BFI Working Paper Series
No. 2013-07

The Determinants of Rising Inequality in Health Insurance and Wages

Rong Hai
Becker Friedman Institute

December 19, 2013

BECKER FRIEDMAN INSTITUTE
FOR RESEARCH IN ECONOMICS
THE UNIVERSITY OF CHICAGO

1126 East 59th Street
Chicago, Illinois 60637
T: 773.702.7587
F: 773.795.6891
bfi@uchicago.edu

The Determinants of Rising Inequality in Health Insurance and Wages

By RONG HAI*

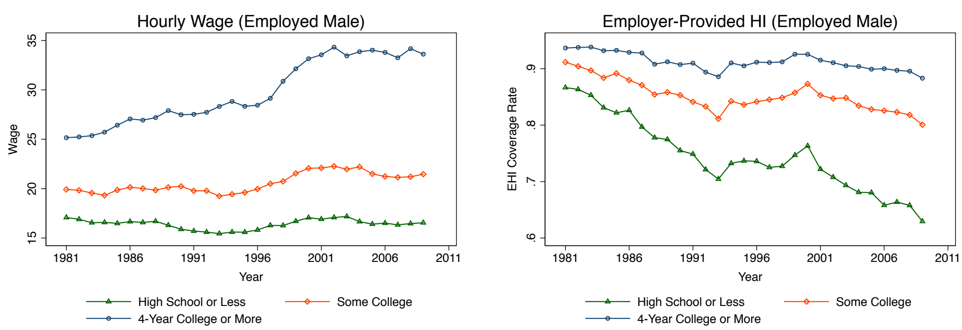
12/19/2013

What has caused the rising gap in health insurance coverage by education in the U.S. over the last thirty years? How does the employment-based health insurance market interact with the labor market? What are the effects of social insurance such as Medicaid? By developing and structurally estimating an equilibrium model, I find that the interaction between labor market technological changes and the cost growth of medical services explains 60% to 70% of the gap. Using counterfactual experiments, I also evaluate the impact of further Medicaid eligibility expansion and employer mandates introduced in the Affordable Care Act on labor and health insurance markets. (JEL I13, J31, J32)

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),

* Becker Friedman Institute for Research in Economics, University of Chicago, 1155E 60th Street, Chicago, IL 60637 (email: ronghai@uchicago.edu). I am grateful to my dissertation advisors Hanming Fang, Petra Todd and Kenneth Wolpin for their guidance and support. I thank Daniel Aaronson, Gadi Barlevy, Marco Bassetto, David Blau, Jeffrey Campbell, Mariacristina De Nardi, Eric French, Donna Gilleskie, Matthew Harris, James Heckman, Luojia Hu, Dirk Krueger, Audrey Light, Lance Lochner, Nicholas Papageorge, Svetlana Pashchenko, Gabriel Picone, Andrew Postlewaite, John Rust, Andrew Shephard, Christopher Taber, Alessandra Voena, and all seminar participants at Federal Reserve Bank of Chicago, Ohio State University, Syracuse University, University of Chicago, University of South Florida, University of Pennsylvania, 2013 North American Summer Meeting, and 2013 Southern Economics Association Annual Meeting for helpful comments.

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 high school or less fell from 87% in 1981 to only 63% in 2009, while coverage among those with a 4-year college degree was relatively stable. The gap in employer-provided health insurance coverage rate between these two groups 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 & EMPLOYER-PROVIDED HEALTH INSURANCE COVERAGE INEQUALITY

Source: March Current Population Survey 1982-2010.

A key finding of the existing literature on inequality is that much of the rise in

[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. Starting from 1992, CPS does not differentiate between high school degree and GED, therefore I do not distinguish between high school dropouts and high school graduates in the education category.

[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.

wage inequality since the 1980's 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 (see for example Pierce (2001), Levy (2006)), but existing research has not yet investigated the causes of the observed changes in health insurance coverage or how these changes relate to wage changes.

The goal of this paper is to address the following three sets of questions that are unanswered in previous studies. First, what are the determinants of the rising inequality in the health insurance coverage gap by education, and what is their individual significance? Second, how does the employment-based health insurance market interact with the labor market? Third, what are the effects of key features of the 2010 Patient Protection and Affordable Care Act (ACA), such as expanding Medicaid eligibility, on the labor market and the employment-based group health insurance market?

To answer these questions, we face three challenges that necessitate a structural model. The first challenge comes from the difficulty of controlling unobservables that individuals act upon to select both their employment and health insurance status. Examples of such unobservables include labor market skill endowment and degree of risk aversion. Secondly, causal inferences are difficult to draw given the complex equilibrium interactions between labor and health insurance market. For example, the pool of workers who select into the labor market also affects the pool of workers who choose health insurance coverage and thus the equilibrium health insurance premium. Furthermore, ex ante policy evaluation of ACA requires a structure model that allows for equilibrium interaction not only in the labor market but also in the health insurance market. Finally, a comprehensive panel dataset which could facilitate an analysis without a structural model is unavailable. Specifically, such a comprehensive data set requires not only individual level panel information on labor market activity, health insurance, medical expenditure and health, but also aggregate information on the labor market and the health insurance market that are representative to the U.S. economy over the last 30 years.

To overcome the challenges discussed above, I develop and structurally estimate an overlapping generations equilibrium model of labor and health insurance markets. Three types of aggregate exogenous changes are incorporated as possible determinants of the health insurance coverage and wage trends over time: skill-biased technological changes, changes over time in the cost of medical care services, and the expansion of Medicaid eligibility. Individuals belong to one of three education groups: high school or less, some college, and 4-year college or more. Besides observed characteristics such as age and gender, individuals also differ in their unobserved labor market endowment and preferences of leisure and risk.

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: wages plus health insurance, or pure wages. Both compensation packages have the same monetary value, which depends on the education-specific skill price and the worker's efficiency skill units. An individual's skill production is education-specific and depends on health and work experience.

Individuals are risk averse and have preferences over health, leisure, and consumption. The demand for health insurance is derived from the following two parts. First, health insurance insures against medical expenditure risk, which depends on the cost of medical services and the individual's health, health insurance and other characteristics such as age and education. Second, it improves the individual's future health and hence future human capital level. Furthermore, an individual's choices about work and compensation are also affected by the implicit tax subsidy provided by employer-provided health insurance in a progressive tax system, as well as government social safety net programs such as Medicaid.[4]

In equilibrium, three education-specific skill prices are determined by equalizing the aggregate supply of education-specific skill units and aggregate demand generated from an aggregate production function every period. Similarly, the price of health insurance premium at each period is equal to the equilibrium average medical expenditure among covered workers. Lastly, individuals' expectations about future prices changes are self-fulfilling.

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, and by combining data from 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.

The individual effects of labor market technological changes, cost growth of medical services, and historical Medicaid eligibility expansion on health insurance coverage gap are quantitatively small. However the interaction of these factors are quantitatively important determinants of the observed health insurance disparity. Specifically, in the presence of both labor market technological changes and cost growth of medical services, the coverage rate of employed male workers with at most a high school degree declines from 92% in 1981 to 71% in 2009, while the coverage rate of employed male workers with at least a college degree decreases slightly from 96% in 1981 to 89% in 2009. The induced health insurance coverage gap between these two groups of workers is 17 percentage points in 2009, account-

[4]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. 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).

ing for 68% of observed coverage disparity in the data.

I analyze the impact of policies that were introduced in the 2010 Patient Protection and Affordable Care Act (ACA), and find that (i) further Medicaid eligibility expansion increases the employment rate by 4 percentage points for men with at most a high school degree, leads to less health insurance coverage disparity and larger wage inequality, and increases Medicaid expenditure on working age population by 5 times; and (ii) the introduction of an employer mandate reduces both wage and health insurance coverage inequality but also lowers the employment rate by 2 percentage points for men with at most a high school degree.

The literature shows that access to health insurance has important effects on both labor force participation and job choice (see an overview by Currie and Madrian (1999) and Gruber (2000)). Recent studies that investigate the relationship between health insurance and labor markets include Dey and Flinn (2005), Blau and Gilleskie (2008), Manovskii and Bruegemann (2010), Pashchenko and Porapakkarm (2012), Cole et al. (2012), Kolstad and Kowalski (2012), Aizawa and Fang (2013), and Garthwaite et al. (2013). Building upon these studies, this paper analyzes the equilibrium interaction between employer-provided health insurance and wages over time and investigates the impact of key features of the ACA on wage and health insurance coverage distribution.

