i.d productivity shock (ϵ_a^j),

$$\log(s_a^j) = \sum_k \kappa_{0,k,\text{sex}}^j \cdot \mathbf{1}(type = k) + \kappa_1^j h_a + \kappa_2^j expr_a + \kappa_3^j expr_a^2 + \epsilon_a^j$$

where $\epsilon_a^j \sim N(0, \sigma_j^2)$.

2.1.2 Preferences and the Budget Constraint

Individuals' preferences are defined over consumption (c_a), health status (h_a) and employment status (d_a^e). Specifically, an individual's per-period utility function is,

$$u^*(c_a, d_a^e; h_a, a, \epsilon_a^l) = 1 - \exp(-\gamma c_a) + \phi_h h_a + (\Gamma_{a,t} + \epsilon_a^l)(1 - d_a^e) \tag{2}$$

where $\Gamma_{a,t}(\cdot)$ is individual's value of home time including value of leisure as well as value of home production, and $\epsilon_a^l \sim N(0, \sigma_l^2)$ is a age-varying preference shock. $\Gamma_{a,t}(\cdot)$ depends on an individual's unobserved type, presence of dependent children, health, age, gender, education and time,

$$\begin{aligned}\Gamma_{a,t} = &\sum_k \phi_{0,k}^{\text{sex}} \mathbf{1}(type = k) + \phi_1^{\text{sex}} Z_a^{ch} + \phi_2^{\text{sex}} \mathbf{1}(a \geq 45)(a - 45) + \phi_3^{\text{sex}}(1 - h_a) \\ &+ \phi_4^{\text{sex}} \mathbf{1}(educ = SC) + \phi_5^{\text{sex}} \mathbf{1}(educ = CG) + \text{Time Trend}_t^{\text{sex}}\end{aligned}$$

where $\text{Time Trend}_t^{\text{sex}} = \phi_6^{\text{sex}}(t - 1981)\mathbf{1}(1981 \leq t \leq 2000) + \phi_7^{\text{sex}}(t - 2000)\mathbf{1}(t > 2000)$ captures the productivity progress in the home sector over time. The evolution of the presence of dependent children, $Z_a^{ch} \in \{0, 1\}$, is modeled as exogenous and probabilistic.

Individuals face a progressive tax on labor income, given by the function $\mathcal{T}(\cdot)$. If an individual chooses the compensation package that includes wage and health insurance, then the premium payment (both from the employer (λp_t) and from the worker ($(1 - \lambda)p_t$)) is tax exempt.[8] Denote by $\widetilde{\mathcal{T}}(w)$ the after tax labor income function, that is $\widetilde{\mathcal{T}}(w) = w - \mathcal{T}(w)$.

[8] Prior to 1954, there was no statutory provision that explicitly allowed a tax exclusion for coverage under employer-provided accident and health insurance. In 1954, Section 106 was enacted as part of a comprehensive revision of the Internal Revenue Code. At the time, it consisted only of what later became Section 106(a), though the wording has changed several times. The enactment of Section 106 provided a basis for excluding employer payments for individual insurance and certain other coverage such as union plans. The tax exclusion in Section 106(a) of the Internal Revenue Code also applies to employee-paid premiums under premium conversion plans. Under these arrangements, which must be set up by employers, employees reduce their taxable wages in exchange for their employers using the money to pay health insurance. From an accounting perspective, the premiums are no longer considered to be paid by the employees. The premium conversion plans are allowed under cafeteria plan provisions in Section 125, which was enacted in 1978.

Therefore the budget constraint of an individual is

$$c_a = \widetilde{\mathcal{T}}(w_a - (1-\lambda) \cdot p_t \cdot I_a^e) \cdot d_a^e - p_t^m M_a \cdot (1 - I_a) + \text{transfer}_{a,t} \tag{3}$$

where $1 - \lambda$ is the fraction of group health insurance premium (p_t) paid by the individual if the individual is covered by employer-provided health insurance at time t, p^m is the cost of medical services, M_a represents the individual's medical services consumption, therefore $p_t^m M_a$ is individual's total medical services expenditure, and I_a is an indicator for individual's health insurance coverage.[9] Individuals can be insured either by employer-provided health insurance ($I_a^e = 1$) or by Medicaid ($I_a^c = 1$).[10] That is, $I_a = 1$ if $I_a^e = 1$ or $I_a^c = 1$. I will discuss the Medicaid coverage rule in Section 2.1.4.

I assume the existence of a consumption floor, c^{min}, provided by the government. This captures social safety net programs other than Medicaid, such as Supplemental Security Income, Unemployment Insurance, Food Stamps, and uncompensated care.[11]

$$\text{transfer}_{a,t} = \max\{0, c_t^{min} - (\widetilde{\mathcal{T}}(w_a - (1-\lambda) \cdot p_t \cdot I_a^e) \cdot d_a^e - p_t^m M_a \cdot (1 - I_a))\} \tag{4}$$

Treating c^{min} as sustenance level, it is required that $c_a \geq c^{min}$ and that employment ($d_a^e = 1$) is feasible only if $w_a \geq c^{min}$.

An individual maximizes the expected present discounted value of remaining lifetime utility from current age a to age A. All individuals retire at age $A + 1$, the only difference in utility level among retirees at age $A + 1$ comes from their health status at age $A + 1$.[12] I normalize the utility for individuals with bad health ($h_{A+1} = 0$) to be zero, let ϕ_{RE} be the utility value of health at age $A + 1$, therefore $u_{A+1} = \phi_{RE} h_{A+1}$. The subjective discount rate is given by δ.

[9] Although here I only consider full coverage ($I_a = 1$) and no coverage ($I_a = 0$), but the model can be extended to include partial insurance.

[10] The no insurance group includes those with private health insurance as well as those with no insurance at all. Both face high medical expenses risk. Private health insurance is a poor substitute for employer-provided coverage, as high administrative costs and adverse selection problems can result in prohibitively expensive premiums. Moreover, private insurance is much less likely to cover pre-existing medical conditions. See French and Jones (2004) for same argument. Because the model includes a consumption floor to capture insurance provided by other social safety net programs, the none group also includes those who are covered by other social safety net programs.

[11] Uncompensated care is an overall measure of hospital care provided for which no payment was received from the patient or insurer. In 2004 85% of uncompensated care were paid by the government. The major portion is sourced from the disproportionate share hospital (DSH) payment (Kaiser Family Foundation, 2004).

[12] Essentially, I assume that all retired individuals receives the same retirement income and are covered by Medicare.

2.1.3 Medical Services Expenditure and Health Insurance

An individual's medical service expenditure, $p_t^m M_a$, depends on the cost of medical service at time t (p_t) and the individual's medical service consumption level (M_a).

The cost of medical services p_t^m is modeled as an exogenous process that evolves over time:

$$\log p_{t+1}^m - \log p_t^m = g^m + \vartheta_{t+1}^m \tag{5}$$

An individual's medical service consumption M_a is assumed to be exogenous and depend upon five components:[13] health insurance coverage status, $I_a \in \{0, 1\}$; health status, h_a; age; education level ($educ \in \{HS, SC, CG\}$); and an individual-specific age-varying component ϵ_a^m. Specifically, the medical consumption can be modeled as

$$\log M_a = m(I_a, h_a, a, educ) + \sigma_m(h_a) \cdot \epsilon_a^m \tag{6}$$

where $m(I_a, h_a, a, educ)$ is an exogenous function of health insurance, health, age, and education, and $\sigma_m(h_a)$ controls the volatility of medical consumption risk and is a function of individuals' health status.

Studies suggest that the medical expenditure shocks are very volatile and persistent, even after controlling for health status (French and Jones (2004)). Thus I decompose the medical expenditure shock into a predictable component ($\epsilon_{a,0}^m$) and an unpredictable component ($\epsilon_{a,1}^m$): $\epsilon_a^m = \epsilon_{a,0}^m + \epsilon_{a,1}^m$. It is assumed that $\epsilon_{a,0}^m$ is the medical consumption shock that is realized at the beginning of the period before an individual makes health insurance coverage decision, and $\epsilon_{a,1}^m$ is the ex post medical consumption shock that is realized at the end of age a. $\epsilon_{a,0}^m$ and $\epsilon_{a,1}^m$ are independent, and $\epsilon_{a,0}^m \sim N(0, \sigma_{m,0}^2)$ and $\epsilon_{a,1}^m \sim N(0, \sigma_{m,0}^2)$. Moreover, I restrict $\sigma_{m,0}^2 + \sigma_{m,1}^2 = 1$, because that $\sigma_{m,0}^2 + \sigma_{m,1}^2$ can not be separately identified from $\sigma_m(\cdot)$.

There are two health statuses: good ($h_a = 1$) and bad ($h_a = 0$).[14] Transitions among health statuses are exogenous and determined by a Markov process that depends on health state h_a, age a, education and current period health insurance coverage status I_a.[15] Specifically, the probability

[13] Blau and Gilleskie (2001) assume that medical consumption is determined by current health status. French and Jones (2011) assume that medical expenses depend upon health insurance coverage, health, age, employment and a person-specific shock.

[14] Literature has used a binary indicator for self-reported health status as a measure of health status, see Rust and Phelan (1996), Blau and Gilleskie (2001), and French and Jones (2011) among others.

[15] Research has also shown that having health insurance coverage leads to higher health care utilization and better health (see for example Card et al. (2009), Doyle (2005), Currie and Gruber (1996), Currie and Gruber (1994), French and Kamboj (2002), Finkelstein et al. (2011)). Among others, Rust and Phelan (1996) estimate health transition

of making a transition from health status h_a at age a to good health state at age $a+1$ is given by $\Pr_{a+1}(h_{a+1} = 1; h_a, I_a, educ, a)$.[16]

2.1.4 Public Health Insurance (Medicaid)

Medicaid program is the biggest public health insurance program for non-elderly adults in the U.S. It is a means-tested program, but being poor is not the only standard for coverage. To be eligible for Medicaid, low income individuals need to belong to certain eligibility groups based on factors such as presence of dependent children, employment status and age. I model Medicaid coverage ($I^c_{a,t} \in \{0,1\}$) as a function of income threshold (y^{cat}_t) and categorical standard ($d^c_{a,t} \in \{0,1\}$) as follows

$$I^c_{a,t} = d^c_{a,t} \cdot (y_a \leq y^{cat}_t) \cdot \mathbf{1}(I^e_a = 0), \tag{7}$$

where the last term $\mathbf{1}(I^e_a = 0)$ ensures that individuals with private health insurance coverage are not eligible for Medicaid.

The income threshold at time t, y^{cat}_t, is obtained as a fraction of Federal Poverty Level (FPL) that is changing over time. Individuals form an expectation on changes in the income threshold y^{cat}_t according to the following process,

$$\log y^{cat}_{t+1} - \log y^{cat}_t = g^{cat} + \epsilon^{cat}_{t+1} \tag{8}$$

The categorical standard of Medicaid eligibility is complex and it is very hard to incorporate all the factors that may impact the eligibility into the model.[17] I therefore approximate the categorical standard, $d^c_{a,t}$, as a function of model state variables such as age, employment status, presence of dependent children, year and education, separately for men and women.[18]

In particular, I estimate a Probit model separately for men and women whose income below

probability function that depends on age, previous health status and the lowest and highest average wage classes.

[16]Notice although here I do not distinguish between employer-provided insurance versus public health insurance in its effect on health, my model can be extended to allow for the difference in the effect of employer provided health insurance and Medicaid.

[17]For example, marital status impacts medicaid coverage eligibility, however, because that CPS collects individuals' marital information for current year but Medicaid coverage for the previous year, the marital status corresponding to Medicaid coverage period is not available.

[18]Pregnant women and families under Aid to Families with Dependent Children (AFDC) is one of the Medicaid eligibility groups for Medicaid coverage.

the threshold:[19]

$$d^c_{a,t} = \alpha_0 + \sum_i \alpha_{1i}\mathbf{1}(a \in \text{age group}_i) + \sum_j \alpha_{2j}\mathbf{1}(educ = j) + \alpha_3 d^e_a + \alpha_4 Z^{ch}_a$$
$$+ (\alpha_{6i} + \alpha_{8l} Z^{ch}_a) \cdot \mathbf{1}(t \geq 1996) + \epsilon^c_t. \tag{9}$$

The probabilistic feature of Medicaid coverage captures the factors that impact Medicaid coverage but are not included in the model, such as take-up cost as well as state-level differences. Therefore, the eligibility expansion of Medicaid is reflected in both the time dependence of income threshold (y^{cat}_t) and the categorical requirement ($d^c_{a,t}$).

2.2 Individual Optimization

An individual's choice set consists of three mutually exclusive alternatives: (1) Working for a job without employer-provided health insurance (i.e., accepting the employee compensation package that consists of just wages), (2) Working for a job with employer-provided health insurance (i.e., accepting the employee compensation package that includes wages plus health insurance), (3) Not working.

Similarly, an individual's indirect utility can be defined based on choices and Medicaid coverage status: (1) $u_{1,0,a}$: employed at a job with no health insurance and not covered by Medicaid either; (2) $u_{1,1,a}$: employed at a job without health insurance but covered by Medicaid; (3) $u_{2,a}$: employed at a job with health insurance; (4) $u_{3,a}$: not employed.

$$u_{1,0,a}(h_a, \boldsymbol{\epsilon}_a) = 1 - \exp(-\gamma \cdot \xi_{a,t}) + \phi_h h_a \tag{10}$$
$$u_{1,1,a}(h_a, \boldsymbol{\epsilon}_a) = 1 - \exp(-\gamma \cdot \widetilde{\mathcal{T}}(r^j_t s^j_a)) + \phi_h h_a \tag{11}$$
$$u_{2,a}(h_a, \boldsymbol{\epsilon}_a) = 1 - \exp(-\gamma \cdot \widetilde{\mathcal{T}}(r^j_t s^j_a - p_t)) + \phi_h h_a \tag{12}$$
$$u_{3,a}(h_a, \boldsymbol{\epsilon}_a) = 1 - \exp(-\gamma \cdot c^{min}_t) + \phi_h h_a + (\Gamma_a + \epsilon^l_a) \tag{13}$$

where $\boldsymbol{\epsilon}_a = \{\epsilon^l_a, \epsilon^m_{a,0}, \epsilon^j_a\}$ and $\xi_{a,t}$ is the certainty equivalent consumption value for the individual.[20]

[19] Medicaid was enacted in 1965 by Title XIX of the Social Security Act. Historically, Medicaid eligibility for non-elderly adults is closely tied to AFDC cash assistance. The 1996 welfare reform, Personal Responsibility and Work Opportunity Act of 1996, ended the linkage between eligibility for cash assistance and for Medicaid, and allowed higher eligibility thresholds. Hence, I analyze the changes in Medicaid program eligibility by dividing it into three periods: (1) prior 1965, no Medicaid; (2) 1965-1995; (3) 1996 and after.

[20] For an individual with disposable income level $y^d_a = \widetilde{\mathcal{T}}(r^j_t s^j_a) > c_{min}$ and realized medical expenditure component $\overline{M}_{a,t} = p^m_t \exp(m(I_a, h_a, a, educ) + \sigma_m(h_a)\epsilon^m_{a,0})$, the certainty equivalent consumption $\xi_{a,t}$ is implicitly defined as

Because Medicaid is free but private health insurance is not, the flow utility for an employed worker who is covered by Medicaid is always higher than when he or she is covered by private health insurance, that is, $u_{1,1,a}(h_a, \boldsymbol{\epsilon}_a) > u_{2,a}(h_a, \boldsymbol{\epsilon}_a)$.

Let $\Omega_{a,t}$ denote the information set of an individual at beginning of age a and time t. An individual's value function $V_a(\Omega_{a,t})$ is given by the maximum value among the three alternative-specific value functions $V_{\cdot,a}(\Omega_{a,t})$,

$$V_a(\Omega_{a,t}) = \max\{V_{1,a}(\Omega_{a,t}), V_{2,a}(\Omega_{a,t}), V_{3,a}(\Omega_{a,t})\} \tag{14}$$

where

$$\begin{aligned}
V_{1,a}(\Omega_{a,t}) =& (1 - I^{c,e}_{a,t})u_{1,0,a}(h_a, \boldsymbol{\epsilon}_a) + I^{c,e}_{a,t}u_{1,1,a}(h_a, \boldsymbol{\epsilon}_a) + \delta\pi^s_{a+1}\mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = I^{c,e}_{a,t}, d^e_a = 1] \\
V_{2,a}(\Omega_{a,t}) =& u_{2,a}(h_a, \boldsymbol{\epsilon}_a) + \delta\pi^s_{a+1}\mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = 1, d^e_a = 1] \\
V_{3,a}(\Omega_{a,t}) =& u_{3,a}(h_a, \boldsymbol{\epsilon}_a) + \delta\pi^s_{a+1}\mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = d^c_{a,t}, d^e_a = 0]
\end{aligned}$$

$I^{c,e}_{a,t} = d^c_{a,t} \cdot \mathbf{1}(r^j_t s^j_a \le y^{cat})$ is an indicator function of Medicaid coverage when employed. The value function at age $A+1$ is $V_{A+1}(\Omega_{A+1,\cdot}) = u_{A+1} = \phi_{RE}h_{A+1}$.