I. The Model

A. Setup

The population of the economy at each calendar year t consists of both males and females aged $a = a_0$ to A. Each individual's education level j belongs to one of three categories: high school or less (HS), some college (SC), and 4-year college or more (CG). Furthermore, individuals differ by their individual heterogeneity, indexed by a discrete type $k \in \{1,\ldots,K\}$, along four dimensions: labor market skill endowment, health production endowment, risk aversion, and value of leisure.[5] From now onwards, I use subscript a to denote an individual's age and use subscript t to denote a specific calendar year.

At the beginning of each period, which corresponds to one year, an age-a individual chooses among three mutually exclusive alternatives $n \in \{1,2,3\}$: (i) working for a job without employer-provided health insurance (i.e., accepting a compensation package of just wages), $n = 1$, (ii) working for a job with employer-provided health insurance (i.e., accepting a compensation package of wages plus health insurance), $n = 2$, and (iii) not working, $n = 3$.

Let r_t^j be the competitively determined skill rental price at time t associated with education level j, and let s_a^j denote the education-specific efficiency skill units that an individual possesses at age a. Then an individual's market marginal productivity is the product of r_t^j and s_a^j. Furthermore, the individual's wages (w_a) and health insurance compensation ($I_a^e \in \{0,1\}$) at age a and year t must satisfy the following equation:[6]

$$w_a + \lambda p_t \cdot I_a^e = r_t^j s_a^j, \quad j \in \{HS, SC, CG\} \tag{1}$$

where $\lambda \in (0,1)$ is the share of the health insurance premium paid by the employer if the individual is covered by employer-provided health insurance ($I_a^e = 1$), and $p_t > 0$ is the equilibrium group health insurance premium at time t. Equation (1) is the zero profit condition for employers, thus employers are indifferent between

[5]The individual heterogeneity (i.e., type) includes not only the individual's cognitive abilities that affect the individual's productivity in the market and home sectors, but also socio-emotional skills or personality traits that shape individuals preferences over risk and leisure.

[6]Using data on Massachusetts Health Reform, Kolstad and Kowalski (2012) finds that jobs with employer-based health insurance (EHI) pay lower wages, and that the compensating differential for EHI is only slightly smaller in magnitude than the average cost of EHI to employers.

offering a compensation package that consists of just wages and a compensation package comprised of wages plus health insurance.

An individual's education-specific skill units (s_a^j) depends on the individual's initial skill endowment ($\kappa_{0,\text{gender},k}^j$), health status that is determined at the end of the previous period (h_a), work experience (expr_a), and a productivity shock (ε_a^j):

$$\text{(2)} \qquad \log(s_a^j) = \sum_k \kappa_{0,\text{gender},k}^j \cdot \mathbf{1}(\text{type} = k) + \kappa_1^j h_a + \kappa_2^j \text{expr}_a + \kappa_3^j \text{expr}_a^2 + \varepsilon_a^j$$

where $\varepsilon_a^j \sim N(0, \sigma_j^2)$. Note $\kappa_{0,\text{gender},k}^j$ is the gender-type specific parameter that introduces permanent heterogeneity among individuals of the same education category even after controlling for all the observables. Given an individual's current employment decision ($d_a^e \in \{0,1\}$), the individual's experience at age $a+1$ is given by $\text{expr}_{a+1} = \text{expr}_a + d_a^e$.

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

$$\text{(3)} \qquad u^*(c_a, d_a^e; h_a, a, \varepsilon_a^l) = 1 - \exp(-\gamma c_a) + \phi_h h_a + (\Gamma_{a,t} + \varepsilon_a^l)(1 - d_a^e)$$

where $\Gamma_{a,t}(\cdot)$ is the value of home time and $\varepsilon_a^l \sim N(0, \sigma_l^2)$ is an age-varying preference shock. I allow $\Gamma_{a,t}(\cdot)$ to depend on the individual's unobserved type, presence of dependent children, age, health, education, and calendar time, specifically:

$$\begin{aligned}\Gamma_{a,t} = &\sum_k \phi_{0,k} \mathbf{1}(\text{type} = k) + \phi_1 Z_a^{ch} + \phi_2 \mathbf{1}(a \geq 45)(a - 45) + \phi_3 (1 - h_a) \\ &+ \phi_4 \mathbf{1}(j = SC) + \phi_5 \mathbf{1}(j = CG) + \phi_6 t + \phi_7 t^2\end{aligned}$$

where Z_a^{ch} is an indicator variable for the presence of dependent children.[7] Moti-

[7]The evolution of the presence of dependent children (Z_a^{ch}) is modeled as exogenous and proba-

vated by the observed patterns between employment and age (see Figure 7), I allow an individual's valuation of home time to vary proportionally with age after age 45.[8] Finally, $\phi_6 t + \phi_7 t^2$ captures the productivity progress in the home sector over time.

An individual is either insured $I_a = 1$ (through employer-provided health insurance or Medicaid) or not insured $I_a = 0$.[9] An insured individual does not pay his medical expenses ($p_t^m m_a$).[10] Employer-provided health insurance is tax exempt. Let $\mathscr{T}(\cdot)$ be the progressive income tax schedule and $\widetilde{\mathscr{T}}(w)$ the after tax income function.[11] Then an individual's budget constraint can be written as follows:

$$c_a = \widetilde{\mathscr{T}}(w_a - (1-\lambda) \cdot p_t \cdot I_a^e) \cdot d_a^e - p_t^m m_a \cdot (1 - I_a) + \text{transfer}_{a,t} \tag{4}$$

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, and transfer$_{a,t}$ is government transfers that guarantee a minimum consumption floor (c_t^{min}).[12] The existence of a consumption floor captures social safety net programs other than Medicaid, such as Supplemental Security Income, Unemployment Insurance, Food Stamps, and uncompensated care.[13]

bilistic. Please see online appendix for details of parameterization and estimation.

[8]This specification is more parsimonious than the alternative specification of $\phi_{2,0} a + \phi_{2,1} a^2$.

[9]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 and is much less likely to cover pre-existing medical conditions as high administrative costs and adverse selection problems can result in prohibitively expensive premiums. 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. See French and Jones (2004) for a similar argument.

[10]Here I only consider full coverage and no coverage, but the model can be extended to include partial insurance.

[11]Appendix E.E2 describes the parameterization and estimation of $\mathscr{T}(\cdot)$.

[12]transfer$_{a,t} = \max\{0, c_t^{min} - (\widetilde{\mathscr{T}}(w_a - (1-\lambda) \cdot p_t \cdot I_a^e) \cdot d_a^e - p_t^m m_a \cdot (1 - I_a))\}$.

[13]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).

As noted, an individual's medical services expenditure, $p_t^m m_a$, is the product of the cost of medical service at time t (p_t) and the amount of medical service consumption the individual purchases at age a (m_a). An individual's medical service consumption m_a is assumed to be exogenous and depends upon health insurance coverage status, health status, age, education, gender, and an individual-specific age-varying component as follows:[14]

$$(5) \qquad \log(m_a) = \mu_m(I_a, h_a, a, j, \text{gender}) + \sigma_m(h_a, a, j, \text{gender}) \cdot \underbrace{(\varepsilon^m_{a,0} + \varepsilon^m_{a,1})}_{\varepsilon^m_a}$$

where $\mu_m(I_a, h_a, a, j, \text{gender})$ is an exogenous function of health insurance, health, age, education and gender, $\sigma_m(h_a, a, j, \text{gender})$ controls the volatility of medical consumption risk and is a function of an individuals' health, age, education and gender. The medical expenditure risk (ε^m_a) is decomposed into a predictable component ($\varepsilon^m_{a,0}$), that is known to the individual (but not to the econometrician) when making employment-coverage decisions, and an unpredictable component ($\varepsilon^m_{a,1}$), that is realized after the decisions been made.[15]

Health status is assumed to be either good ($h_a = 1$) or bad ($h_a = 0$).[16] The transition dynamic of health status depends on current health status h_a, health insurance coverage status I_a, education, age and unobserved heterogeneity k.[17] Specifically,

[14] See Blau and Gilleskie (2001) and French and Jones (2011) for a similar specification.

[15] Studies suggest that the medical expenditure shocks are very volatile and persistent, even after controlling for observed individual characteristics such as health status (French and Jones (2004)). Thus, I decompose the medical expenditure shocks and allow individuals to make their employment and health insurance coverage decisions based on the predictable component $\varepsilon^m_{a,0}$ which is unobserved by the econometrician.

[16] 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.

[17] 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 a health transition probability function that depends on age, previous health status and the lowest and highest average wage classes.

the probability of making a transition from health status h_a at age a to good health status at age $a+1$ is given by:[18]

$$\Pr_{a+1}(h_{a+1}=1; h_a, I_a, j, a, k) = \frac{\exp(X_a^h\beta)}{1+\exp(X_a^h\beta)} \tag{6}$$

where $X_a^h\beta = \sum_k \beta^j_{0,\text{gender},k} \cdot \mathbf{1}(\text{type}=k) + \beta_1^j h_a + \beta_2 I_a + \beta_3 a + \beta_4 \mathbf{1}(j=SC) + \beta_5 \mathbf{1}(j=CG) + \beta_6 a^2$.

Medicaid is the biggest public health insurance program for non-elderly adults in the U.S. It is a means-tested program, and 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_t^{cat}) and categorical standard ($d^c_{a,t} \in \{0,1\}$) as follows

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

where the last term $\mathbf{1}(I^e_a = 0)$ ensures that individuals with private health insurance coverage are not eligible for Medicaid.[19]

B. Individual Optimization

An individual maximizes the expected present discounted value of remaining lifetime utility by making employment (including health insurance) decisions from age a_0 to A. The subjective discount rate is $\delta \in (0,1)$.

Denote by $\Omega_{a,t}$ the information set of an individual at the beginning of age a and

[18] Notice although 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.

[19] Details regarding how I approximate the Medicaid eligibility rule can be found in Appendix E.E3.

time t. Let $V_{n,a}(\Omega_{a,t})$ and $u_{n,a}$ denote the value function and utility function associated with choice n respectively. Thus, an individual's value function ($V_a(\Omega_{a,t})$) at age a and period t is given by the maximum value among the three alternative-specific value functions,

$$V_a(\Omega_{a,t}) = \max\{V_{1,a}(\Omega_{a,t}), V_{2,a}(\Omega_{a,t}), V_{3,a}(\Omega_{a,t})\}. \tag{8}$$

where $V_{n,a}(\Omega_{a,t}) = u_{n,a} + \delta\mathbb{E}(V_{a+1}(\Omega_{a+1,t+1})|n, \Omega_{a,t})$.[20] The value function at age $A+1$, $V_{A+1}(\cdot)$, is allowed to depend on health, i.e., $V_{A+1} = \phi_{RE} h_{A+1}$.

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.[21] Therefore, if an individual is eligible for Medicaid, the individual does not choose a job with employer-provided health insurance, i.e., $V_{1,a}(\Omega_{a,t}) > V_{2,a}(\Omega_{a,t})$. If an individual is not eligible for Medicaid, then the individual's optimal decision rule on employer-provided health insurance is summarized in Proposition 1.[22]

Proposition 1. *If $d^c_{a,t} \cdot \mathbf{1}(r^j_t s^j_a \leq y^{cat}) = 0$, then an employed individual's health insurance choice is characterized by the following threshold behavior*

$$I^e_a = \begin{cases} 1 & \text{if } \xi_{a,t} \leq \xi^*_{a,t} \\ 0 & \text{otherwise} \end{cases}$$

where $\xi_{a,t}$ is the certainty equivalent consumption value for the individual in the presence of risky medical expenditure, and $\xi^*_{a,t}$ is the threshold value for health insurance coverage that is increasing in the individual's marginal productivity ($r^j_t s^j_a$)

[20]Please refer to online appendix for detailed specification of $V_{n,a}(\Omega_{a,t})$.

[21]Here I assume that the take-up cost of Medicaid is small and there is no quality difference between Medicaid and employer-provide health insurance.

[22]Proof of Proposition 1 is provided in online appendix.

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*.*

C. Aggregate Production and Changes

To close the model, I assume there is an aggregate production function of constant elasticity of substitution (CES) form:[23]

$$C_t \equiv \zeta_t \left\{ z_t^{HS}(S_t^{HS})^{\nu} + z_t^{SC}(S_t^{SC})^{\nu} + z_t^{CG}(S_t^{CG})^{\nu} \right\}^{1/\nu} \tag{9}$$

where ζ_t represents the Hicks-neutral technical change, z_t is the education-specific skill-augmenting technological change, and S_t is the aggregate quantity of education-specific skills. Skill-biased technology changes (SBTC) involve increases in z_t^{SC}/z_t^{HS} and z_t^{CG}/z_t^{HS}. The aggregate elasticity of substitution between different skills is $1/(1-\nu)$.[24]

I assume that SBTC follows a deterministic quadratic time trend as follows (see e.g. Autor et al. (2008)):

$$\log(z_t^j/z_t^{HS}) = g_{z0}^j + g_{z1}^j t + g_{z2}^j t^2, \quad j = SC, CG. \tag{10}$$

[23]A canonical model of changes in wage structure and skill differentials assumes a CES production function of only two skills, high and low (e.g. Katz and Murphy (1992) and Autor et al. (2008)). Here I include three skills groups into a CES production function, assuming the elasticity of substitution between different skill groups is the same. Alternatively, one could specify one of the following two nested-CES functional forms: $C_t = \zeta_t \left\{ z_t^{HS}(S_t^{HS})^{\nu_1} + (z_t^{SC}(S_t^{SC})^{\nu_2} + z_t^{CG}(S_t^{CG})^{\nu_2})^{\nu_1/\nu_2} \right\}^{1/\nu_1}$ or $C_t = \zeta_t \left\{ (z_t^{HS}(S_t^{HS})^{\nu_1} + z_t^{SC}(S_t^{SC})^{\nu_1})^{\nu_2/\nu_1} + z_t^{CG}(S_t^{CG})^{\nu_2} \right\}^{1/\nu_2}$. Ex ante it is difficulty to determine which one of the three specifications is the best, except that the current specification under Equation 9 is most parsimonious. However, as shown later by the goodness of model fit (Section III.B), the current model specification provides a good description of the aggregate economy as it replicates the aggregate time trends well.

[24]The three skills are gross substitutes when $1/(1-\nu) > 1$ (or $\nu > 0$), and gross complements when $1/(1-\nu) < 1$ (or $\nu < 0$).

Aggregate neutral technical change, ζ_t, is assumed to evolve according to:[25]

$$\log \zeta_{t+1} - \log \zeta_t = g^{\zeta} + \vartheta^{\zeta}_{t+1}. \tag{11}$$

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

$$\log p^m_{t+1} - \log p^m_t = g^m + \vartheta^m_{t+1}. \tag{12}$$

D. Model Equilibrium

In a competitive labor market, the equilibrium price, r^j_t, is given by the marginal product of aggregate education-specific skills S^j_t:

$$r^j_t = \frac{\partial C_t}{\partial S^j_t} = \zeta_t \left(z^{HS}_t (S^{HS}_t)^{\nu} + z^{SC}_t (S^{SC}_t)^{\nu} + z^{CG}_t (S^{CG}_t)^{\nu} \right)^{1/\nu - 1} z^j_t (S^j_t)^{\nu - 1} \tag{13}$$

where

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

and $L_{a,t}$ is the total number of age-a individuals who exist in the economy at time t. Compared to previous studies on changes in wage structure and skill differentials, here I draw a distinction between the equilibrium skill price and the wage rate: only the equilibrium skill price provides a full description of the labor market opportunity.

As shown by Equation 13, $\nu < 1$ is the necessary condition for a relative rise in

[25] The key mechanisms accounting for changes in workers' relative compensation are the relative changes in technologies and skill supplies (e.g., z^{CG}_t / z^{HS}_t and S^{CG}_t / S^{HS}_t), not the absolute terms. Moreover, the absolute levels of $\log \zeta_t$, z^{HS}_t, and S^{HS}_t can not be distinguished from each other. Without loss of generality, I normalize $z^{HS}_t = 1$ for all t. Under such normalization, the estimated $\log \zeta_t$ also absorbs the effect of z^{HS}_t over time.

S_t^j/S_t^{HS} to decrease the relative skill price r_t^j/r_t^{HS} for $j = SC, CG$.