It is easy to see $V_{1,a}(\Omega_{a,t}) > V_{2,a}(\Omega_{a,t})$, therefore if an individual is eligible for Medicaid ($d^c_{a,t} \cdot \mathbf{1}(r^j_t s^j_a \le y^{cat}) = 1$), then the individual does not work for a job with employer-provided health insurance.[21] If an individual is not eligible for Medicaid, then the individual's optimal decision rule on employer-provided health insurance is summarized in Propositions 1. The details of the proof is provided in Appendix A.

Proposition 1. *If $d^c_{a,t} \cdot \mathbf{1}(r^j_t s^j_a \le y^{cat}) = 0$, then an employed individual's health insurance choice*

below,

$$\begin{aligned}
\exp(-\gamma\xi_{a,t}) &= \mathbb{E}_{\epsilon^m_{a,1}} \exp(-\gamma \cdot \max\{y^d_a - \overline{M}_{a,t}\exp(\sigma_m(h_a)\epsilon^m_{a,1}), c^{min}_t\}) \\
&= \exp(-\gamma c^{min}_t) \cdot Pr(\epsilon^m_{a,1} \ge \bar{\epsilon}^m_a) + \exp(-\gamma y^d_a)\mathbb{E}(\exp(\gamma\bar{M}_{a,t}\exp(\sigma_m(h_a)\epsilon^m_{a,1}))|\epsilon^m_{a,1} < \bar{\epsilon}^m_a) \cdot Pr(\epsilon^m_{a,1} < \bar{\epsilon}^m_a)
\end{aligned}$$

where $\bar{\epsilon}^m_a = \frac{1}{\sigma_m(h_a)}(\log(y^d_a - c^{min}_t) - \log(\overline{M}_{a,t}))$. Notice that when there is no consumption floor, i.e., $c^{min}_t = -\infty$, then an individual's consumption equivalent is given by $\xi_{a,t} = y^d_a - \frac{1}{\gamma}\log\left(\mathbb{E}_{\epsilon^m_{a,1}}\exp(\gamma\overline{M}_{a,t}\exp(\sigma_m(h_a)\epsilon^m_{a,1}))\right)$.

[21] The underlying assumptions are that the take-up cost of Medicaid is small and there is no quality difference between Medicaid and employer-provide health insurance. Relaxing these two assumptions will reduce the extent of crowding out.

is characterized by the following threshold behavior

$$I_a^e = \begin{cases} 1 & \textit{if } \xi_{a,t} \le \xi_{a,t}^* \\ 0 & \textit{otherwise} \end{cases}$$

where $\xi_{a,t}^*$ *is the threshold value for health insurance coverage that is increasing in the individual's marginal productivity* ($r_t^j s_a^j$) *and the net continuation value of having health insurance* $\Delta CV_{a+1}(\Omega_{a,t}) = \mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = 1, d_a^e = 1] - \mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = 0, d_a^e = 1])$*, but is decreasing in health insurance premium* p_t.

In general, there is no explicit expression for the threshold value for employer-provided health insurance coverage ($\xi_{a,t}^*$). As an illustration, I consider the following special case. When there is no consumption floor ($c_t^{min} = -\infty$), then the consumption equivalent

$$\xi_{a,t} = \widetilde{\mathcal{T}}(r_t^j s_a^j) - \frac{1}{\gamma} \log \left(\mathbb{E}_{\epsilon_{a,1}^m} \exp(\gamma \overline{M}_{a,t} \exp(\sigma_m(h_a)\epsilon_{a,1}^m)) \right).$$

If net continuation value of having health insurance is zero ($\Delta CV_{a+1}(\cdot) = 0$), then the threshold value for health insurance coverage is $\xi_{a,t}^* = \widetilde{\mathcal{T}}(r_t^j s_a^j - p_t)$. Therefore an individual obtain health insurance from his or her employer if and only if

$$\frac{1}{\gamma} \log \left(\mathbb{E}_{\epsilon_{a,1}^m} \exp(\gamma \overline{M}_{a,t} \exp(\sigma_m(h_a)\epsilon_{a,1}^m)) \right) \ge \widetilde{\mathcal{T}}(r_t^j s_a^j) - \widetilde{\mathcal{T}}(r_t^j s_a^j - p_t).$$

An individual's demand for health insurance is affected by the following components. First, an individual's demand for health insurance increases with the risk aversion coefficient. Second, an individual chooses to work for a job with health insurance when the expected component of medical expenses ($\overline{M}_{a,t}$) is high; this could either because of individual characteristics, such as health, age or education, or because of the realized medical consumption shock $\epsilon_{a,0}^m$. Lastly, tax exclusion treatment also increases individuals' demand for health insurance, by lowering the relative prices of health insurance especially for high income individuals. Once the consumption floor is introduced, the analysis becomes more complicated. The demand for health insurance is reduced disproportionately among lower income individuals (also more likely to be less educated individuals), because that they more often receive the government transfer that guarantees the minimum consumption floor.

2.3 Aggregate Production and Equilibrium

2.3.1 Aggregating the Economy

There is an aggregate production function of the constant elasticity of substitution (CES) form

$$C_t = \zeta_t F(S_t^{HS}, S_t^{SC}, S_t^{CG}) \tag{15}$$

$$= \zeta_t \left\{(1-\alpha_t^{SC}-\alpha_t^{CG})(g_t^{HS}S_t^{HS})^{\nu} + \alpha_t^{SC}(g_t^{SC}S_t^{SC})^{\nu} + \alpha_t^{CG}(g_t^{CG}S_t^{CG})^{\nu}\right\}^{1/\nu} \tag{16}$$

$$\equiv \zeta_t \left\{z_t^{HS}(S_t^{HS})^{\nu} + z_t^{SC}(S_t^{SC})^{\nu} + z_t^{CG}(S_t^{CG})^{\nu}\right\}^{1/\nu}, \tag{17}$$

where ζ_t represents the aggregate neutral technological change, z_t is the education-specific skill-augmenting technological change, and S_t is the aggregate quantity of education-specific skills. The aggregate elasticity of substitution between different types of skills is $1/(1-\nu)$.[22] The price of the final good is normalized to be one in every period.

As we can see, the skill-augmenting technology z_t^j consists of two components: α_t^j and g_t^j. Skill-Biased Technical Change (SBTC) involves either an increase in α_t^j or an increase in g_t^j/g_t^{HS}, $j = SC, CG$. A rise in α_t^{CG}, referred as 'extensive' SBTC, raises the marginal productivity of 4-year-college workers and at the same time lowers the marginal productivity of high school workers. A relative increase in g_t^{CG}, some times referred as 'intensive' SBTC, enhances the marginal productivity of 4-year-college workers without necessarily lowering the marginal product of lower educated workers. $\nu > 0$ is the necessary condition for a relative rise in g_t^{CG} to increase the relative productivity of workers of 4-year-college degrees. A similar statement applies for α_t^{SC} and g_t^{SC}. The key question for changes in workers' relative compensation is how z_t^{SC}/z_t^{HS} and z_t^{CG}/z_t^{HS} evolve over time, instead of the changes in the levels of α^j, g^j, and z^j. From this point forward, I refer to z_t^{SC}/z_t^{HS} and z_t^{CG}/z_t^{HS} as SBTC, and I normalize $z_t^{HS} = 1$ for all t.

I assume that the skill-augmenting technological change, z_t^j, follows a deterministic time trend[23],

$$\log z_t^j = g_{z0}^j + g_{z1}^j t + \vartheta_{t+1}^j, \tag{18}$$

for $j = SC, CG$.

[22] It is straightforward to extend the model to allow for the elasticity of substitution between 4-year-college skills and high-school skills to be different from the elasticity of substitution between some-college skills and high-school skills. My current specification is a parsimonious way of modeling the demand side change for different types of skills.

[23] See Autor et al. (2008) for similar specification of skill-biased technical change

Aggregate neutral technical change, ζ_t, is assumed to evolve according to:[24]

$$\log \zeta_{t+1} - \log \zeta_t = g^{\zeta} + \vartheta^{\zeta}_{t+1} \tag{19}$$

2.3.2 Model Equilibrium

The aggregate quantity of education-specific skills supplied at time t, S^j_t, is a function of the total amount of education-specific worker-skills employed

$$S^j_t = \sum_{a=a_0}^{A} \sum_{l=1}^{L_{a,t}} s^j_{i,a,t} d^e_{i,a,t}$$

In a competitive labor market, the equilibrium price of education-specific skills is given by its marginal product,

$$r^j_t = \zeta_t \frac{\partial F(S^{HS}_t, S^{SC}_t, S^{CG}_t)}{\partial S^j_t} \tag{20}$$

$$= \zeta_t \left(z^{HS}_t (S^{HS}_t)^{\nu} + z^{SC}_t (S^{SC}_t)^{\nu} + z^{CG}_t (S^{CG}_t)^{\nu} \right)^{1/\nu - 1} z^j_t (S^j_t)^{\nu-1} \tag{21}$$

The equilibrium health insurance premium is given by the average medical services expenditure of those who are covered by health insurance, that is,

$$p_t = \frac{\sum_{a=a_0}^{A} \sum_{i=1}^{L_{a,t}} p^m_t \cdot M_{i,a,t} \cdot I^e_{i,a,t}}{\sum_{a=a_0}^{A} \sum_{i=1}^{L_{a,t}} I^e_{i,a,t}} \tag{22}$$

Equilibrium Definition The equilibrium of the economy consists of (i) value functions: $V_a(\Omega_{a,t})$ and associated policy functions, taking equilibrium prices (r^j_t, p_t) and their forecasting rules $\Phi^j(\cdot)$ as given; (ii) equilibrium skill prices: r^j_t that determined by marginal productivity of aggregate skill units (Equation (20)); (iii) equilibrium health insurance premium: p_t is given by the average medical expenditure of the covered (Equation (22)); (iv) forecasting rules: Φ^j is consistent with agents' policy functions and aggregate dynamics of ζ_t and z^j_t.

To solve the model, I assume that forecasting rules for the changes in skill prices and health

[24] Notice that under the normalization of $z^{HS}_t = 1$, the estimated $\log \zeta_t$ also absorb the effect of z^{HS}_t over time.

insurance premium can be approximated as follows,

$$\log r^j_{t+1} - \log r^j_t = \rho^j_0 + \sum_l \rho^j_{1,l}(\log r^l_t - \log r^l_{t-1}) + \rho^j_2(\log p_t - \log p_{t-1}) \tag{23}$$

$$\log p_{t+1} - \log p_t = \rho^p_0 + \sum_l \rho^p_{1,l}(\log r^l_t - \log r^l_{t-1}) + \rho^p_2(\log p_t - \log p_{t-1}) \tag{24}$$

where ρ's are reduced form parameters that are consist with the model.

Therefore, the aggregate-level state variable vector that is relevant for an individual's optimization problem, denoted by $\boldsymbol{\psi}_t$, only includes aggregate variables in the current period and in the previous time period,

$$\boldsymbol{\psi}_t \equiv \{t, \{\log z^j_t, \log r^j_t, \log r^j_{t-1}\}_{j=HS,SC,CG}, \log \zeta_t, \log p^m_t, \log p_t, \log p_{t-1}\}$$

Let $\overline{\Omega}_a = \{type, sex, educ, h_a, expr_a, Z^{ch}_a\}$ denote the set of individual-level state variables net of the idiosyncratic shocks ($\boldsymbol{\epsilon}_a \equiv (\epsilon^l_a, \epsilon^m_{a,0}, \epsilon^j_a)$). Therefore, an individual's information set is $\Omega_{a,t} = \{\boldsymbol{\psi}_t, \overline{\Omega}_a, \boldsymbol{\epsilon}_a\}$.

3 Data

To estimate the model, I need both longitudinal macro data and micro data on individual characteristics and choices. Moreover, I need information on individuals' medical expenditure patterns and on the premiums in the group heath insurance market over time. However, such a comprehensive data set that provides information on all four aspects does not exists. Therefore, I combine data from the following four sources: the 1982-2010 March Current Population Survey, the 1996 Survey of Income and Program Participation, the 2005 Medical Expenditure Panel Survey, and the 1981-2009 Employment Cost Index from the Bureau of Labor Statistics.

3.1 March Current Population Survey (March CPS)

The March CPS provides nationally representative data concerning family characteristics, educational attainment, health insurance coverage, previous year's labor market activity and income, and Medicaid coverage.

I use the March CPS data from 1982 to 2010, which covers earnings from 1981 to 2009, to measure the aggregate level and distribution of health insurance coverage and wages by year, education groups, age and gender. The sample only includes individuals aged 25 to 64. Individuals who are in the military, institutionalized, self-employed or working for non-paid jobs are excluded. A worker is considered employed if the worker works no less than 800 hours annually. Hourly wages are equal to the annual earnings divided by hours worked.[25] An individual is covered under employer-provided health insurance if the individual is covered by a group plan provided by an employer (including the spouse's employer). Calculations are weighted by CPS sampling weights and are deflated using 2005 GDP deflator.

Figure 2 presents the educational distribution over years in CPS sample. The proportion of the age 25-65 population who were college graduates grew steadily throughout the sample period, especially for women. 4-year college graduates comprised about 22% of male in 1981 and 30% by 2009. 15% of women have 4-year college degree in 1981, and this ratio grew to 32% in 2009.

Figures 3 to 5 report the employment rate, hourly wage rate and employer provided health insurance coverage rate across education groups over time, for males and females respectively. From 1981 to 2009, the male employment rate declines steadily. For males with at most a high school degree, the decline in employment rate is as high as 10 percentage points. At the same time, the female employment rose by 7 percentage points. Wages for higher educated workers have grown much faster than for those with lower education. Females experience faster wage growth than males. Wage rates increase by 34% for male workers with 4-year college or more, and increase by 58% for female workers with 4-year college degree or more. Wages grew by only 8% for male workers with some college degree, and it grew by 31% for female workers with some college degree. Male workers with at most high school degree experience 3% decrease in wage rate, while female workers with high school degree or less experience 24% increase in wage rate.

3.2 Survey of Income and Program Participation (SIPP)

The longitudinal data on health, health insurance, employment transition, labor earnings, and individual characteristics transition is obtained from Census Bureau's Survey of Income and Program Participation (SIPP) 1996 panel. The SIPP panel is a nationally representative sample of the U.S. non-institutionalized population. People selected into the SIPP sample are interviewed once every 4 months and up to 4 years. SIPP has detailed information on individuals' labor market activity, health insurance coverage, Medicaid coverage, and number of children in the family. In addition,

[25]Hourly earner of below \$1/hour in 1982 dollars using personal consumption expenditures (PCE) deflator (\$1.86/hour in 2005 dollars under PCE deflator) are dropped. Top-coded earnings observations are multiplied by 1.5.

the 1996 SIPP collects information on individuals' health and medical usage once a year, and on their work history. I only includes individuals aged 25 to 64 in the sample.[26]

3.3 Medical Expenditure Panel Survey (MEPS)

The Medical Expenditure Panel Survey (MEPS) data provide detailed information about the usage and expenditure of health care. Medical expenditure is defined to include all health care services such as office and hospital-based care, home health care, dental services, vision aids and prescribed medicines but not over-the-counter drugs. The expenditure data were derived from both households and the health care provider surveys, which makes the data set a reliable source for medical expenditure data. Specifically, I use MEPS 2005 to estimate individuals' medical expenditures.[27]

3.4 Employment Cost Index (ECI)

I use 1981Q4-2009Q4 Employment Cost Index (ECI) on health insurance benefits and 2005Q4 Employer Costs for Employee Compensation Survey (ECEC) to generate the average health insurance benefits per covered employee paid by an employer (λp_t). Both series are from Bureau of Labor Statistic's (BLS).

I first convert ECI series - which provides changes over time - into dollars using the information from ECEC survey 2005Q4.[28] Then, I calculate the cost of providing health insurance per covered employee over time as the ratio of average costs of providing health insurance benefits and average coverage rate from CPS data.

4 Estimation Strategy

I use a two-step strategy to estimate the model parameters.[29] In the first step, I estimate parameters that can be identified without using the model. For example, I estimate medical consumption function and health transitions directly from data. In the second step, I estimate the rest of the parameters using simulated method of moments (SMM).