Assumption.

$$\nu < 1$$

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

$$p_t = \frac{\sum_{a=a_0}^{A} \sum_{i=1}^{L_{a,t}} p_t^m \cdot m_{i,a,t} \cdot I_{i,a,t}^e}{\sum_{a=a_0}^{A} \sum_{i=1}^{L_{a,t}} I_{i,a,t}^e}. \tag{14}$$

Definition (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_t^j, p_t) and their forecasting rules as given; (ii) equilibrium skill prices: r_t^j that are determined by the marginal productivity of aggregate skill units (Equation (13)); (iii) equilibrium health insurance premium: p_t is given by the average medical expenditure of those who are covered (Equation (14)); (iv) forecasting rules are consistent with agents' policy functions and aggregate dynamics of ζ_t and z_t^j.*

E. Model Solution

To solve the model, I assume that individuals' forecasting rules for the changes in the logarithm of equilibrium prices (including skill prices and health insurance premium) can be approximated by a linear function of changes in the previous period's prices and changes in current exogenous aggregate variables following Lee and Wolpin (2006). The details of the solution algorithm are described in the online Appendix C.

II. Estimation Strategy

A. 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 premium in the group heath insurance market over time. However, such a comprehensive data set 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. Online Appendix A provides detailed data description and summary statistics.

B. Initial Conditions

The initial condition of each individual at age 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.[26] The underlying assumption is that conditional on unobserved type, these observable initial conditions are exogenous. Finally, the joint distribution of education, health status, and presence of dependent children at age 25 comes from CPS data; the age-25 experience distribution is obtained from NLSY 1979-1994 for each education group and gender.

[26]Online Appendix F.F1 provides a detailed description on type probability specification.

C. Identification

The identification of individual level parameters relies on two sets of exclusion restrictions. The first set of exclusion restrictions requires that there are some variables that affect the selection equations but not the outcome equation (i.e. compensation equation in current context). One such variable is the presence of dependent children, which does not enter compensation determination directly. However, the presence of dependent children impacts an individual's valuation of leisure, and thus affects the individual's work decision directly. Furthermore, the presence of dependent children impacts an individuals' decisions on private health insurance coverage by entering the eligibility rule of Medicaid. The second set of exclusion restrictions requires that some variables enter employee compensation determination but not enter the utility function directly. Examples of such variables are experience and experience squared.

Furthermore, the risk aversion coefficient is identified largely from the wage differential between two otherwise identical workers: one with employer-provided health insurance and one without. This wage differential is the required wage increase in order for the worker to "give up" employer-provided health insurance, which measures on the individual's risk aversion. The utility of health is mainly identified by the life-cycle pattern of health insurance coverage. As an individual ages, although the insurance value of health insurance increases due to rising medical expenditure risk, the remaining lifetime utility of health declines, which offsets the individual's demand for health insurance and generates a relatively flat health insurance demand in the late part of the lifecycle.

The distribution of unobserved types is identified largely by exploiting the panel structure of the data. Conditional on all observables, the persistence of individuals' outcomes (and choices) over time helps separate unobserved individual heterogeniety from transitory uncertainty. Finally, the parameters in the aggregate production function are mainly identified by the exogenous changes in cohort size over time, which allows for exogenous variation in aggregate labor supply over time.

D. Estimation Method

The estimation method is simulated method of moments (SMM).[27] 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. The weighting matrix is the inverse of the diagonal matrix of the variance and covariance matrix of these moments.[28]

III. Estimation Results

A. Key Parameter Estimates

Risk Aversion: As seen in Table 3, the estimated absolute risk aversion coefficients range from 1.15E-04 to 2.95E-04 for men and from 1.53E-04 to 3.94E-04 for women. Type 3 individuals are most risk averse and type 2 individuals are least risk averse. Studies on risk preference estimate an average absolute risk aversion between 6.6E-05 and 6.7E-03 (Gertner (1993), Metrick (1995), Cohen and Einav (2007), Einav et al. (2011)).[29] On average, females are more risk averse than males

[27]Maximum Likelihood Estimation method in this case is computational infeasible. A brief discussion can be found in Appendix D.D2.

[28]Online Appendix D.D1 provides a detailed description on the estimation method, moment conditions, and standard error calculation.

[29]Note that risk aversion estimates in this paper should not be directly compared with the estimates from existing studies. This is because this paper introduces (1) three types of risk (i.e., medical expenditure risk, health risk and earnings risk), which have not been jointly incorporated

(see, for example Cohen and Einav (2007)).

Preferences over Health and Leisure: As seen in Table 3, the consumption value of good health is slightly higher for men than for women. However women have a higher valuation of good health at terminal age 65 than men, potentially reflecting the longer life expectancy of women. There is large heterogeneity in the value of leisure among individuals: type 3 individuals value leisure the most and type 2 the least. On average, women value leisure more than men. Women value home production much more when there are dependent children ($\phi_1 = 0.091$) while the opposite is true for men ($\phi_1 = -0.155$). The valuation of leisure increase with age both for men and women at a similar rate. More importantly, both men and women value leisure more when in bad health status than when in good health status (ϕ_3 is positive and significant). Lastly, the value of home time decreases over time at a much higher rate for women than for men, reflecting the relatively large impact of technical improvement on women's productivity in the home sector.

Health Transition: As seen in Table 5, the transition process of health is very persistent: for a change in current health status from bad to good, the odds of being in good health next period (versus bad health) increase by a factor of 5.3. Current health insurance coverage increases the odds of being in good health next period by a factor of 1.2. Compared with individuals with high school or less, *ceteris paribus*, the odds of good health increases by a factor of 1.3 and 2.1 for individuals with some college and 4-year college respectively. The probability of being in good health deteriorates with age at an increasing rate. Finally, there is moderate heterogeneity among individuals' initial endowments in the health production function. Type 1 individuals have the highest health endowment and thus a higher probability of being in good health than both type 2 and type 3 individuals otherthings being

in the previous literature; (2) social insurance such as Medicaid and a minimum consumption floor, which effectively reduces the actual consumption risk an individual faces.

TABLE 1—ELASTICITY OF SUBSTITUTION AND SKILL-BIASED TECHNOLOGY CHANGES

Aggregate Production	ν		ES ($\frac{1}{1-\nu}$)	
	0.420	(0.0184)	1.724	(0.0545)
SBTC	j=SC		j=CG	
g_{z0}^{j}	-0.531	(0.0134)	-0.277	(0.0066)
g_{z1}^{j}	0.020	(0.0010)	0.027	(0.0007)
$g_{z2}^{j} \cdot 100$	-0.012	(0.0028)	-0.011	(0.0009)

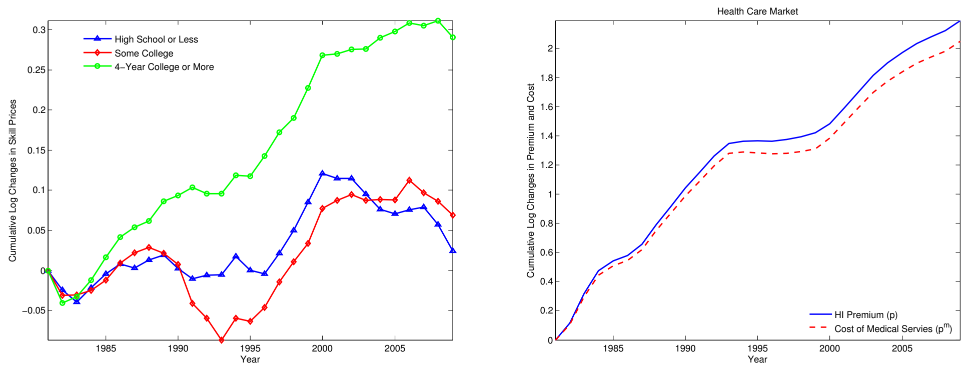
Standard errors in parentheses

equal.

Skill Production: The parameter estimates for the production functions of logarithm of the education-specific skills are reported in Table 6. Good health increases the education-specific skill level by 8.7% for high-school skills, by 12.3% for some-college skills, and by 18.2% for 4-year-college skills. Work experience increases human capital level at a decreasing rate. There is also large heterogeneity in the initial skill endowment.

Aggregate Production and Sequences: As seen in Table 1, the estimated elasticity of substitution among the three education-specific skills is 1.724. This implies that on average, a 10 percent increase in the relative supply of college equivalents reduces the relative skill price by 5.8 percent. Literature estimates the elasticity between low skill and high skill below 2.0 and above 1.0 (see Heckman et al. (1998), Lee and Wolpin (2010), Goldin and Katz (2007)). The estimated growth rate of the logarithm of SBTC is 0.027 for workers with 4-year college or more and 0.020 for workers with some college, and are both decreasing over time.[30] Figure 2 plots the aggregate prices in the labor market and the health care market.

[30]Autor et al. (2008) estimate the growth rate of skill-biased technological changes of college skills to be 0.028 using a quadratic time trend, for the period 1963-2005.



LABOR MARKET HEALTH CARE MARKET

FIGURE 2. CUMULATIVE LOG CHANGES IN PRICES

B. Model Fit

Time Series Pattern: As shown from Figures 4 to 6, the model successfully replicates the following time series patterns in the U.S. labor and health insurance markets over the last 30 years: (i) a slight decline in employment rate among men across all education groups and a rapid increase in women's employment rate for the same time period; (ii) a sharp decline in employer-provided health insurance coverage among less educated workers and relatively stable coverage among more educated workers both for men and women; and (iii) a relatively rapid wage growth among more educated workers both for males and females, a stagnant and slightly U-shaped wage growth among less educated male workers, and a relatively rapid wage growth among less educated female workers.

Life-cycle Pattern: The model also replicates the important patterns on employment, health insurance coverage, and wage patterns across different age groups (see Figures 7 to 9). In particular, the model replicates the large increase in health insurance coverage in the earlier part of life and the hump-shaped health insurance coverage over the later part of life very well for less educated workers. However, the model slightly over predicts the health insurance coverage after age 45 for workers with a 4-year college degree (see Figure 8).

Health Distribution: As seen in Figure 10, the model replicates the health distribution across insurance-employment groups: the worst health distribution is among those not employed and the best is among those with employer-provided health insurance. This pattern is generated from three mechanisms of the model: (1) ex ante selection based on risk aversion; (2) ex ante selection based on health: healthy individual select into employment group, resulting in a better health distribution among the employed;[31] (3) ex post productivity of health insurance: health insurance coverage increase health stochastically.

IV. Inequality Decomposition

In this section, I quantify the impact of the following three factors on health insurance and wage inequality via counterfactual simulation: (1) labor market technological changes; (2) changes in the cost of medical services; (3) historical Medicaid eligibility expansion. To do this, I perform the following thought experiment: suppose that all other factors, except the labor market technological changes, had remained at their 1981 level,[32] 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. Figures 3 and 11 plot the evolution of the health insurance coverage gap over time under each simulation scenario.

When I let the labor market technologies change over time but set all other factors to their 1981 level, the employer-provided health insurance rate increases by

[31] Because health is productive and healthy individuals value leisure less than unhealthy individuals.

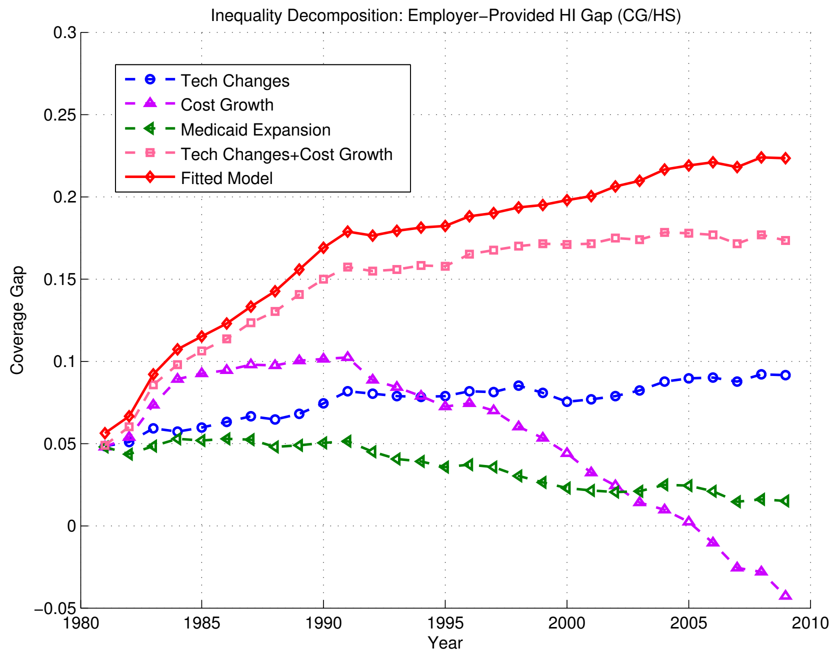
[32] Specifically, I let the labor market technologies change according to their estimated time trend. I shut down the changes in all other estimated time-varying processes, such as cost of medical services, Medicaid eligibility rule, and the minimum consumption floor.

1 to 3 percentage points for all education groups from 1981 to 2009 (Figure G1). The health insurance coverage gap between 4-year college male workers and high school male workers increases to 9 percentage points in 2009, compared to 22 percentage points in the fitted model. The same gap for female workers increases to 10 percentage points in 2009, compared to 21 percentage points in the fitted model. The labor market technological changes disproportionally increase wages of highly skilled workers: the wage rate of 4-year college male workers increases from $25 in 1981 to $34 in 2009, and account for most of the rising wage inequality.[33]

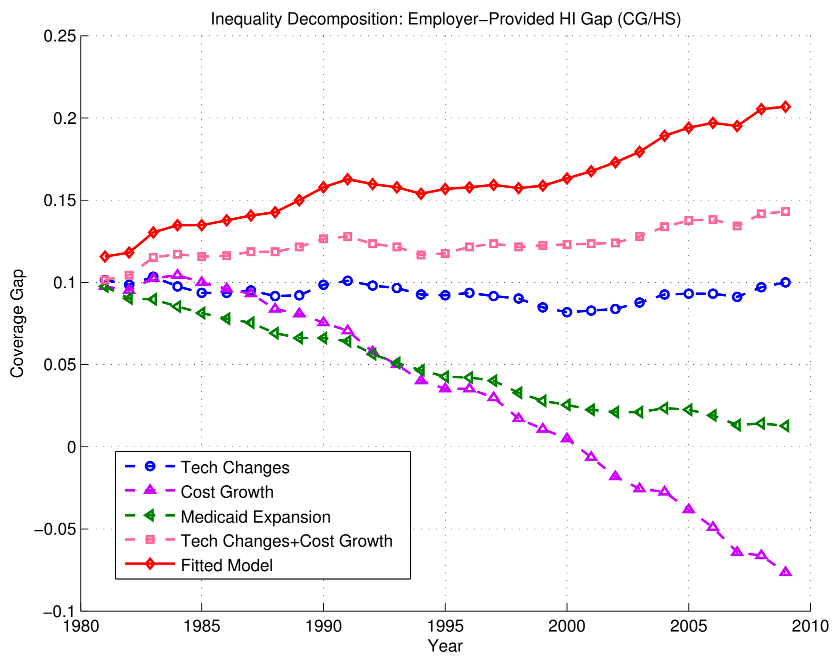
When I let the cost of medical care services grow but fix all other factors, health insurance coverage rates drop from 92% in 1981 to 74% in 2009 for male workers with at most a high school degree, and from 97% to 70% for male workers with at least a 4-year college. Because the relative prices of college workers decline over time in the absence of labor market technological changes, higher educated workers respond more to the rising health insurance premium and drop health insurance. As a result, the health insurance coverage gap between 4-year college workers and high school workers decreases over time and becomes negative in 2009. The impact of rising cost on wage inequality is quantitatively small.

To investigate the impact of Medicaid eligibility expansion on health insurance coverage inequality, I let both the income threshold level and categorical standard evolve according to estimated process and fix other factors of the model to their 1981 level. The impact of Medicaid eligibility expansion from 1981 to 2009 on employer-provided health insurance coverage for all education groups is quantitatively small, as is the impact on wages. The employer-provided health insurance coverage gap between 4-year college male workers and high school male workers is 1 percentage point in 2009, compared to 22 percentage points in the fitted model. The impact of Medicaid eligibility expansion since 1980 on log wage ratio

[33]See Figure 4(a) in online appendix.



(a) Male



(b) Female

FIGURE 3. EMPLOYER-PROVIDED HI COVERAGE GAP (CG/HS)

is quantitatively negligible as well (Figure G4).

As shown from the above discussion, the proportion of the rising gap of health insurance that can be explained by each individual factor is not quantitatively large. The most important determinant of rising inequality of health insurance coverage by education is the interaction between labor market technological changes and the cost growth of medical services. Specifically, in the presence of both labor market technological changes and cost growth of medical services, the coverage rate of employed male workers with at most a high school degree declines from 92% in 1981 to 71% in 2009, while the coverage rate of employed male workers with at least a college degree decreases slightly from 96% in 1981 to 89% in 2009. The induced health insurance coverage gap between these two groups of workers is 17 percentage points in 2009, accounting for 77% of coverage gap in the fitted model (68% of observed coverage disparity in the data). Similarly, the health insurance college-high school coverage gap of employed females is 14 percentage points in 2009, accounting for 67% of the coverage inequality in fitted model (64% of the observed coverage inequality in the data). (see Figures 3(a) and 3(b)).