[26]Individuals who are in the military, institutionalized, self-employed or working for non-paid jobs are excluded.

[27]I only includes individuals aged 25 to 64 in the sample. Individuals who are in the military, institutionalized, self-employed or working for non-paid jobs are excluded.

[28]The ECEC survey is based on the average employer cost presented in a dollar and cents, per employee, per hour worked format. Therefore, each employee's annualized cost is calculated as the per hour cost multiplied by 2080 hours, consist with the annualized income calculation in CPS data.

[29]Maximum Likelihood Estimation method in this case is computational infeasible, a brief discussion can be found in Appendix D.

Section 4.1 and 4.2 discuss initial condition and identification for estimation. Section 4.3 and 4.4 describe the first step and second step estimation in detail respectively.

4.1 Initial Conditions

The initial condition of each individual at age of 25 includes unobserved type and observed characteristics such as sex, education level, past labor market participation experience, health status, and presence of dependent children. I allow for flexible correlation between observed individual characteristics at age 25 and unobserved types.[30] The underlying assumption is that conditional on unobserved type, the initial conditions are exogenous.[31] The unobserved type can be broadly interpreted not only as innate abilities but also family investment and any other factors that impact individuals' initial conditions at age 25.

The joint distribution of education, health status and presence of dependent children at age 25 comes from CPS data.[32] The age-25 experience distribution is obtained from NLSY 1979-1994 for each education group and gender.

4.2 Identification

I infer skill levels from employee compensations, because that skill level is not directly observable. The constant terms in the skill production functions cannot be separately identified from the level of skill rental prices, so I normalize the population average of the constant term for male workers in each education group to be zero, that is $\sum_k \kappa_{0,k}\pi_k = 0$ for male, where π_k is probability distribution of type k individuals among males. Other parameters in the skill production function are mainly identified by moments conditions of wages conditional on health status, experience for each education group.

The risk aversion coefficient is identified largely from the health insurance coverage rate across different education groups. Under CARA utility function, if there is no consumption floor (i.e. $c^{min} = -\infty$), then there is no income effect on an individual's demand for health insurance. Therefore, the observed correlation between income and health insurance demand identify consumption

[30] Please refer to Appendix E.

[31] From 1981 to 2009, the percentage of men with 4 year college degree or more increases only by 8 percentage points, the percentage increase for men with some college is 5 percentage points. This implies that the contribution of education to changes of unobserved types for men over time is small. However, the changes in unobserved types among women over the same time period is a possible concern. In 2009, 32% of women have with 4 year college degree or more, compared to 15% in 1981. Therefore, I allow for interaction between female dummy and education dummy in the specification.

[32] CPS starts to collect individuals' health status information from 1995.

floor.

The utility of health is mainly identified by the life-cycle variation of health insurance coverage. To see this, given a risk aversion coefficient, the expected medical expenditure increases sharply with age, which implies that the insurance value is rising sharply along life-cycle. However, the observed health insurance coverage is relatively flat as an individual ages. The difference between the observed lifecycle profile of health insurance coverage and the medical expenditure identifies the utility of health. As individuals age, the remaining lifetime utility of health declines, which off-sets the individuals' demand for health insurance, and generate a relative flat health insurance demand in the late part of lifecycle. Parameters that govern the utility of leisure are mainly identified by the moments condition of employment choice conditional on age and the presence of dependent children.

4.3 First-Step Estimation

4.3.1 Medicaid Care Expenditure

Recall from Equation (6) that health insurance coverage, health status, age and education affect the logarithm of medical services consumption through the mean shifter $m(\cdot)$; health status also impact the medical services consumption through the variance shifter $\sigma(\cdot)$. I assume that $m(\cdot)$ is a linear function of health insurance coverage status, health status, age and two education dummies and $\sigma(\cdot)$ is a linear function of health status,

$$m(I_a, h_a, a, educ) = \alpha_{0,m} + \alpha_{1,m} I_a + \alpha_{2,m} h_a + \alpha_{3,m} a + \alpha_{4,m} \mathbf{1}(\text{female} = 1) + \sum_{j=SC,CG} \alpha_{5,j,m} \mathbf{1}(educ = j)$$

$$\sigma_m(h_a) = \sigma_{0,m} + \sigma_{1,m} h_a$$

Therefore the medical services consumption function is characterized as follows,

$$\begin{aligned} \log M_a = & \alpha_{0,m} + \alpha_{1,m} I_a + \alpha_{2,m} h_a + \alpha_{3,m} a + \alpha_{4,m} \mathbf{1}(\text{female} = 1) \\ & + \sum_{j=SC,CG} \alpha_{5,j,m} \mathbf{1}(educ = j) + (\sigma_{0,m} + \sigma_{1,m} h_a) \cdot \epsilon_a^m \end{aligned}$$

To estimate the medical services consumption model, I use 2005 MPES data. In the data, we observe individuals' total medical services expenses ($p_t^m M_a$) instead of medical services consumption (M_a). Therefore, I estimate the logarithm of medical services expenses ($p_t^m M_a$) by maximum likelihood using the following model:[33]

$$\log(p_t^m M_a) = \log p_t^m + \alpha_{0,m} + \alpha_{1,m} I_a + \alpha_{2,m} h_a + \alpha_{3,m} a + \alpha_{4,m} \mathbf{1}(\text{female} = 1) + \sum_{j=SC,CG} \alpha_{5,j,m} \mathbf{1}(educ = j) + (\sigma_{0,m} + \sigma_{1,m} h_a) \cdot \epsilon_a^m \tag{25}$$

where $\epsilon_a^m \sim N(0,1)$.

4.3.2 Health Transition

As noted, health is assumed to be either good, $h_a = 1$, or bad, $h_a = 0$. I estimate the transition probability of being in good health at age $a+1$ using a Logit regression model that depends on current health status, health insurance coverage, age and education,[34]

$$\text{Prob}_a(h_{a+1} = 1; h_a, I_a, educ) = (1 + \exp(-\boldsymbol{X}_a^h \boldsymbol{\alpha}_h))^{-1}$$

where

$$\boldsymbol{X}_a^h \boldsymbol{\alpha}_h = \alpha_{0,h} + \alpha_{1,h} h_a + \alpha_{2,h} I_a + \alpha_{3,h} a + \sum_{j=SC,CG} \alpha_{4,j,h} \mathbf{1}(educ = j) + \alpha_{5,h} \mathbf{1}(\text{female} = 1)$$

4.3.3 Transition Probability Regarding the Presence of Dependent Children

The transition function of the presence of dependent children are estimated using a Logit regression model that depends on the presence of dependent children, education, age, age square and sex,

$$\text{Prob}_a(Z_a^{ch} = 1 | Z_{a-1}^{ch}, a, educ) = (1 + \exp(-\boldsymbol{X}_a^{ch} \boldsymbol{\alpha}_{ch}))^{-1}$$

where

$$\boldsymbol{X}^{ch} \boldsymbol{\alpha}_{ch} = \alpha_{0,ch} + \alpha_{1,ch} Z_{a-1}^{ch} + \sum_{j=SC,CG} \alpha_{2,j,ch} \mathbf{1}(educ = j) + \alpha_{3,ch} a + \alpha_{4,ch} a^2 + \alpha_{5,ch} \mathbf{1}(\text{female} = 1)$$

[33] The cost of medical services at 2005 ($p_{t=2005}^m$) and the constant term of the medical services consumption function ($\alpha_{0,m}$) can not be separately identified. In fact the level of the cost of medical services is directly related to how we define the medical consumption unit. Therefore, without loss of generality, I set $\alpha_{0,m} = 0$.

[34] For similar specification, please refer to van der Klaauw and Wolpin (2008).

4.4 Second-Step Estimation

The estimation method is simulated method of moments (SMM). The objective of SMM estimation is to find the parameter vector that minimizes the weighted average distance between sample moments and simulated moments from the model. Specifically, I fit three sets of predicted moments to their data analogs: the mean employment rate, the mean employer-provided health insurance coverage rate and the mean wage rate by year, age, education and gender. Table 1 lists the targeted moments. The weighting matrix is the inverse of the diagonal matrix of the variance and covariance matrix of these moments.

Table 1: Targeted Moments

Targeted Moments from CPS	# of Moments
Employment rate by year, age and sex	$29 \times 40 \times 2$
Employment rate by year, education and sex	$29 \times 3 \times 2$
Employment rate by year, sex and presence of dependent children	$29 \times 2 \times 2$
EHI% among the employed by year, age and sex	$29 \times 40 \times 2$
EHI% among the employed by year, education and sex	$29 \times 3 \times 2$
Mean wage by year, education and sex	$29 \times 3 \times 2$
Standard deviation of wage by year, education and sex	$29 \times 3 \times 2$
Targeted Moments from SIPP	**# of Moments**
Employment rate by 4 age groups, health and sex	$4 \times 2 \times 2$
EHI% among the employed by 4 age groups, health and sex	$4 \times 2 \times 2$
One-period choice transition probabilities by 4 age groups, education and sex	$3 \times 4 \times 3 \times 2$
Distribution of 4 experience groups by education and sex	$3 \times 3 \times 2$
Mean wage by education, health and sex	$3 \times 2 \times 2$
Mean wage by education, 4 experience groups and sex	$3 \times 4 \times 2$

EHI refers to employer-provided health insurance. Notice that SIPP data covers 1996-2000 period, thus when matching moments from SIPP, I also restrict the model generated simulated moments to the same time period.

Beginning at age 25, given pre-determined individual state variables $\overline{\Omega}_a$, macro economic variables $\boldsymbol{\psi}_t$ and forecasting rule $\boldsymbol{\Phi}(\cdot)$, an individual draws $\boldsymbol{\epsilon}_a$ and calculates the realized three alternative specific value functions, and chooses the alternative that yields the highest value. An individual's state space is then updated according to the alternative chosen, and the macro economics variables are updated. The decision process is repeated for age $a = 26, \ldots, 64$.

Let θ be the individual level parameter vector that impacts individuals' labor supply and health insurance demand. I denote the parameter vector that governs the aggregate demand for different skills as θ^d, therefore $\theta^d = \{\nu, \{g^j_{z0}, g^j_{z1}, g^j_{z2}\}_{j=SC,CG}\}$. Parameters represented by ρ's are reduced form parameters that characterize the forecasting rule of equilibrium variables. So, the objective of the estimation in the second stage is to estimate (θ^d, θ) and find a set of value of ρ's that are consistent with the model system.

Conditional on aggregate variables $\{\{\log r^j_t, \log r^j_{t-1}\}_{j=HS,SC,CG}, \log p^m_t, \log p_t, \log p_{t-1}\}$, an individual's optimization problem does not depend on the parameter value of θ^d. Therefore, instead of searching over parameter space for (θ^d, θ), I search over θ and estimate (θ^d, ρ) using model generated data based on θ. Specifically, for any set of parameter values of θ, I simulate the behavior of samples of 1200 individuals per cohort at each time, starting from cohorts that turned age 25 in 1941, and thus will be age 64 in 1981, and ending with cohorts that turned age 25 in 2009. The algorithm is an extension of the iterative method developed in Lee and Wolpin (2006). The algorithm is as follows

Step 1. Choose a set of parameter values for equilibrium skill prices process $\{\log r^j_t\}_{j=HS,SC,CG}$, equilibrium health premium process $\log p_t$ and medical services prices process $\log p^m_t$.

Step 2. For each year, I use a iterative algorithm to find the equilibrium skill prices process $\{\log r^j_t\}_{j=HS,SC,CG}$ and underlying medical services prices process $\log p^m_t$ for each period $t = 1941, \ldots, 2009$, given observed data on workers' wages, health insurance and health insurance premium over time.

Specifically, I calculate the vector $(\log r^j_t, \log p^m_t)$ as a fixed point to the following system of equations:

$$\log r^j_t = \overline{lcompen}_t - \frac{\sum_i \log(s^j_i) \cdot \mathbf{1}(working_i = 1)}{\sum_i \mathbf{1}(working_i = 1)}$$
$$\log p^m_t = \log p_t - \log\left(\frac{\sum_{a=a_0}^{A}\sum_{i=1}^{L_{a,t}} \exp(m(I^e_{i,a}, h_{i,a}, a_i, educ_i) + \sigma_m(h_{i,a}) \cdot \epsilon^m_{i,a}) \cdot I^e_{i,a,t}}{\sum_{a=a_0}^{A}\sum_{i=1}^{L_{a,t}} I^e_{i,a,t}}\right)$$

where $\log p_t$ is equilibrium health insurance premium and $\overline{lcompen}_t$ is the average value of logarithm of compensation value among employed workers at time t, both are obtained by combining data from CPS and ECI.[35] The first equation is derived from the zero profit condition of employers in the

[35] Specifically, I calculate $\overline{lcompen}_t$ from data as follows,

$$\overline{lcompen}_t = \frac{\sum_i \log(w_i + \lambda p_t I^e_i) \cdot \mathbf{1}(working_i = 1) \cdot weights_i}{\sum_i \mathbf{1}(working_i = 1) \cdot weights_i}$$

where wages w_i and health insurance coverage status I^e_i of individual i if working $working_i$ comes from CPS data, and p_t is calculated based on ECI and CPS.

labor market, and the second equation follows from health insurance market equilibrium condition.

Step 3. Estimation θ^d via regression on the derived skill prices as follows,

Under the equilibrium condition Equation (20), the following equations hold in equilibrium

$$\log r_t^{SC} - \log r_t^{HS} = \log z_t^{SC} - \log z_t^{HS} + (\nu - 1)(\log S_t^{SC} - \log S_t^{HS})$$
$$\log r_t^{CG} - \log r_t^{HS} = \log z_t^{CG} - \log z_t^{HS} + (\nu - 1)(\log S_t^{CG} - \log S_t^{HS})$$

Under the normalization $z_t^{HS} = 1$ for all t, I could estimate g_z^j and ν using the following OLS regression,

$$\log r_t^{SC} - \log r_t^{HS} = g_{z0}^{SC} + g_{z1}^{SC} t + (\nu - 1)(\log S_t^{SC} - \log S_t^{HS}) + \epsilon_t^{SC,o}$$
$$\log r_t^{CG} - \log r_t^{HS} = g_{z0}^{CG} + g_{z1}^{CG} t + (\nu - 1)(\log S_t^{CG} - \log S_t^{HS}) + \epsilon_t^{CG,o}$$

where $\epsilon_t^{j,o}$ is an i.i.d error term.

The parameter for $\log \zeta_t$ is estimated as follows,

$$\log \zeta_t = \log r_t^{HS} - (1/\hat{\nu} - 1) log(z_t^{HS}(S_t^{HS})^{\nu} + z_t^{SC}(S_t^{SC})^{\nu} + z_t^{CG}(S_t^{CG})^{\nu}) - (\hat{\nu} - 1) \log S_t^{HS}$$

Step 4. Update the value of parameters that govern the forecasting rule of equilibrium prices (Equation 23 and 24) by estimating OLS model using the premium series and derived sequence of skill prices.

Step 5. Repeat the step 1-4 until the series of equilibrium prices and aggregate shocks converge.

5 Results

5.1 First-Step Parameters

The share of health insurance premium paid by the firm is in the range of 75-85% (Kaiser Family foundation), so I set the fraction of health insurance premium paid by the employer to be $\lambda = 0.8$.[36] I set the subjective discount factor (δ), which has proven difficult to pin down in the dynamic discrete choice literature, to be 0.95, a 5 percent discount rate. The variance of the transitory component of medical consumption is set to be $\sigma_{m,1}^2 = 0.6668$, following French and Jones (2004).

[36]My model could potentially be extended to the case where the share of health insurance premium paid by employers varies over time, however, due to limited data, I assume that this fraction is constant.

Therefore, $\sigma^2_{m,0} = 1 - \sigma^2_{m,1} = 0.3332$.

5.1.1 Medical Services Consumption

Table 3 presents the estimation results for individuals' medical consumption expenses (Equation (25)). The positive and significant coefficient for health insurance coverage (0.702) implies that an individual's medical care consumption is higher when covered by health insurance. As expected, good health reduces medical expenditure. Medical care services consumption also increases as the individual ages. Finally, the positive and significant coefficients for some college dummy and the 4-year college dummy are consistent with many empirical finding that higher educated individuals tend to utilize medical services more, other things being equal. The standard deviation of log medical care consumption is given by $\sigma_m(h) = 1.563 - 0.185 \cdot h$. Good health reduces the volatility of medical consumption shock.