V. Health Care Policy Analyses

In this section, I conduct policy experiments to evaluate two health care policies that were introduced in ACA: further Medicaid expansion and employer mandates. Under ACA, 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. The goal of this section is not to provide a complete evaluation of ACA, but to provide insight on the quantitative effects of key policy elements related to Medicaid and employment policy, which have already been embedded in the estimated model.[34] Specifically, I implement policy experiments associated with further Medicaid eligibility expansion and employer mandates as follows:

(i) Further Medicaid eligibility expansion: all individuals whose income is lower than 133% of FPL is eligible for Medicaid coverage. In this experiment, I set the income threshold of Medicaid coverage (y_t^{cat}) to be 133% of FPL. More importantly, I set $d_{a,t}^c = 1$ so there is no categorial screening for Medicaid eligibility. This change is substantial, especailly for low income men without children or disabilities.

(ii) Employer mandates: employers that do not offer coverage to its employees are required to pay a fee of $2000 per employee.[35] Thus in labor market equilibrium, the following equality must hold: $w + \mathbf{1}(I^e = 1)\lambda p = r_t^j s_a^j - \mathbf{1}(I^e = 0) \times$ penalty.

I start by simulating a benchmark scenario where there are no policy changes in the year 2014 (case [1]). Then, I conduct the following three policy experiments assuming only further Medicaid eligibility expansion is introduced (case [2]), only employer mandates are introduced (case [3]), and both Medicaid eligibility expansion and employer mandates are introduced (case [4]).[36]

Table 2 shows the changes in equilibrium prices and government Medicaid expenditures and tax revenues in each policy experiment relative to the benchmark

[34]The ACA reform is very complex. Generally speaking, the policies proposed in 2010 ACA consists of further Medicaid expansion, employer mandates, individual mandates, and health insurance exchange. Please refer to Aizawa and Fang (2013) and Handel et al. (2013) for studies on ACA and health insurance exchange.

[35]Here I do not differentiate the size of different employers, effectively this imposes a $2000 penalty on small businesses. Thus the estimated effect here is likely to be larger than what is actually under ACA.

[36]When conducting the above analyses, I allow both the SBTC and the cost of medical service to change according to the estimated process, and fixed the rest of the components of the economy to their 2009 levels. Furthermore, I did not impose a balanced government budget constraint in these experiments, thus all the results here should be interpreted with caution.

scenario. Under further Medicaid eligibility expansion, the labor market opportunity improves for high skilled workers and deteriorates for low skilled workers: high school skill price declines by 0.79% and 4-year college skill price increases by 0.53%, compared to the benchmark case. The introduction of employer mandates, however, raises the high school skill price by 0.47% and reduces the 4-year college skill price by 0.23%. The impact of further Medicaid eligibility expansion on the private group health insurance premium is negative but small (-0.63%) as some low income workers and high medical expenditure workers switch their coverage from employer provided health insurance to Medicaid. The effect of employer mandates on the premium is negative and relatively large (-2.27%), as employer mandates ameliorates the adverse selection problem in the employment-based group health insurance market. The further expansion of Medicaid raises the government Medicaid expenditure by 5 times, compared to the benchmark case. The introduction of employer mandates increases the Medicaid expenditure by 2%.

In comparison to the benchmark scenario, further Medicaid eligibility expansion increases the employment rate of men and women with at most a high school degree by 4 percentage points and 7 percentage points respectively (Table 7). This result suggests that before the policy change, many low skill individuals choose not to work in order to obtain coverage from Medicaid.[37] Now under further Medicaid expansion, many low-skilled individuals choose to work without losing Medicaid coverage. The overall health insurance coverage rates rise dramatically, however, there are large crowding out effects of Medicaid on private health insurance coverage. As shown in Table 8, the employer-provided health insurance drops by 2 to 5 percentage points among the employed workers with at most a high school degree. The wage rates of these low skilled workers decrease by 5% for men and 8.5% for

[37] In 2009, 19% of individuals who are not working are covered by Medicaid (author's calculation from March CPS).

TABLE 2—CHANGES IN LABOR AND HEALTH CARE MARKETS RELATIVE TO BENCHMARK CASE

	(2) / (1)	(3) / (1)	(4) / (1)
Changes in HS skill prices (%)	-0.79	0.47	-0.68
Changes in SC skill price (%)	-0.23	-0.01	-0.34
Changes in CG skill price (%)	0.53	-0.23	0.53
Changes in EHI premium (%)	-0.63	-2.37	-3.01
Changes in total Medicaid expenditure (%)	513.14	2.27	522.72
Changes in government revenue (%)	1.01	8.27	10.76

Note: (1): Benchmark case (no policy changes); (2): Medicaid only; (3): employer mandates only; (4) Medicaid and employer mandates. In the benchmarket case, the predicted total Medicaid expenditure for enrolled individuals age 25-64 is $503 million, and the predicted government revenue (i.e., Federal income tax revenue in this case) is $1.1 billion. In colum 3 and 4, the government revenue includes both income tax revenue and fines from employer mandates.

women. As a result, among the employed workers, we see a decrease in health insurance coverage inequality, but an increase in wage inequality (Table 9).

Compared to the benchmark case, the introduction of employer mandates lowers employment rate by 2 to 3 percentage points for individuals with at most a high school degree and by 1 percentage point for those with at least a 4-year college degree (Table 7). This suggests that many workers with low valuation of employer-provided health insurance are also marginal workers regarding their employment decisions. As the employer-mandates penalty raises the cost of employment, they choose not to work. Health insurance coverage rate increases by about 2 percentage points in the overall population, compared to the benchmark case. Among the employed workers, the employer-provided health insurance coverage rates increase by 3 to 6 percentage points; wage rates decline for all education groups. As seen in Table 9, the health insurance coverage gap is reduced by 2 to 3 percentage points, compared to the benchmark case; wage inequality stays approximately the same as the benchmark scenario.

When both the further Medicaid expansion and employer mandates are introduced into the economy, the employment rate increases by 2 percentage points for high school men and by 7 percentage points for high school women, compared to the benchmark case. The overall health insurance coverage rate increase to 62% and 80% for high school men and women respectively, compared to 28% and 29% in the benchmark case. The health insurance coverage gap is reduced and the wage inequality is increased.

VI. Conclusion

This paper is the first attempt to understand the reasons for observed inequality in health care access in an equilibrium framework of labor and health insurance markets. The model estimated in this paper combines two distinct features. First, the model allows for complex interactions between labor and health insurance markets in an equilibrium setting. 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. 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. Second, the model allows for rich forms of individual heterogeneity. Individuals differ in not only observed characteristics (for example, gender, age, birth year, education, and health), but also unobserved heterogeneity along dimensions such as labor market endowment and risk aversion.

This paper has two key messages. First, the interaction between the increasing cost of medical services and rising demand for skilled labor is the main determinant of the increasing inequality in health insurance coverage in the US over the last 30 years. Health care policies that control the increase in medical services cost reduce health care access inequality without distorting labor market efficiency. Second, it is important to understand the interaction between skilled labor and unskilled labor in a market equilibrium setting. Policies that further expand Medicaid for the poor, may have the unintended consequence of increasing the wage gap between skilled and unskilled labor.

REFERENCES

Aizawa, Naoki and Hanming Fang, "Equilibrium Labor Market Search and Health Insurance Reform," Working Paper 18698, National Bureau of Economic Research January 2013.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, "Trends in U.S. Wage Inequality: Revising the Revisionists," *The Review of Economics and Statistics*, 06 2008, *90* (2), 300–323.

Blau, David M. and Donna B. Gilleskie, "RETIREE HEALTH INSURANCE AND THE LABOR FORCE BEHAVIOR OF OLDER MEN IN THE 1990s," *The Review of Economics and Statistics*, February 2001, *83* (1), 64–80.

_ and _, "THE ROLE OF RETIREE HEALTH INSURANCE IN THE EMPLOYMENT BEHAVIOR OF OLDER MEN," *International Economic Review*, 2008, *49* (2), 475–514.

Card, David, Carlos Dobkin, and Nicole Maestas, "Does Medicare Save Lives?," *The Quarterly Journal of Economics*, 2009, *124* (2), 597–636.