5.1.2 Health Transition

Table 4 reports the estimated health status transition function. The transition probability of being healthy at age a is modeled as a logistic function that depends on health status, health insurance coverage at age $a-1$ and individuals' characteristics such as age, gender and education. As seen in the table, the transition process of health is very persistent: the coefficient of previous health status is significantly positive (2.294).

The coefficient on health insurance is positive and statistically significant. The probability of having good health is also higher when the individual's education level is higher, the coefficients for some college and 4-year college indicator are 0.313 and 0.761 respectively. However, these coefficients cannot be interpreted as direct impact of health insurance coverage and education on health, because these parameter estimates also incorporate the impact of medical services consumption on health status in a reduced form way.

5.1.3 Transition Regarding the Presence of Dependent Children

Table 5 reports estimation result for the transition function regrading the presence of dependent children.

5.2 Second-Step Parameters

5.2.1 Utility Parameters

Table 6 reports the parameter estimates for the utility function. The estimates suggest large heterogeneity in risk aversion and value of home time among individuals. I estimate an average coefficient of absolute risk aversion of about 1.90E-04 for male and 3.50E-04 for female.[37] To translate the absolute risk aversion estimates into relative risk aversion, I multiply the ARA estimates by average annual income following Cohen and Einav (2007) and find an average relative risk aversion of 7.486 for men and of 10.167 for women.[38]

The value of home time (including both value of leisure and home production value) is positive for women ($\phi_1 = 0.186$) but negative for men ($\phi_1 = -0.012$) in the presence of dependent children. The value of home time increases as individuals age. The consumption value of health and home time are substitutes: individuals value home time more when in bad health status. I also find that the value of home time is decreasing for both men and women over the sample period, reflecting technical improvement in home production sector.

The consumption value of health is 0.159 for men and 0.160 for women. On average, at the age of retirement, women value health more than men, captured by the higher average value of ϕ_{RE} among women. Finally, the estimated consumption floor is $c_t^{min} = 3295.540 + 8.762t$ (Table 7).

5.2.2 Skill Production Function Parameters

The parameter estimates for skill production function are reported in Table 8. Good health increases the human capital level. The coefficient of health in skill production function is 0.050 for workers with high school degree or less, 0.224 for workers with some college degree, and 0.157 for college graduates. Work experience increases human capital level at a decreasing rate. There is also substantial heterogeneity in the initial human capital endowment, captured by parameters $\kappa_{0,k,sex}^{j}$.

[37]The absolute risk aversion coefficient (ARA) is higher for females than for males. This result is consistent with the findings in the literature (see Cohen and Einav (2007) for example). However, these estimates cannot be directly compared with estimates in the literature. In my model, there are three types of risk: medical expenditure risk, health risk and earnings risk. The latter two risks are incorporated through individuals' forward looking value function. Most of the previous literature does not incorporate the effect of current health insurance on future health and therefore future earning potential when estimating the risk aversion coefficients.

[38]Specifically, I use the average after tax earnings for employed male ($39,437) and after tax earnings for employed female ($29,042) from CPS 1981-2009.

5.2.3 Production Function Parameters

The estimated elasticity of substitution among different types of skills, $\frac{1}{1-\nu}$, is 3.06. This implies that on average, a 10 percent increase in the relative supply of college equivalents reduces the skill price ratio by 3.3 percent. The growth rate of the logarithm of the skill-biased technological change is 0.015 for workers with 4-year college or more and 0.009 for workers with some college.[39] The estimated growth rate for neutral technological change ($\log \zeta_t$) is -0.001 . The estimated growth rate of medical care price process is much higher ($g^M = 0.070$), compared to the estimated technology growth rate.

5.3 Model Fit

5.3.1 Employment

As shown in Figure 10, the model successfully replicates the observed patterns of employment rates across different education groups for men. However, the model slightly over predicts the employment rate for workers with more than high school degree after 2000. The model successfully matches female employment rate over time, although it slightly under predicts the employment rate for women with 4-year college degree before 1995.

5.3.2 Employer-Provided Health Insurance

As seen in Figure 11, the model replicates the trends of health insurance coverage rates across different education groups very well, especially for employed males. The model mimics the health insurance coverage rates for employed females reasonable well after 1995, but slightly overstates the health insurance coverage rates before 1995.

5.3.3 Wages

As shown in Figure 12, the model replicates the time series patterns of wages across education groups very well, especially for men. The model fits the slight U-shape for males with less than 4-year college degree, and fast wage growth path for 4-year college graduate males. The model replicates the increase in wages for women with 4-year college and women with at most high school

[39] Autor et al. (2008) estimate the growth rate of skill-biased technological changes of college skills to be 0.006 to 0.028 for the period 1963-2005.

degree reasonably well. However, the model over predicts the wage level for women with some college degree in the earlier part of the sample period.

5.3.4 Life Cycle Pattern

As seen in Figure 13, the model is able to replicate the employment patterns of males and females across different age groups. The employment rate of men monotonically declines over age. The employment rate of women, slightly decline from age 25 to 30, increases from age 31 to age 46, and declines afterwards. The difference in employment patterns between men and women is mainly explained by the gender difference in the value of home time in the presence of dependent children.

Figure 14 shows that the model is also able to account for key health insurance coverage patterns over the life cycle for both men and women: the large increase in health insurance coverage in the earlier part of life (age 25 to 44) and the hump-shaped health insurance coverage over age 45 to 64. Individuals demand health insurance because of two reasons. First, health insurance insures against medical expenditure risk. Second, health insurance is an investment in health, which is both a consumption good and an investment good. As an individual ages, the insurance value of health insurance becomes larger as the medical expenditure risk is increasing with age. However, as an individual approaches his or her retirement, the incentive to invest in health declines. When the latter dominates the former, we see a decline in health insurance coverage rate in the later part of life.

6 Inequality Decomposition

In this section, I quantify the individual significance of the causes of observed inequality via simulation. To do this, I use the estimated model as the baseline case. Then I perform the following thought experiment. Suppose that the skill-biased technology does not change over time, when compare to the baseline world, how would the U.S. labor and health insurance market evolve? What would be the corresponding employment, wage, and health insurance coverage rate? Similarly, I conduct the same thought experiment with respect to changes in the cost of medical services and Medicaid eligibility expansion.

6.1 No Skill-Biased Technological Change (No SBTC)

To investigate the individual impact of skill-biased technological change on health insurance coverage inequality, I set the skill-augmenting technologies to their 1981 level, $z_t^j = z_{1981}^j$ for all t and $j \in \{HS, SC, CG\}$.

Figures 15 to 17 plot the employment rate, employer-provided health insurance coverage rate, and hourly wage rate among the employed from 1981 to 2009 for men and women respectively. Compared to the benchmark case, when the skill-biased technological change is shut down, the employment rates drop slightly for both men and women. Workers with a college degree or more experience large wage decrease, and workers with less than college education also experience moderate wage loss. In this case, the employer provided health insurance coverage rates decline for all three education groups, especially for workers with higher education.

As seen from figure 18 and 19, in the absence of skill-biased technological change, the employer-provided health insurance coverage gap between 4-year college male workers and high school male workers would have been 6 percentage points in comparison to the benchmark case of 24 percentage points in 2009, and the wage inequality (measured as log wage ratio) between these two group of workers would have been 25 percent in comparison to the benchmark case of 68 percent.

6.2 No Medical Services Cost Growth

When I set the cost of medical care services to its 1981 level, I find that (i) the employment rates rise for all three education groups; (ii) Employer provided health insurance coverage rates increase for all three education groups, especially for less educated workers; (iii) wages rise for all three education groups as well, but the wage increase for higher educated workers is a little bit bigger than less educated workers (see figures 20 to 22).

As we can see from figures 23 and 24, in the absence of medical services cost increase, then the employer-provided health insurance coverage gap would be 16 percentage points, compared to the benchmark gap of 24 percentage points; the log wage ratio between male workers with at least a 4-year college degree and male workers with at most a high school degree in 2009 would be 72 percent, compared to 68 percent.

6.3 No Medicaid Eligibility Expansion

To investigate the impact of Medicaid eligibility expansion on health insurance coverage inequality, I fix the both the income threshold level and categorical eligibility to the 1981 level. Figures 25 to 27 plot the employment rate, employer-provided health insurance coverage rate, and the wage rate among the employed from 1981 to 2009 for men and women respectively. The changes (relative to the baseline case) in employment rate, wage rate and health insurance coverage from eliminating the Medicaid eligibility expansion is very small. This is mainly because that the magnitude of historical Medicaid eligibility expansion with respect to non-elderly adults was very small.

Similarly, if the eligibility criteria of Medicaid is set to its 1981 level, the employer-provided health insurance coverage gap between 4-year college male workers and high school male workers is the same as the benchmark case of 24 percentage points in 2009, and the wage inequality stays the same as well (see figures 28 and 29).

6.4 Comparison

Figures 30 and 31 plot the employer-provided health insurance coverage disparity under different simulations for men and women respectively. Figures 32 and 33 plot log wage ratio under different simulations for men and women respectively. As we can see, skill-biased technological change and rising cost of medical care services are the two most important factors determining the level and patterns of wages and employer-provided health insurance over time. Skill-biased technological change leads to rising inequality in both wage and health insurance. Rising cost of medical services reduces wage inequality but leads to employer-provided health insurance coverage disparity. In the absence of skill-biased technological change, the employer-provided health insurance coverage gap between 4-year college male workers and high school male workers would have been 6 percentage points in comparison to the benchmark case of 24 percentage points in 2009, and the wage inequality between these two group of workers would have been 25 percent in comparison to the benchmark case of 68 percent. Rising cost of medical services reduces wage inequality but leads to employer-provided health insurance coverage disparity. In the absence of medical services cost increase, the employer-provided health insurance coverage gap is 16 percentage points, again compared to the benchmark gap of 24 percentage points; the log wage ratio between male workers with at least a 4-year college degree and male workers with at most a high school degree in 2009 is 0.72, again compared to the benchmark log wage ratio of 0.68.

7 Health Care Policy Analyses

I conduct policy analyses on two health care policies that were introduced in PPACA: (i) employer mandates: employers that do not offer coverage to its employee is required to pay a fee of $2000 per employee;[40] (ii) further Medicaid eligibility expansion: all individuals whose income is lower than 133% of FPL is eligible for Medicaid coverage.

Under PPACA, the health insurance system will continue to be employer-based. Tax deductibility of employer contributions to health insurance remains in effect. Individual purchase of insurance remains not tax deductible. When conducting the analyses, I allow both the SBTC and the cost of medical service to change according to the estimated process, and fixed the rest components of the economy to their 2009 levels. Tables 10 and 11 report the effects of counterfactual health care policies on employment, wage and health insurance coverage for males and females respectively. Table 12 reports the policy impact on health insurance coverage inequality and wage inequality among the employed workers. Finally, Table 13 reports the changes in welfare under different policy experiments.

7.1 Employer Mandates

I investigate the impact of employer mandates on health care and labor market outcomes. A $2000 dollar penalty is imposed on employers who do not offer health insurance. Therefore the zero profit condition for employers in the labor market is given by

$$w + \mathbf{1}(I^e = 1)\lambda p = r_t^j s_a - \mathbf{1}(I^e = 0) \cdot \text{ penalty} \tag{26}$$

Compared to the benchmark case, I find that the introduction of employer mandates lowers employment rate by 3 percentage points for men with at most a high school degree and by 1 percentage point for men with some college, while the employment rate among men with at least a 4-year college degree stays the same. This is because the penalty raises the cost of employment especially for less educated workers who would have chosen not having insurance had there is no employer mandates. The employer-provided health insurance coverage increases for all education groups. Specifically, the coverage rate for employed males with at most a high school degree, some college, and at least a 4-year degree increases by 9 percentage points, 4 percentage points

[40] Under PPACA, employers with more than 50 employees will be required to offer coverage or pay a fee of $2000 per full-time employee, excluding the first 30 employees from the assessment.

and 2 percentage points respectively. As a result, the health insurance coverage disparity between employed male college workers and employed male high school workers is reduced to 17 percentage points, in comparison to the gap of 24 percentage points in the baseline case.

7.2 Further Medicaid Eligibility Expansion

I find that the 133% FPL Medicaid expansion increases the employment rate of less educated individuals. The employment rate for males with at most a high school degree increases to 74 percent, in comparison to 69 percent in the baseline case. The employment rate for females with at most a high school degree increases by 2 percentage points compared to the baseline case. This is because that before such extensive eligibility expansion, the income eligibility threshold for Medicaid, though increasing, remains low. In order to be eligible for Medicaid, an individual would not work. Therefore for low skill individuals who value Medicaid, they will choose to not work in order to be eligible for Medicaid. Under the further expansion, the income eligibility threshold is increased, low skill individuals optimally choose to work and could be on Medicaid at the same time. The increase in low skill workers' employment rate leads to increase in the skill prices of 4-year college skills due to the imperfect substitutability among different types of skills. As a result, in equilibrium, the wages for high school workers goes down, and wages for 4-year college workers increase. This leads to an increase in wage gap by education. The employer-provided health insurance coverage rate drops for less educated workers because many of these workers will be on Medicaid (crowd-out effect of public health insurance). However the overall disparity in the health insurance coverage declines due to the Medicaid coverage.

8 Conclusion

In this paper, I develop a dynamic equilibrium model to analyze the relationship between employer-provided health insurance coverage and wages. I use the model to investigate the determinants of rising inequality in health insurance and wages, and quantitatively assess their individual contribution. I also use the model to evaluate the effects of health care policies on labor market outcomes and welfare.

The model estimated in this paper is innovative in at least three dimensions. First, health is modeled not only as a consumption good that enters an individual's utility function, but also as a form of human capital that enters an education-specific skill production function. Second, the model allows for interaction between labor market and health insurance market. The health status distribution among those who are employed, not only impacts the equilibrium health insurance premium in the insurance market, but also determines the total skills supplied in the labor market and thus affects the equilibrium skill prices. Third, the model allows for rich forms of individual heterogeneity. Individuals differ in dimensions such as gender, age, birth year, education, health, labor market experience, and the presence of dependent children. I also allow for unobserved individual heterogeneity along four dimensions: initial skill endowment, level of risk aversion, value of leisure, and value of health at retirement.

The estimated model is able to replicate the observed trends in both wages and health insurance coverage in the U.S. over the last 30 years: (i) a relatively rapid wage growth among more educated workers and stagnant wage growth among less educated workers, and (ii) a sharp decline in employer-provided health insurance coverage among less educated workers and relatively stable coverage among more educated workers. The model is also able to account for key health insurance coverage patterns over the life cycle: the large increase in health insurance coverage in the earlier part of life (age 25 to 44) and the hump-shaped health insurance coverage over age 45 to 64.

I find that skill-biased technological change increases both wage inequality and health insurance inequality. The rising cost of medical care services, on the other hand, increases health insurance inequality but reduces wage inequality. The quantitative impact of Medicaid eligibility expansion on the inequality trends is found to be small. I find that although the introduction of employer mandates increases the employer-provided health insurance coverage rate, it also reduces the employment rate of less educated individuals. I also find that further Medicaid eligibility expansion reduces health insurance coverage inequality but increases wage inequality.

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Appendix A Model Proofs

Proof of Proposition 1. When $d^c_{a,t} \cdot \mathbf{1}(r^j_t s^j_a \leq y^{cat}) = 0$,

$$V_{1,a}(\Omega_{a,t}) = u_{1,0,a}(h_a, \boldsymbol{\epsilon}_a) + \delta\pi^s_{a+1}\mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = 1, d^e_a = 1]$$
$$V_{2,a}(\Omega_{a,t}) = u_{2,a}(h_a, \boldsymbol{\epsilon}_a) + \delta\pi^s_{a+1}\mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = 1, d^e_a = 1]$$

An individual prefers a job with health insurance offer to a job without health insurance offer if and only if $V_{2,a}(\Omega_{a,t}) \geq V_{1,a}(\Omega_{a,t})$, that is

$$-\exp(-\gamma\widetilde{\mathcal{T}}(r^j_t s^j_a - p_t)) + \exp(-\gamma\xi_{a,t}) + \delta\pi^s_{a+1}\Delta CV_{a+1}(\Omega_{a,t}) \geq 0$$

where $\Delta CV_{a+1}(\Omega_{a,t}) = \mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = 1, d^e_a = 1] - \mathbb{E}[V_{a+1}|\Omega_{a,t}, I_a = 0, d^e_a = 1])$.

Denote the threshold value for health insurance as $\xi^*_{a,t}$, then

$$\xi^*_{a,t} = -\frac{1}{\gamma}\log\Big(\exp(-\gamma\widetilde{\mathcal{T}}(r^j_t s^j_a - p_t)) - \delta\pi^s_{a+1}\Delta CV_{a+1}(\Omega_{a,t})\Big)$$

if $\exp(-\gamma\widetilde{\mathcal{T}}(r^j_t s^j_a - p_t)) - \delta\pi^s_{a+1}\Delta CV_{a+1}(\Omega_{a,t}) > 0$, and $\xi^*_{a,t} = \infty$ otherwise. Individuals choose to work for a job with health insurance when their consumption equivalent value is lower than the threshold value $\xi^*_{a,t}$.

□

Appendix B Approximating Progressive Labor Income Taxes

I assume the following functional form for labor income taxes,

$$\mathcal{T}(y) = \tau_0 + y - \tau_1\frac{y^{\tau_2+1}}{\tau_2+1} \tag{27}$$

This specification is the same as the one in Storesletten et al. (2010) and Kaplan (2012), and is similar to the one used by Guvenen et al. (2009). Under this specification, the logarithm of one minus the marginal tax rate is linear in log labor earnings,

$$\log(1 - \tau'(y)) = \log(\tau_1) + \tau_2 \log y$$

Both Storesletten et al. (2010) and Guvenen et al. (2009) provide evidence that one minus the marginal tax rate is approximately log-linear in earnings for the US.

To estimate (τ_1, τ_2) I regress logarithm of one minus marginal tax rates for each individual in the sample on annualized labor wage income. Marginal tax rates are calculated using the NBERs TAXSIM program. The estimated parameter values are $\log(\tau_1) = 1.0355$ and $\log(\tau_2) = -0.1266$ with an R^2 of 0.38. I set τ_0 to the value that equates the actual average tax rate in the sample (as computed by TAXSIM) to that implied by Equation 27.[41] A regression of the actual tax liability on the predicted tax liability yields an R^2 of 0.93. Figure 8 plot the approximated labor income taxes along individuals' wage income.

Appendix C Approximating Medicaid Coverage Eligibility Rules

In the median states, the income eligibility threshold for adults is 63% of the poverty level.[42] Denote by FPL the poverty level for one person family, the mean and standard deviation of $\log(FPL_t) - \log(FPL_{t-1})$ from 1982 to 2009 are 0.0058 and 0.0118 respectively (deflated using 2005 GDP deflator). Therefore, I set the mean and standard deviation of the logarithm of income threshold evolution process to be $g^{cat} = 0.0058$ and $\sigma^{cat} = 0.0118$. On average, FPL increase by 34% for one additional person. For example, in 2005, FPL for one person family is \$9,570, and for each additional person add \$3,260, thus the annual income threshold adjusted by the presence of dependent children is $y^{cat} = 0.63 \cdot (9570 + 3260 \cdot Z^{ch})$.

To estimate the categorical eligibility, $d^c_{a,t}$, I estimate a Probit model for individuals with no private health insurance, excluding those whose earnings exceeds the calculated Medicaid income threshold. The estimation results are reported in Table (2).

Appendix D Discussion on MLE

This section discusses the possibility of estimating the model using maximum likelihood estimation and why it is not preferred. First, notice that the solution of the optimization problem at each age a and time t, can be represented by the set of regions in the three-dimensional $\boldsymbol{\epsilon}_a$ space over which each of the alternatives would be optimal. Let $Y_{a,t}$ denote the observed individual level data on choice, wage and health insurance coverage at age a and time t. Therefore, the joint probability of

[41]The actual average tax rate in the sample equals to 0.1437, and thus $\tau_0 = 322.5875$.

[42]The Kaiser Commission on Medicaid and the Uninsured, *5 Key Questions and Answers About Medicaid*, Chartpack, May 2012

observed data and aggregate shocks is given by

$$
\begin{aligned}
&Pr[Y_{25,t},\dots,Y_{a,t+(a-25)},\{\boldsymbol{\psi}_t,\dots,\boldsymbol{\psi}_{t+(a-25)}\}|\overline{\Omega}_{25}] \\
=&\Pi_{\Delta a=1}^{a-25}Pr[Y_{25+\Delta a,t+\Delta a}|\{\overline{\Omega}_{25+\Delta a},\boldsymbol{\psi}_{t+\Delta a}\}]Pr(\overline{\Omega}_{25+\Delta a},\boldsymbol{\psi}_{t+\Delta a}|Y_{25+\Delta a-1,t+\Delta a-1},\overline{\Omega}_{a+\Delta a-1},\boldsymbol{\psi}_{t+\Delta a-1})
\end{aligned}
$$

where the equality comes from the fact that both the individual state $\overline{\Omega}_a$ and the growth rate of aggregate state $\boldsymbol{\psi}_t$ are Markov process.

There is no closed-form representation for the probability function, $Pr[Y_{25+\Delta a,t+\Delta a}|\{\overline{\Omega}_{25+\Delta a},\boldsymbol{\psi}_{t+\Delta a}\}]$. It can only be obtained through simulation. Specifically, we need to calculate the choice probability via simulation for every observed individual states and aggregate states. Because aggregate variables such as rental price of skills, technology process, and the cost of medical services, are not directly observed from data, hence we need to integrate over these aggregate variables in order to calculate the individual's choice probability. However, because that all these variables follow non-stationary process, the performance of simulation based integration is poor and very sensitive to the distributional assumption on these variables.

Second major issue with MLE is due to the initial condition. March CPS data is a cross section data, each individual is only observed once in the data set. Hence, to calculate the likelihood function, I need to integrate over all possible histories of the individual before the observed age that are consistent with this individual's state at the observed age. For example, if an age 45 individual is observed in the data, in order to calculate the likelihood function for this individual, I need to simulate all the possible history that could have happened between age 25 to 44 that are consistent with this individual's state at age 45, and then integrate over these histories.

Therefore, instead of using simulated MLE, I use a two-step estimation. The applied estimation method, describe in the rest of the section, deals with the initial condition and missing data naturally and is relative robust to the distribution assumptions.

Appendix E Initial Joint Distribution of Individual-Level State Variables

I assume that the conditional probability of a type i individual with education $j \in \{SC, CG\}$ is

$$
Pr(educ = j|type = k, t) = \frac{\exp(\pi_{1,k}^{j} + \pi_{2,k}^{j} \cdot t)}{1 + \exp(\pi_{1,k}^{SC} + \pi_{2,k}^{SC} \cdot t) + \exp(\pi_{1,k}^{CG} + \pi_{2,k}^{CG} \cdot t)} \tag{28}
$$

and $Pr(educ = HS|type = k, t) = 1 - Pr(educ = SC|type = k, t) - Pr(educ = CG|type = k, t)$. I allow π^j's to differ by sex.

Therefore, given the observed education choice j at age 25, the probability of being the unobserved endowment type k is

$$Pr(type = k|educ = j, t) = \frac{Pr(educ = j|type = k, t)\pi_0^k}{\sum_{k'} Pr(educ = j|type = k', t)\pi_0^{k'}}$$

where π_0^k is the population probability of being type k and $\sum_k \pi_0^k = 1$.

Appendix F Tables

Table 2: Medicaid Coverage

	Male	Female
Age≥30	0.123**	-0.119**
	(0.018)	(0.009)
Age≥35	0.162**	-0.210**
	(0.018)	(0.010)
Age≥40	0.169**	-0.253**
	(0.018)	(0.010)
Age≥45	0.093**	-0.306**
	(0.018)	(0.011)
Age≥50	-0.010	-0.350**
	(0.018)	(0.011)
Age≥55	-0.213**	-0.415**
	(0.017)	(0.011)
Age≥60	-0.524**	-0.537**
	(0.016)	(0.011)
Some College	-0.382**	-0.374**
	(0.011)	(0.007)
4-year College or More	-0.685**	-0.974**
	(0.015)	(0.010)
employed	-0.521**	-0.243**
	(0.021)	(0.012)
Having Dependent Children < 18 yrs	0.210**	0.173**
	(0.014)	(0.009)
Post 1996	0.202**	0.296**
	(0.010)	(0.008)
Having Dependent Children < 18 yrs, Post 1996	-0.264**	-0.244**
	(0.019)	(0.011)
Constant	-0.796**	-0.739**
	(0.014)	(0.010)
Observations	174580	474900

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 3: Medical Services Consumption Function (Maximum Likelihood Estimation)

$m(I_a, \text{health}_a, a, \text{education})$		
Covered by HI	0.702**	(0.035)
Healthy	-0.662**	(0.030)
Age-25	0.036**	(0.001)
Female	0.370**	(0.029)
Some college	0.213**	(0.036)
4-Year college or more	0.267**	(0.036)
Constant	5.809**	(0.045)
$\sigma(\text{health}_a)$: standard deviation		
Healthy	-0.185**	(0.020)
Constant	1.563**	(0.013)
Observations	11228	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$

Table 4: Health Transition (Logit Regression)

	Healthy	
Healthy previous year	2.294**	(0.029)
Covered previous year	0.229**	(0.037)
Age	-0.032**	(0.002)
Some college	0.313**	(0.034)
4-Year college or more	0.761**	(0.040)
Female	-0.112**	(0.029)
Constant	0.118	(0.077)
Observations	29554	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$

Table 5: Transition Function of Having Children under 18

	Kids < 18 yrs	
Kids < 18 yrs, previous year	6.442**	(0.075)
Some college	0.121*	(0.073)
4-year college or more	0.403**	(0.074)
Age	-0.222**	(0.030)
Age square/100	0.133**	(0.034)
Female	-0.026	(0.060)
Constant	3.209**	(0.631)
Observations	29554	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$

Table 6: Utility Parameters: $u^*(c_a, d^e_a; h_a, a, \epsilon^l_a) = 1 - \exp(-\gamma c_a) + \phi_h h_a + (\Gamma_{a,t} + \epsilon^l_a)(1 - d^e_a)$

$$\Gamma_{a,t} = \sum_k \phi^{\text{sex}}_{0,k}\mathbf{1}(type = k) + \phi^{\text{sex}}_1 Z^{ch}_a + \phi^{\text{sex}}_2 \mathbf{1}(a \geq 45)(a - 45) + \phi^{\text{sex}}_3(1 - h_a)$$
$$+ \phi^{\text{sex}}_4 \mathbf{1}(educ = SC) + \phi^{\text{sex}}_5 \mathbf{1}(educ = CG) + \text{Time Trend}^{\text{sex}}_t$$
$$\text{Time Trend}^{\text{sex}}_t = \phi^{\text{sex}}_6(t - 1981)\mathbf{1}(1981 \leq t \leq 2000) + \phi^{\text{sex}}_7(t - 2000)\mathbf{1}(t > 2000)$$

	Male		Female	
ϕ_1: value of home time × presence of dependent children	-0.012	(0.0010)	0.186	(0.0001)
ϕ_2: value of home time × (age-45) if age > 45	0.017	(0.0011)	0.020	(0.0001)
ϕ_3: value of home time × unhealthy	0.057	(0.0009)	0.081	(0.0004)
ϕ_4: value of home time × some college	0.071	(0.0010)	0.007	(0.0001)
ϕ_5: value of home time × 4-year college or more	0.021	(0.0053)	0.008	(0.0000)
ϕ_6: time trend for value of home time, before 2000	0.000	(0.0006)	-0.009	(0.0003)
ϕ_7: time trend for value of home time, after 2000	0.000	(0.0005)	-0.003	(0.0005)
ϕ_h: utility of being healthy	0.159	(0.0000)	0.160	(0.0003)
σ_l: s.d of shocks to value of home time	0.046	(0.0004)	0.040	(0.0000)
ϕ_0: constant term, value of home time				
Type 1	0.163	(0.0008)	0.169	(0.0003)
Type 2	0.008	(0.0012)	0.017	(0.0005)
Type 3	0.251	(0.0006)	1.767	(0.0006)
ϕ_{RE}: value of health at age 65				
Type 1	0.305	(0.0006)	0.288	(0.0007)
Type 2	0.101	(0.0005)	0.008	(0.0006)
Type 3	0.162	(0.0014)	4.922	(0.0008)
γ: risk aversion				
Type 1	2.01E-04	(0.0003)	2.90E-04	(0.0002)
Type 2	1.66E-04	(0.0007)	1.64E-04	(0.0004)
Type 3	2.02E-04	(0.0005)	6.32E-04	(0.0005)

Standard errors in parentheses

Table 7: Consumption Floor: $c^{min}_t = c^{min}_0 + g^c t$

c^{min}_0: initial value of consumption floor	3295.540	(10.0001)
g^c: time trend	8.762	(0.0051)

Standard errors in parentheses

Table 8: Skill Production: $\log(s_a^j) = \sum_k \kappa_{0,k,sex}^j \cdot \mathbf{1}(type = k) + \kappa_1^j h_a + \kappa_2^j expr_a + \kappa_3^j expr_a^2 + \epsilon_a^j$

	High School or Less j=HS		Some College j=SC		4-Year College or More j=CG	
Male						
κ_{01}^j: constant term for type 1	0.654		-0.438		0.104	
κ_{02}^j: constant term for type 2	0.315	(0.0004)	-0.100	(0.0009)	0.349	(0.0053)
κ_{03}^j: constant term for type 3	-1.206	(0.0000)	0.687	(0.0012)	-0.518	(0.0002)
Female						
κ_{01}^j: constant term for type 1	0.104	(0.0004)	-0.727	(0.0009)	-0.430	(0.0001)
κ_{02}^j: constant term for type 2	-0.235		-0.389		-0.185	
κ_{03}^j: constant term for type 3	-1.756		0.398		-1.052	
κ_1^j: Health	0.050	(0.0004)	0.224	(0.0007)	0.157	(0.0003)
κ_2^j: Experience	0.033	(0.0002)	0.037	(0.0004)	0.032	(0.0004)
κ_3^j: Experience square	0.001	(0.0008)	0.001	(0.0008)	0.001	(0.0004)
s.d of shocks	0.405	(0.0001)	0.487	(0.0015)	0.429	(0.0021)

Standard errors in parentheses

Table 9: Production Function, Technology Changes and Medical Price Changes

Final Goods			
ν	0.673		
SBTC	High School or Less	Some College	4-Year College or More
g_{0z}	0 (normalization)	0.083	0.272
g_{1z}	0 (normalization)	0.009	0.015
Neutral Technology Change			
g^{ζ}	-0.001	s.d of $\log \zeta$	0.022
Medical Care Prices			
g^M	0.070	s.d of $\log p^M$	0.049

Table 10: Health Care Policy Experiments: Employment, Wages and Employer-Provided HI (Male)

	Baseline	mandate	Medicaid	mandate+Medicaid
			All Male	
HI Coverage				
HS	0.52	0.57	0.81	0.87
CS	0.67	0.70	0.82	0.86
CG	0.80	0.82	0.89	0.91
Employment				
HS	0.69	0.66	0.74	0.69
CS	0.85	0.84	0.84	0.84
CG	0.91	0.91	0.91	0.90
			Employed Male	
HI Coverage				
HS	0.64	0.73	0.75	0.81
CS	0.78	0.82	0.79	0.84
CG	0.88	0.90	0.88	0.91
Employer-Provide HI				
HS	0.64	0.73	0.60	0.69
CS	0.78	0.82	0.77	0.81
CG	0.88	0.90	0.88	0.90
Wages				
HS	16.69	16.98	15.78	16.30
CS	21.42	21.26	21.39	21.14
CG	32.61	32.50	32.75	32.64

Table 11: Health Care Policy Experiments: Employment, Wages and Employer-Provided HI (Female)

	Baseline	mandate	Medicaid	mandate+Medicaid
		All Female		
HI Coverage				
HS	0.47	0.50	0.86	0.91
CS	0.56	0.59	0.87	0.92
CG	0.66	0.68	0.90	0.93
Employment				
HS	0.53	0.53	0.55	0.55
CS	0.66	0.66	0.67	0.67
CG	0.74	0.74	0.74	0.74
		Employed Female		
HI Coverage				
HS	0.70	0.76	0.74	0.84
CS	0.78	0.82	0.81	0.87
CG	0.87	0.90	0.87	0.90
Employer-Provide HI				
HS	0.70	0.76	0.66	0.70
CS	0.78	0.82	0.77	0.80
CG	0.87	0.90	0.87	0.90
Wages				
HS	11.94	11.66	11.61	11.27
CS	16.03	15.84	15.96	15.68
CG	23.37	23.20	23.40	23.23