Cohen, Alma and Liran Einav, "Estimating Risk Preferences from Deductible Choice," *American Economic Review*, September 2007, *97* (3), 745–788.

Cole, Harold L., Soojin Kim, and Dirk Krueger, "Analyzing the Effects of Insuring Health Risks: On the Trade-off between Short Run Insurance Benefits vs. Long Run Incentive Costs," Working Paper 18572, National Bureau of Economic

Research November 2012.

Currie, Janet and Brigitte C. Madrian, "Health, health insurance and the labor market," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Vol. 3 of *Handbook of Labor Economics*, Elsevier, 1999.

_ **and Jonathan Gruber**, "Saving Babies: The Efficacy and Cost of Recent Expansions of Medicaid Eligibility for Pregnant Women," Working Paper 4644, National Bureau of Economic Research February 1994.

_ **and** _ , "Health Insurance Eligibility, Utilization of Medical Care, and Child Health," *The Quarterly Journal of Economics*, May 1996, *111* (2), 431–66.

Dey, Matthew S. and Christopher J. Flinn, "An Equilibrium Model of Health Insurance Provision and Wage Determination," *Econometrica*, 03 2005, *73* (2), 571–627.

Doyle, Joseph J., "Health Insurance, Treatment and Outcomes: Using Auto Accidents as Health Shocks," *The Review of Economics and Statistics*, 2005, *87* (2), pp. 256–270.

Einav, Liran, Amy Finkelstein, Stephen P. Ryan, Paul Schrimpf, and Mark R. Cullen, "Selection on Moral Hazard in Health Insurance," Working Paper 16969, National Bureau of Economic Research April 2011.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and The Oregon Health Study Group, "The Oregon Health Insurance Experiment: Evidence from the First Year," *NBER Working Papers*, July 2011.

French, Eric and John Bailey Jones, "The Effects of Health Insurance and Self-Insurance on Retirement Behavior," *Econometrica*, 2011, *79* (3), 693–732.

_ **and Kirti Kamboj**, "Analyzing the relationship between health insurance, health costs, and health care utilization," *Economic Perspectives*, 2002.

French, Eric Baird and John Bailey Jones, "On the distribution and dynamics of health care costs," *Journal of Applied Econometrics*, 2004, *19* (6), 705–721.

Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo, "Public Health Insurance, Labor Supply, and Employment Lock," Working Paper 19220, National Bureau of Economic Research July 2013.

Gertner, Robert, "Game Shows and Economic Behavior: Risk-Taking on "Card Sharks"," *The Quarterly Journal of Economics*, 1993, *108* (2), pp. 507–521.

Goldin, Claudia and Lawrence F. Katz, "The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005," Working Paper 12984, National Bureau of Economic Research March 2007.

Gruber, Jonathan, "Health insurance and the labor market," in A. J. Culyer and J. P. Newhouse, eds., *Handbook of Health Economics*, Vol. 1 of *Handbook of Health Economics*, Elsevier, 2000, chapter 12, pp. 645–706.

Guvenen, Fatih, Burhanettin Kuruscu, and Serdar Ozkan, "Taxation of human capital and wage inequality: a cross-country analysis," Staff Report 438, Federal Reserve Bank of Minneapolis 2009.

Handel, Benjamin R., Igal Hendel, and Michael D. Whinston, "Equilibria in Health Exchanges: Adverse Selection vs. Reclassification Risk," Working Paper 19399, National Bureau of Economic Research September 2013.

Heckman, James, Lance Lochner, and Christopher Taber, "Explaining Rising Wage Inequality: Explanations With A Dynamic General Equilibrium Model of Labor Earnings With Heterogeneous Agents," *Review of Economic Dynamics*, January 1998, *1* (1), 1–58.

Kaplan, Greg, "Inequality and the life cycle," *Quantitative Economics*, 2012, *3* (3), 471–525.

Katz, Lawrence F. and David H. Autor, "Changes in the wage structure and earnings inequality," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Vol. 3 of *Handbook of Labor Economics*, Elsevier, 1999, chapter 26, pp. 1463–1555.

_ **and Kevin M. Murphy**, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 1992, *107* (1), pp. 35–78.

Kolstad, Jonathan T. and Amanda E. Kowalski, "Mandate-Based Health Reform and the Labor Market: Evidence from the Massachusetts Reform," Working Paper 17933, National Bureau of Economic Research March 2012.

Lee, Donghoon and Kenneth I. Wolpin, "Intersectoral Labor Mobility and the Growth of the Service Sector," *Econometrica*, 2006, *74* (1), 1–46.

_ **and** _ , "Accounting for wage and employment changes in the US from 1968-2000: A dynamic model of labor market equilibrium," *Journal of Econometrics*, May 2010, *156* (1), 68–85.

Levy, Helen, "Health Insurance and the Wage Gap," Working Paper 11975, National Bureau of Economic Research January 2006.

Manovskii, Iourii and Bjoern Bruegemann, "Fragility: A Quantitative Analysis of the US Health Insurance System," 2010 Meeting Papers 787, Society for Economic Dynamics 2010.

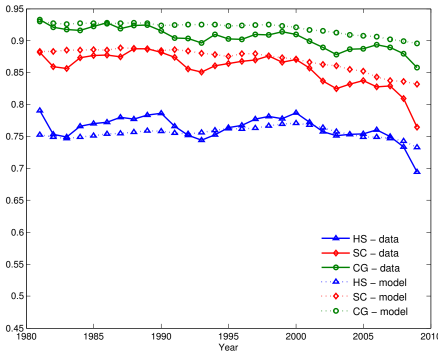
Metrick, Andrew, "A Natural Experiment in "Jeopardy!"," *The American Economic Review*, 1995, *85* (1), pp. 240–253.

Pashchenko, Svetlana and Ponpoje Porapakkarm, "Quantitative analysis of health insurance reform: separating regulation from redistribution," MPRA Paper 41193, University Library of Munich, Germany August 2012.

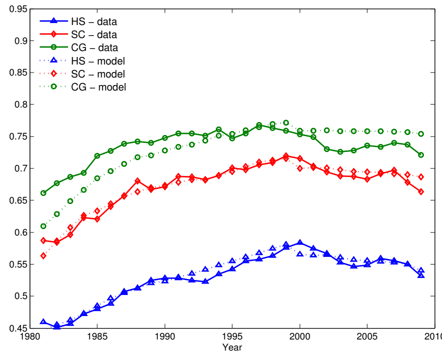
Pierce, Brooks, "Compensation Inequality," *The Quarterly Journal of Economics*, 2001, *116* (4), pp. 1493–1525.

Rust, John Philip and Christopher Phelan, "How Social Security and Medicare Affect Retirement Behavior in a World of Incomplete Markets," Public Economics, EconWPA 1996.

Storesletten, Kjetil, Giovanni L. Violante, and Jonathan Heathcote, "Redistributive Taxation in a Partial-Insurance Economy," 2010 Meeting Papers 1124, Society for Economic Dynamics 2010.