Table 12: Effects on Health Insurance and Wage Inequality

	Employed Male			
	Baseline	mandate	Medicaid	mandate+Medicaid
HI Coverage				
CS/HS	0.13	0.08	0.04	0.03
CG/HS	0.23	0.17	0.13	0.10
Employer-Provide HI				
CS/HS	0.13	0.09	0.18	0.12
CG/HS	0.23	0.17	0.28	0.21
Wages				
CS/HS	0.25	0.22	0.30	0.26
CG/HS	0.67	0.65	0.73	0.69
	Employed Female			
	Baseline	mandate	Medicaid	mandate+Medicaid
HI Coverage				
CS/HS	0.08	0.06	0.07	0.04
CG/HS	0.17	0.13	0.13	0.07
Employer-Provide HI				
CS/HS	0.08	0.06	0.11	0.10
CG/HS	0.17	0.13	0.21	0.20
Wages				
CS/HS	0.29	0.31	0.32	0.33
CG/HS	0.67	0.69	0.70	0.72

Table 13: Health Care Policies Experiments: % Changes in Welfare

	Male		
	Mandate	Medicaid	Mandate+Medicaid
HS	-0.56	0.38	-0.19
age 25-34	-0.88	0.50	-0.29
age 35-44	-0.59	0.46	-0.14
age 45-44	-0.34	0.30	-0.12
age 55-64	-0.24	0.08	-0.24
SC	-0.28	-0.10	-0.43
age 25-34	-0.44	-0.12	-0.68
age 35-44	-0.26	-0.24	-0.55
age 45-44	-0.11	-0.10	-0.21
age 55-64	-0.02	0.43	0.40
CG	-0.09	0.40	0.47
age 25-34	-0.13	0.52	0.62
age 35-44	-0.09	0.37	0.44
age 45-44	-0.05	0.24	0.26
age 55-64	-0.01	0.31	0.33

	Female		
	Mandate	Medicaid	Mandate+Medicaid
HS	-0.21	0.06	-0.18
age 25-34	-0.27	-0.60	-0.90
age 35-44	-0.22	-0.18	-0.44
age 45-44	-0.21	0.10	-0.15
age 55-64	-0.17	0.79	0.63
SC	-0.25	-0.35	-0.68
age 25-34	-0.28	-0.69	-1.10
age 35-44	-0.26	-0.28	-0.63
age 45-44	-0.21	-0.13	-0.36
age 55-64	-0.14	0.47	0.35
CG	-0.13	-0.03	-0.05
age 25-34	-0.15	-0.10	-0.12
age 35-44	-0.11	-0.02	-0.02
age 45-44	-0.10	-0.02	-0.04
age 55-64	-0.08	0.54	0.50

Appendix G Figures

Figure 2: Education Distribution Over Time

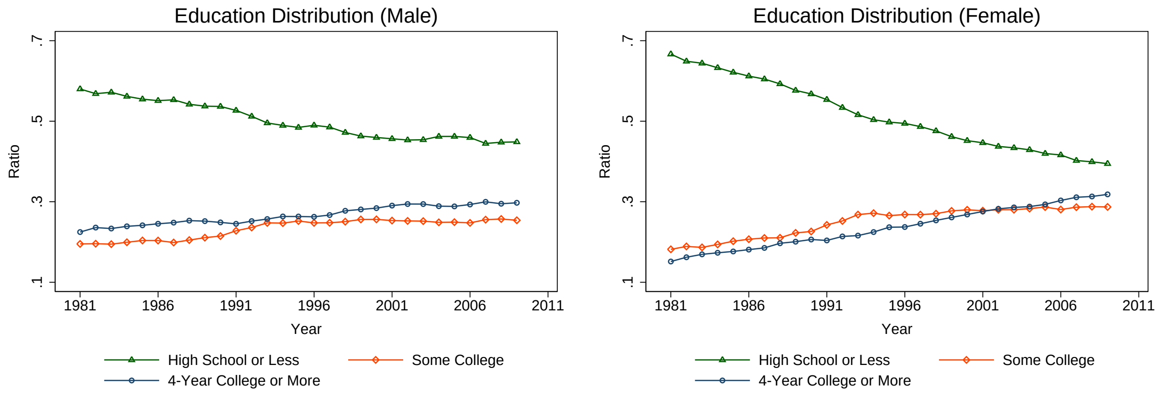


Figure 3: Employment Rate Over Time

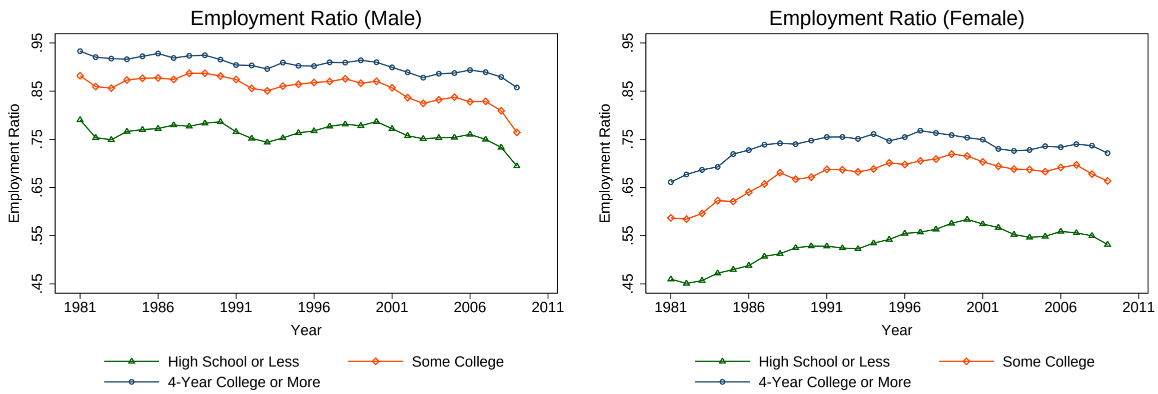


Figure 4: Wage Rate Over Time

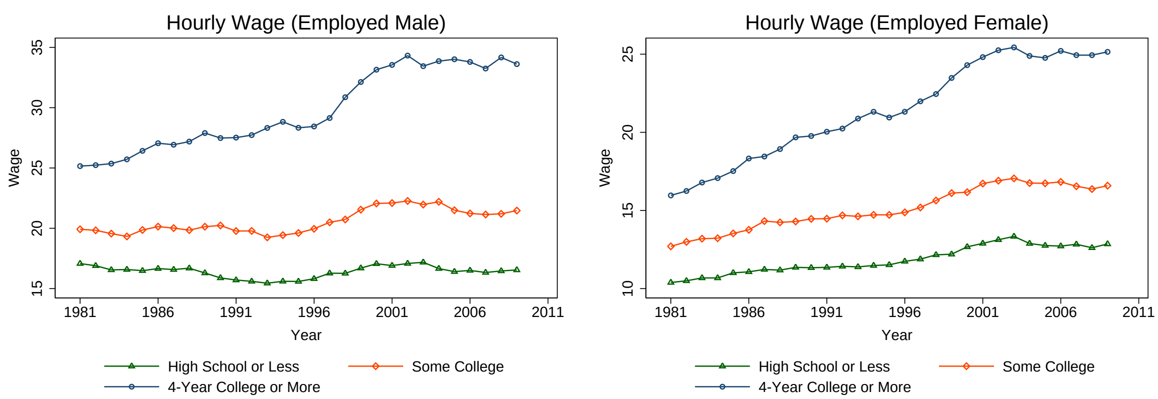


Figure 5: Employer-Provided HI Over Time

Figure 6: Wages Inequality Over Time

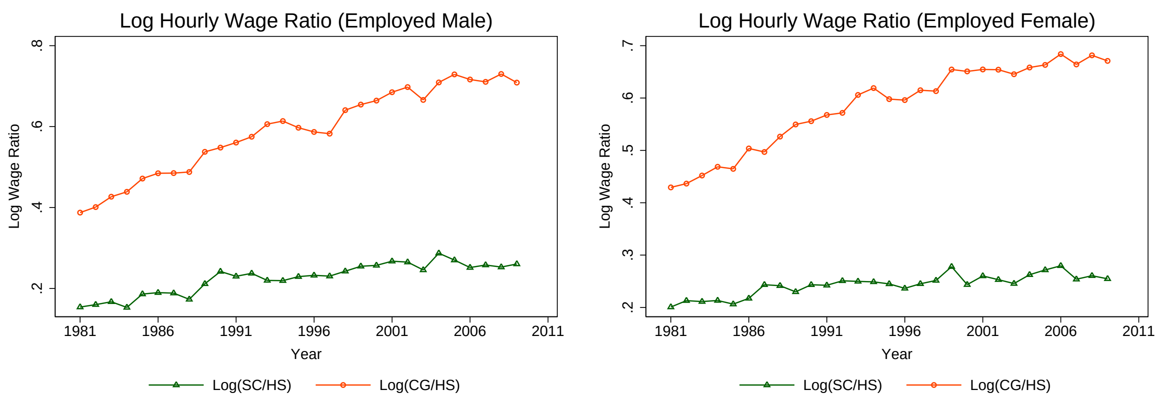


Figure 7: Employer-Provided HI Inequality Over Time

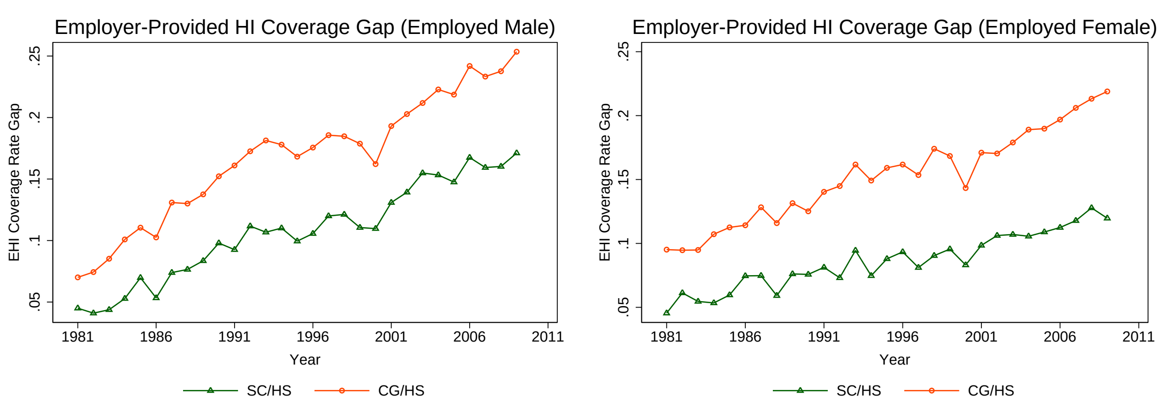


Figure 8: Approximated Labor Income Tax Schedule

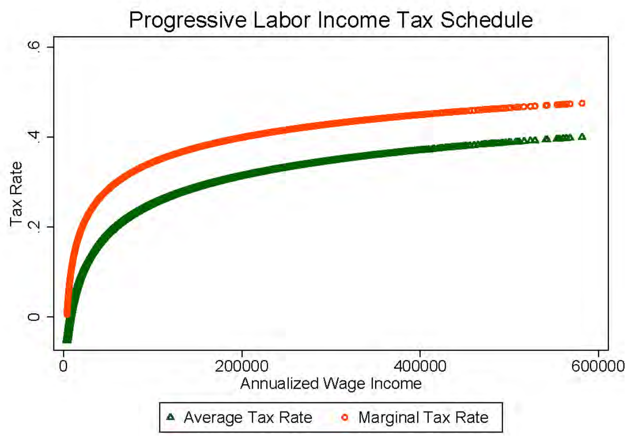


Figure 9

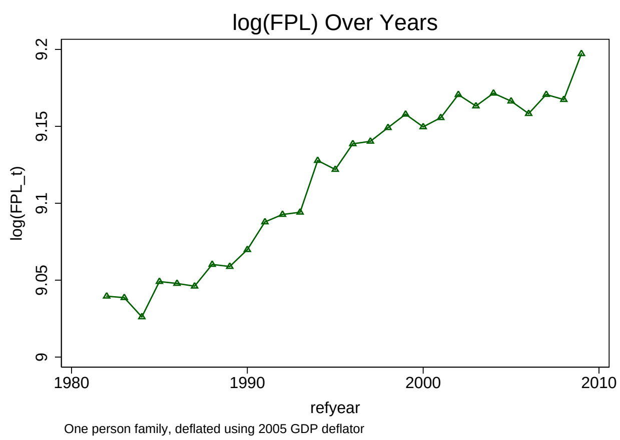
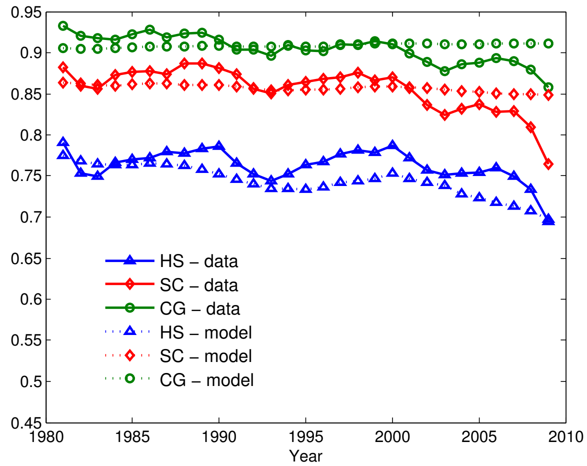
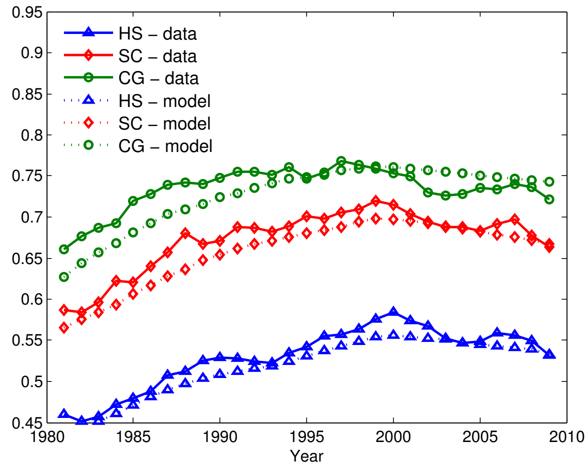


Figure 10: Model Fit: Employment Rate

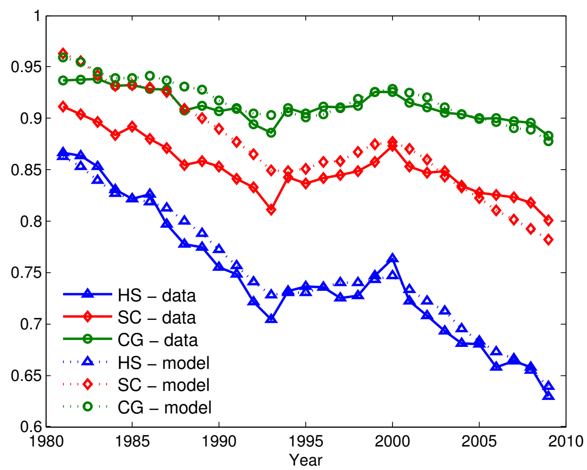


(a) Male

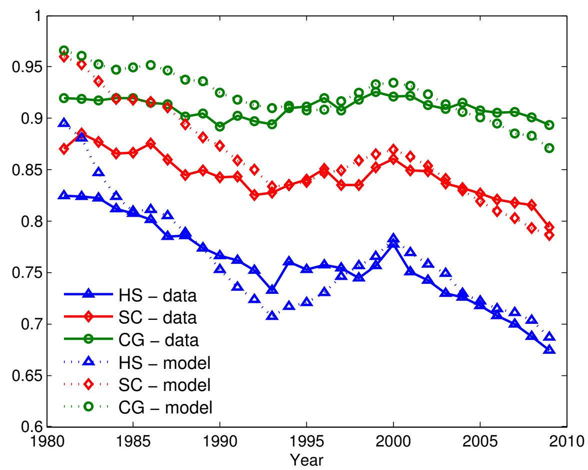


(b) Female

Figure 11: Model Fit: Employer-Provided HI Coverage Rate

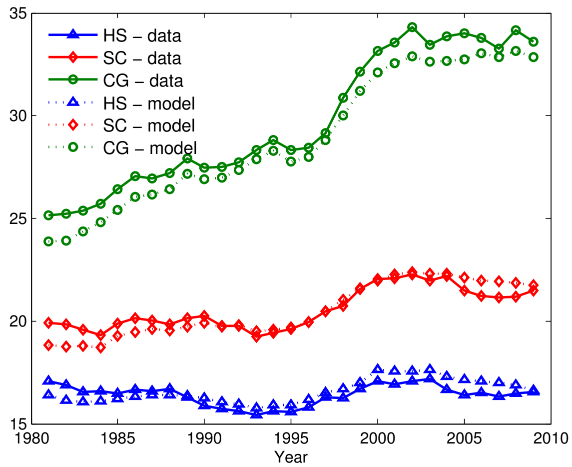


(a) Employed Male

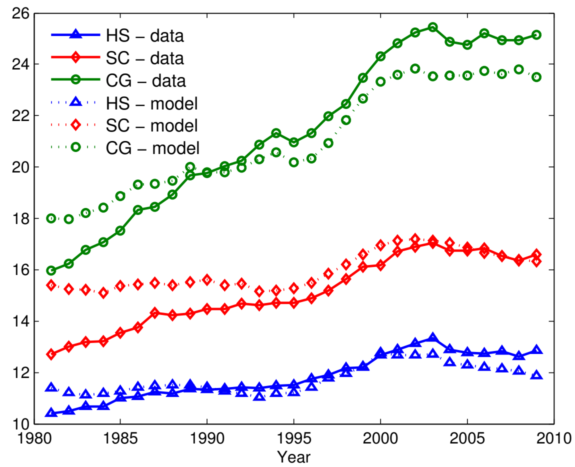


(b) Employed Female

Figure 12: Model Fit: Wage

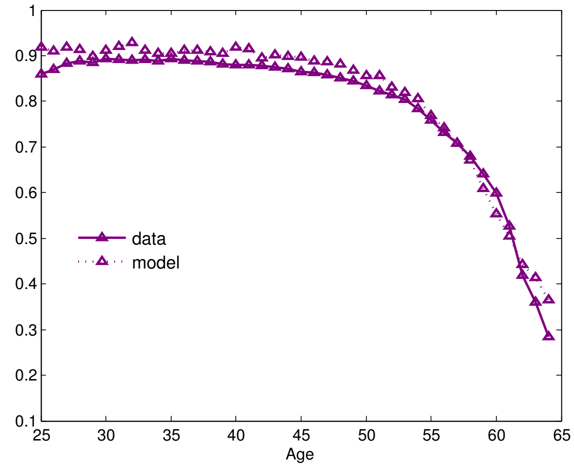


(a) Employed Male

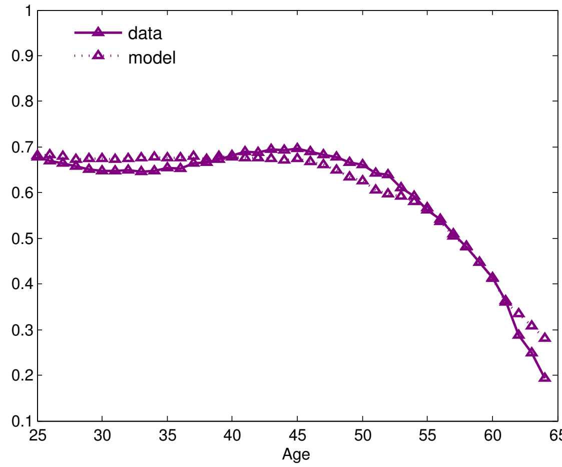


(b) Employed Female

Figure 13: Model Fit: Employment Rate

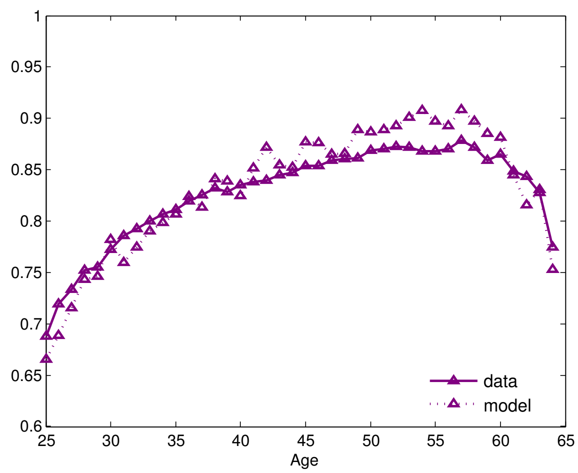


(a) Male

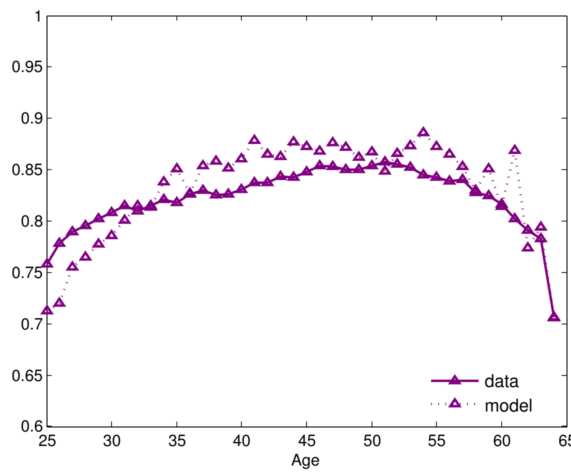


(b) Female

Figure 14: Model Fit: Employer-Provided HI Coverage Rate



(a) Employed Male



(b) Employed Female

Figure 15: Employment Rate (No SBTC)

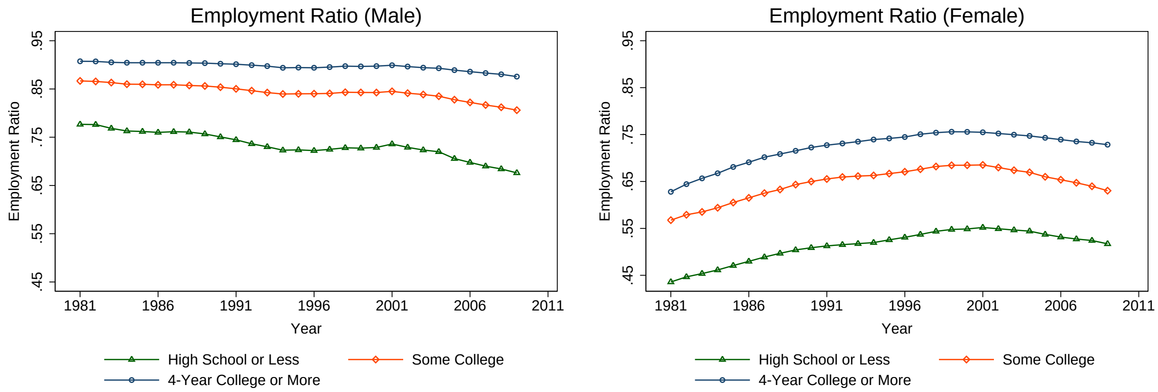


Figure 16: Employer-Provided HI Coverage (No SBTC)

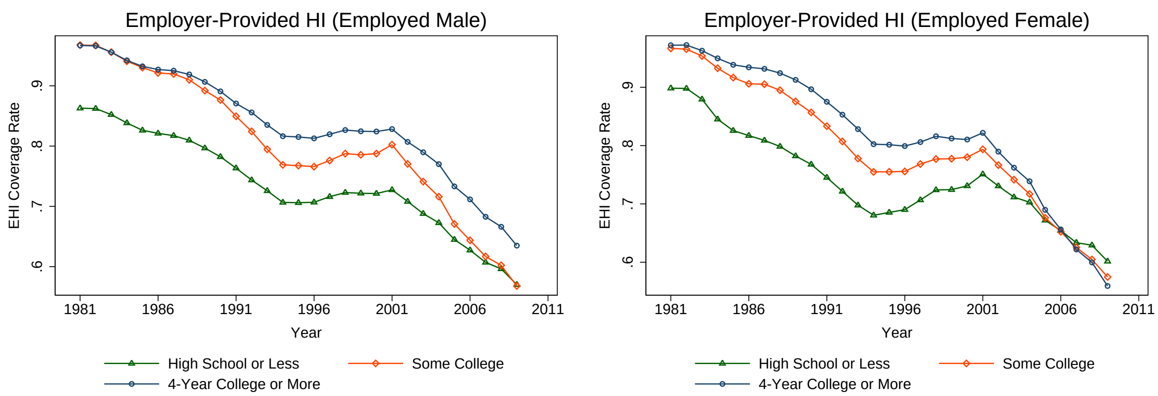


Figure 17: Wages (No SBTC)

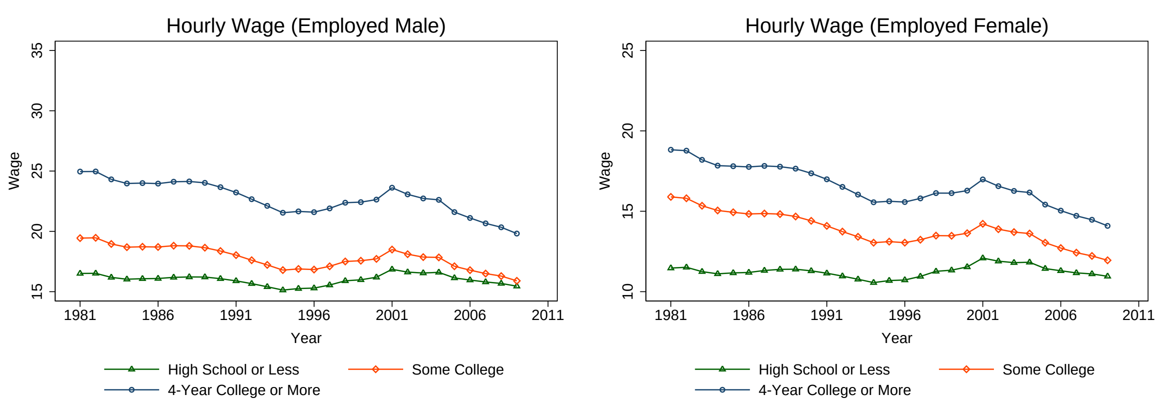


Figure 18: Wage Inequality (No SBTC)

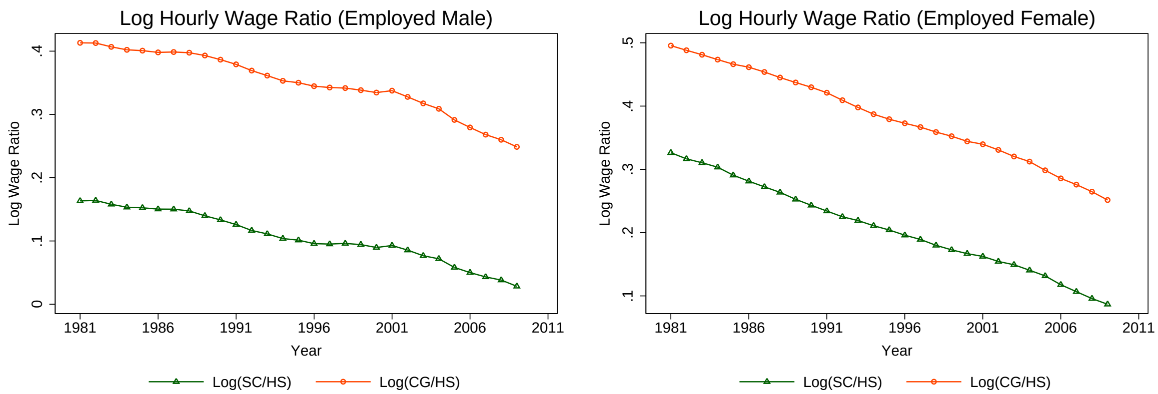


Figure 19: Employer-Provided HI Inequality (No SBTC)

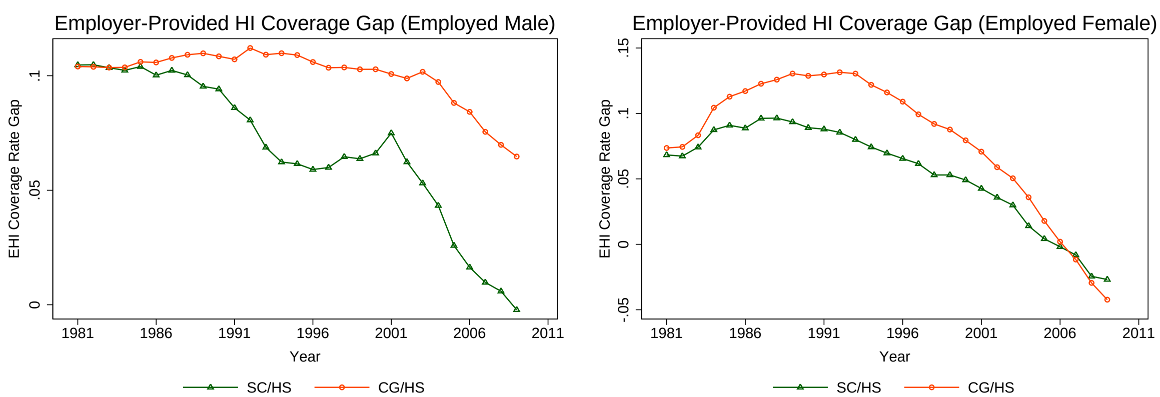


Figure 20: Employment Rate (No Medical Services Cost Growth)

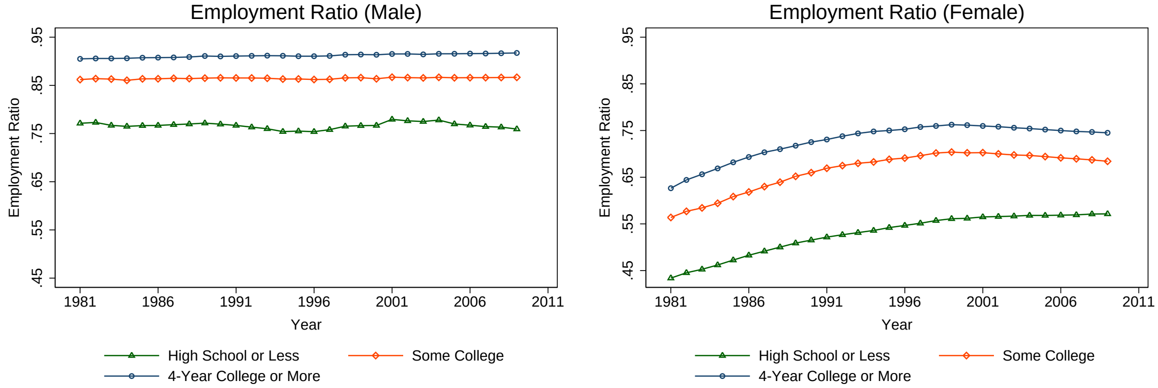


Figure 21: Employer-Provided HI Coverage (No Medical Services Cost Growth)

Figure 22: Wages (No Medical Services Cost Growth)

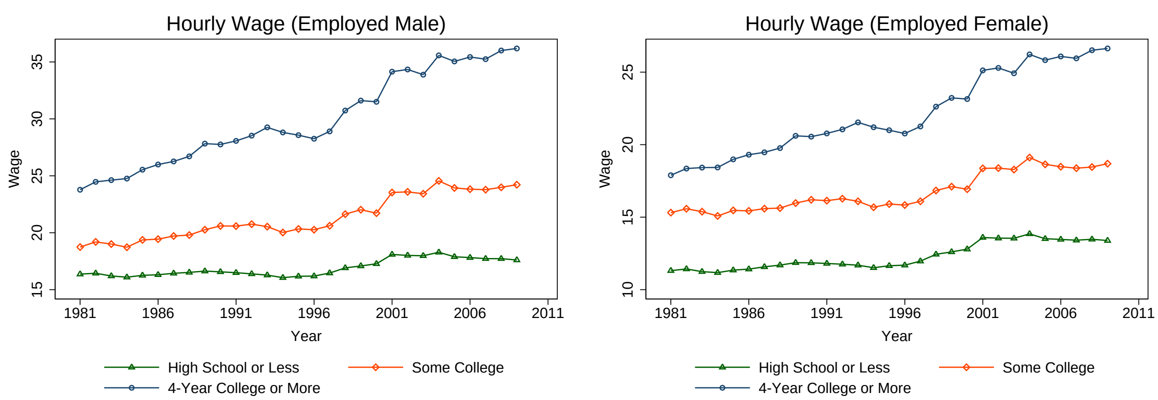


Figure 23: Wage Inequality (No Medical Services Cost Growth)

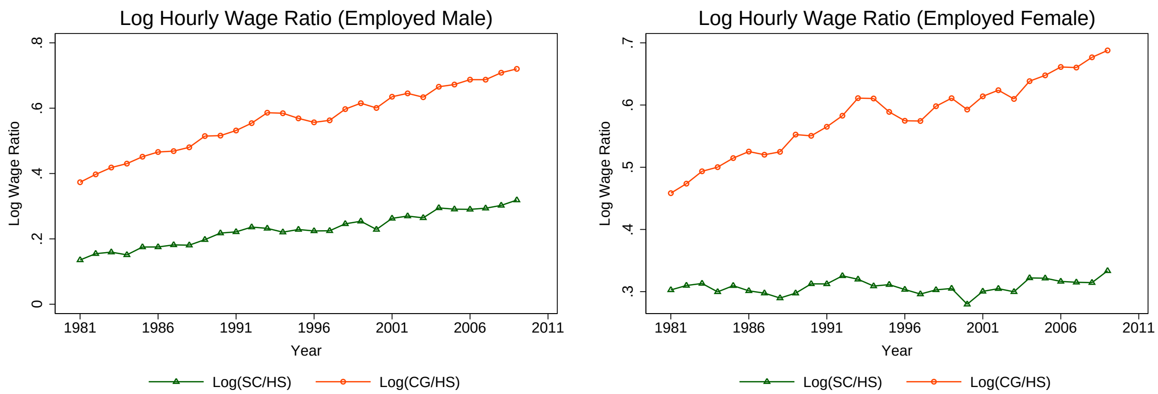


Figure 24: Employer-Provided HI Inequality (No Medical Services Cost Growth)

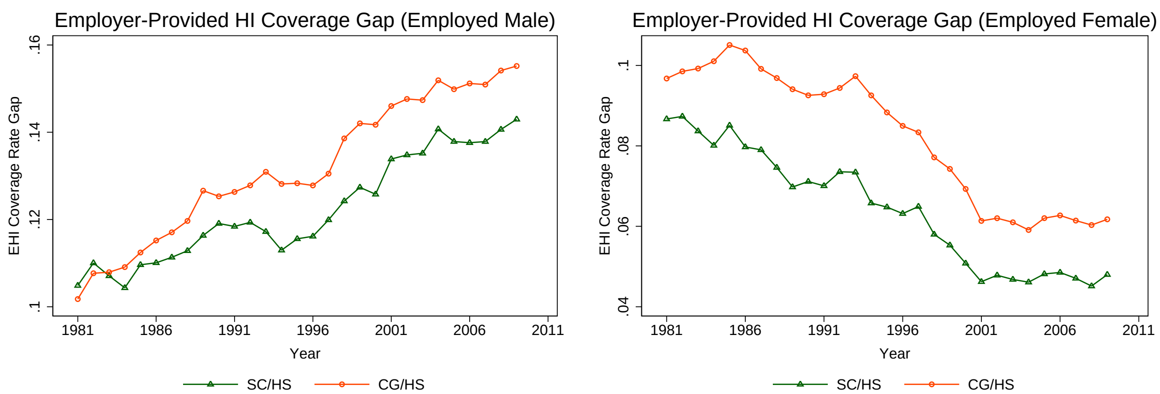


Figure 25: Employment Rate (No Medicaid Expansion)

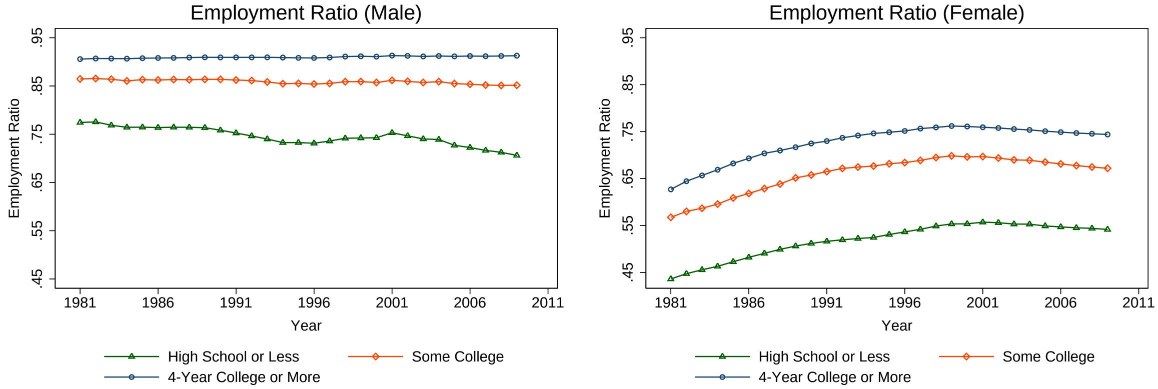


Figure 26: Employer-Provided HI Coverage (No Medicaid Expansion)

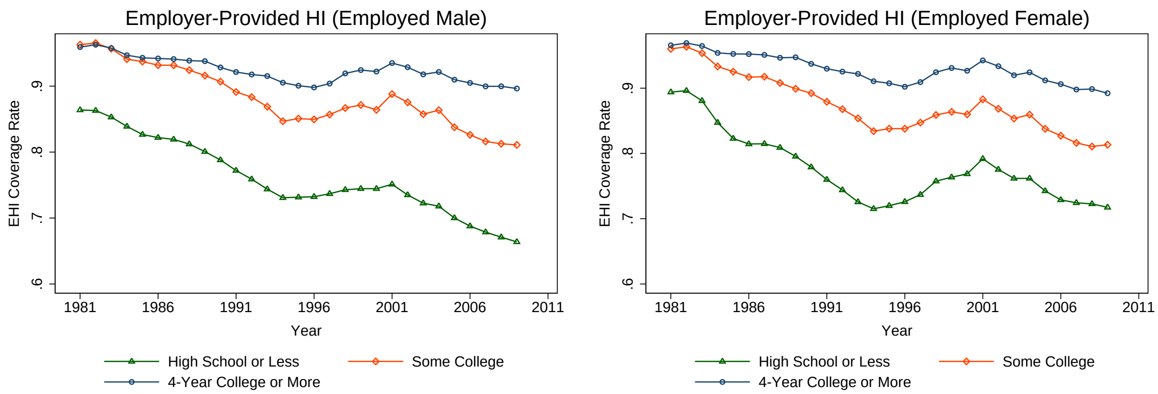


Figure 27: Wages (No Medicaid Expansion)

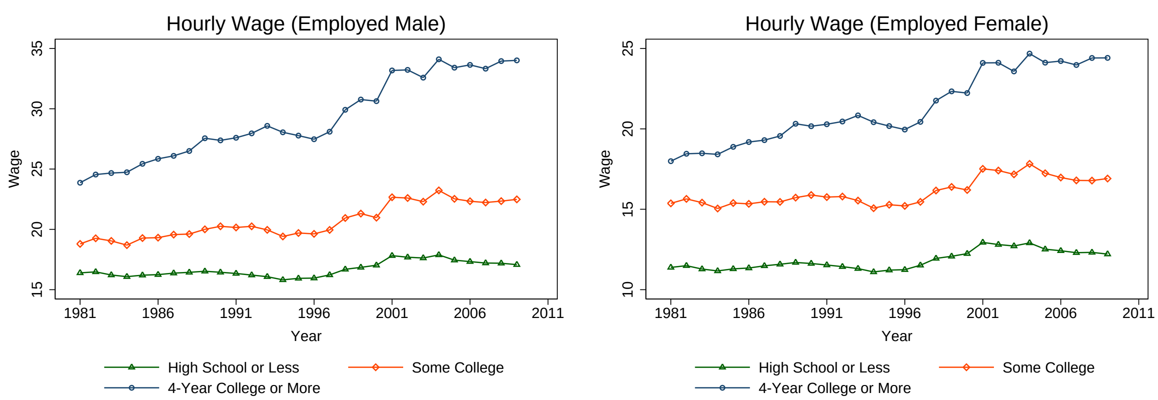


Figure 28: Wage Inequality (No Medicaid Expansion)

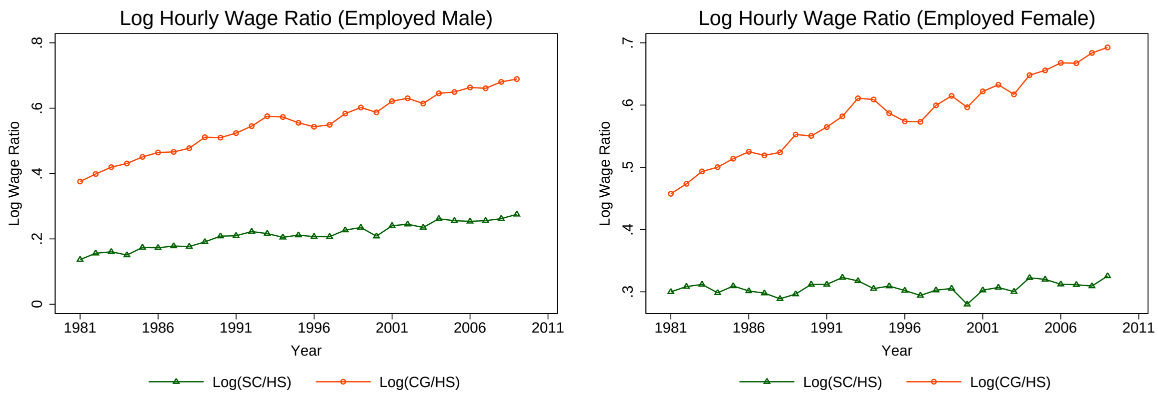


Figure 29: Employer-Provided HI Inequality (No Medicaid Expansion)

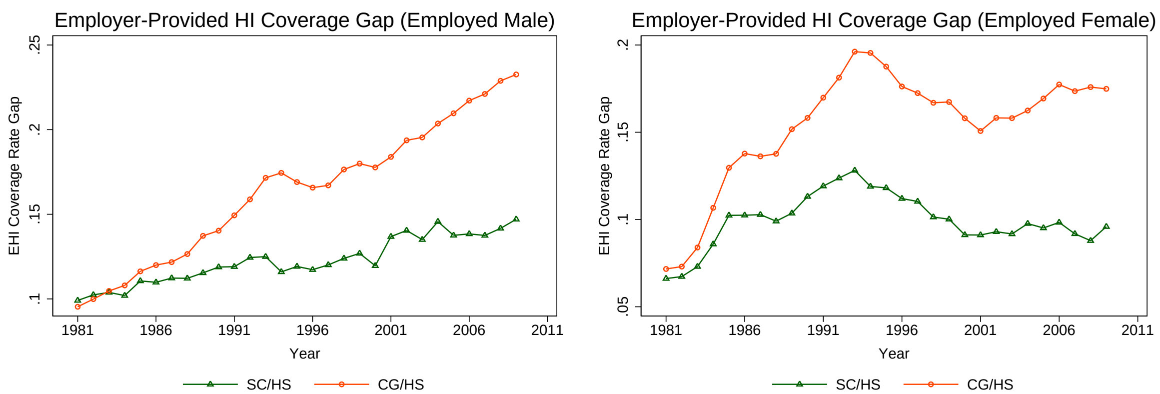


Figure 30: Employer-Provided HI Coverage Gap (Employed Male)

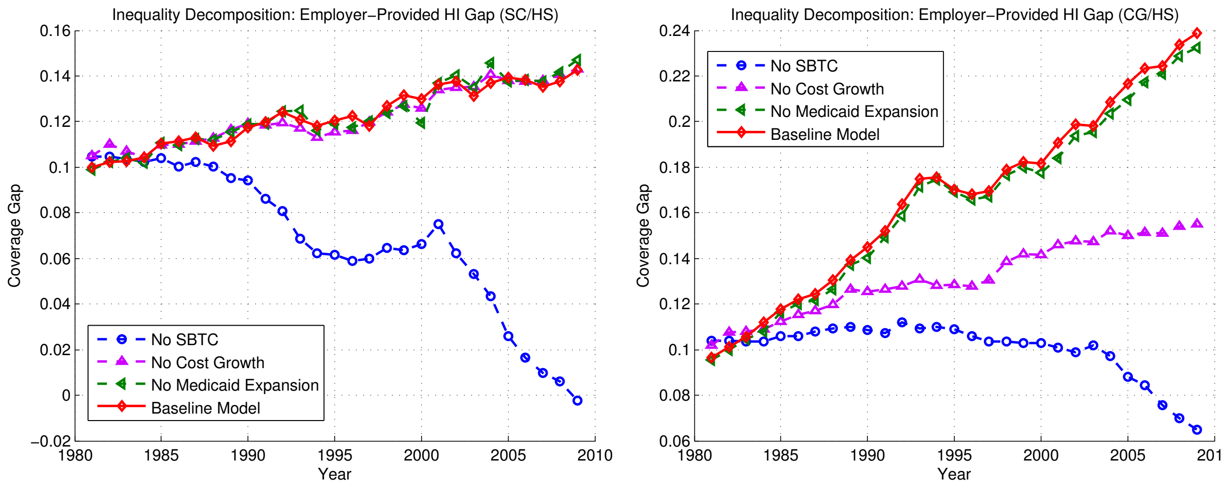


Figure 31: Employer-Provided HI Coverage Gap (Employed Female)

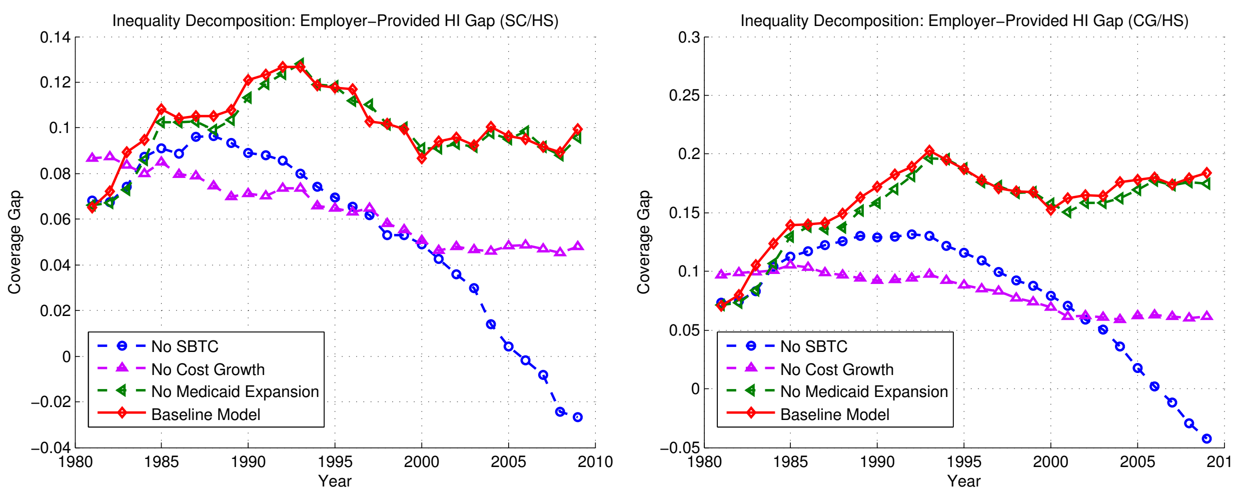


Figure 32: Log Wage Ratio (Employed Male)

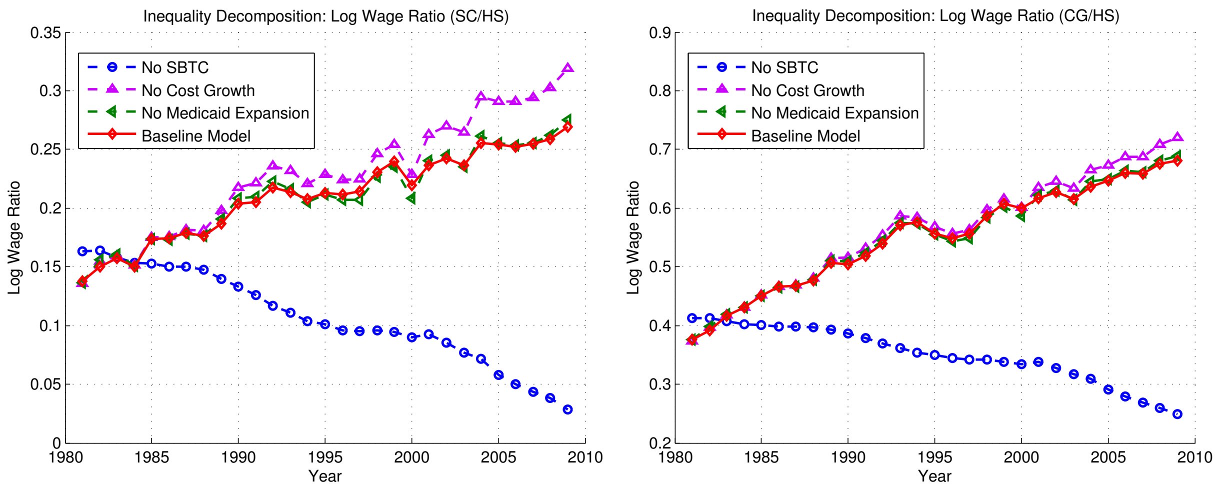


Figure 33: Log Wage Ratio (Employed Female)