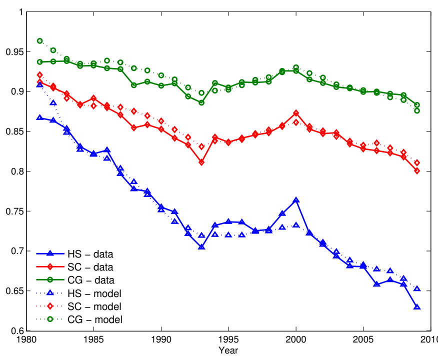


(a) Male

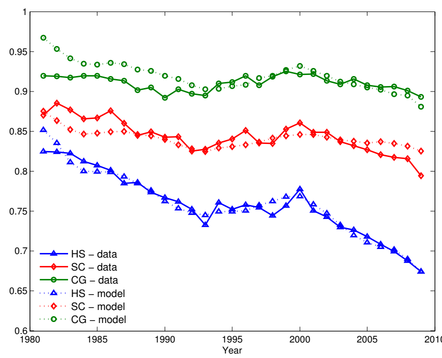


(b) Female

FIGURE 4. MODEL FIT: EMPLOYMENT RATE

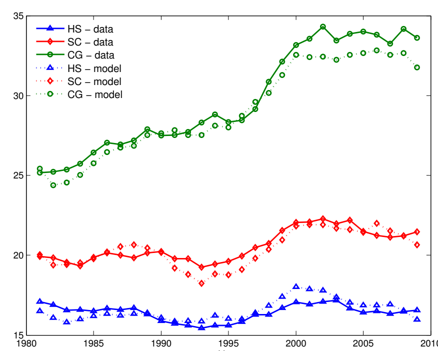


(a) Employed Male

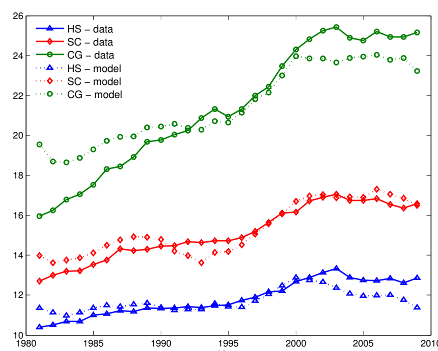


(b) Employed Female

FIGURE 5. MODEL FIT: EMPLOYER-PROVIDED HI COVERAGE RATE



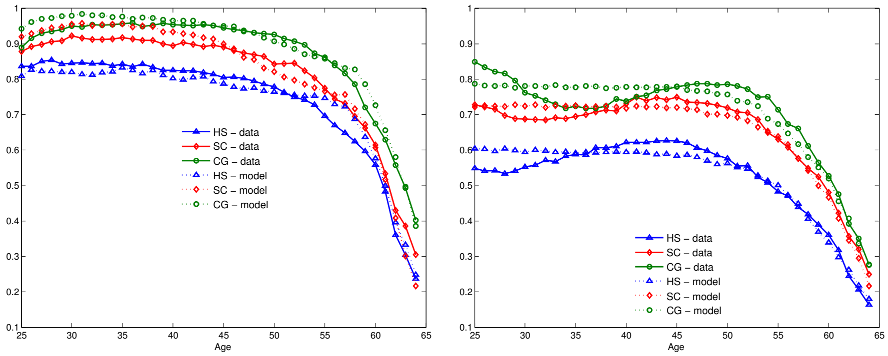
(a) Employed Male



(b) Employed Female

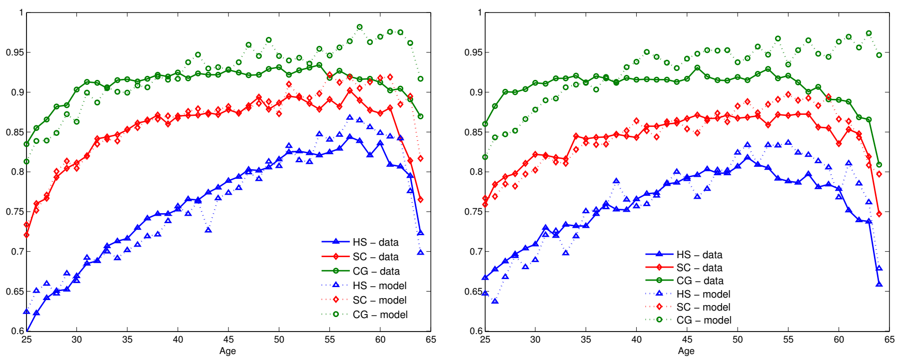
FIGURE 6. MODEL FIT: HOURLY WAGE

Source: Data moments are from CPS 1982-2010.



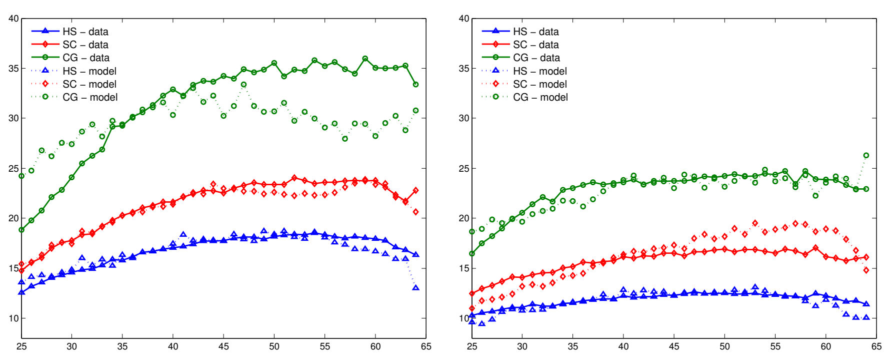
(a) Male (b) Female

FIGURE 7. MODEL FIT ACROSS AGE GROUPS: EMPLOYMENT RATE



(a) Employed Male (b) Employed Female

FIGURE 8. MODEL FIT ACROSS AGE GROUPS: EMPLOYER-PROVIDED HI COVERAGE RATE



(a) Employed Male (b) Employed Female

FIGURE 9. MODEL FIT ACROSS AGE GROUPS: HOURLY WAGE

Source: Data moments are from CPS 1982-2010.

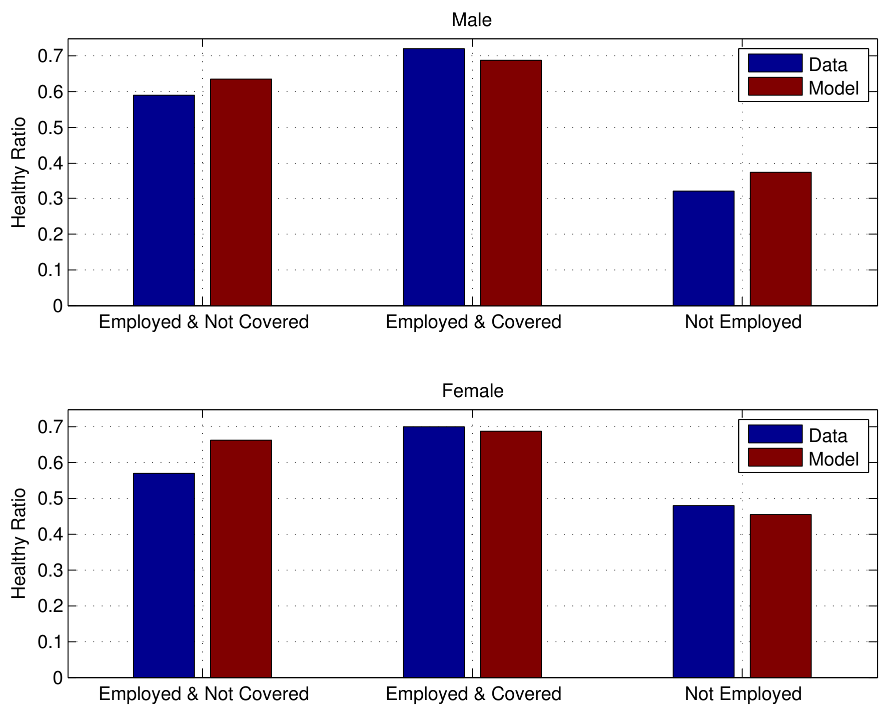
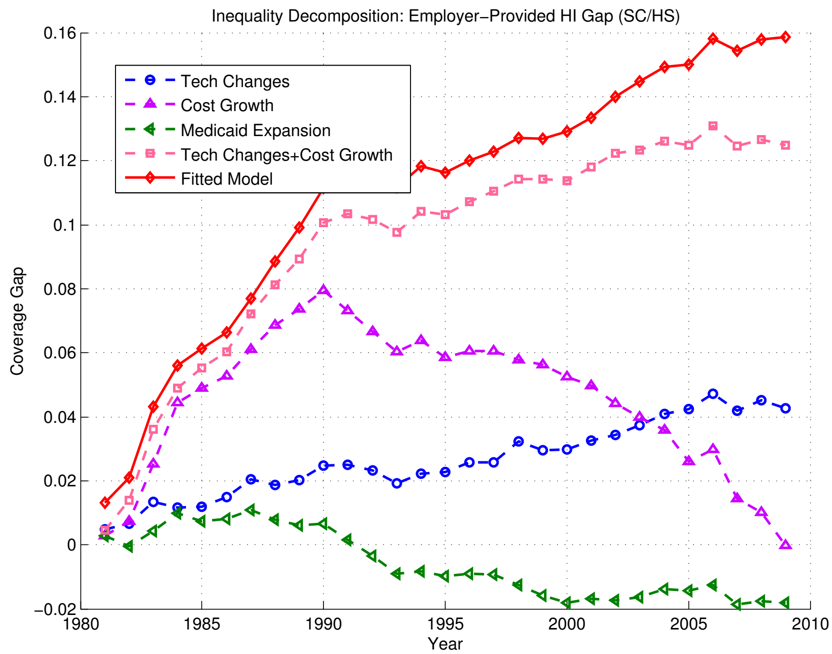
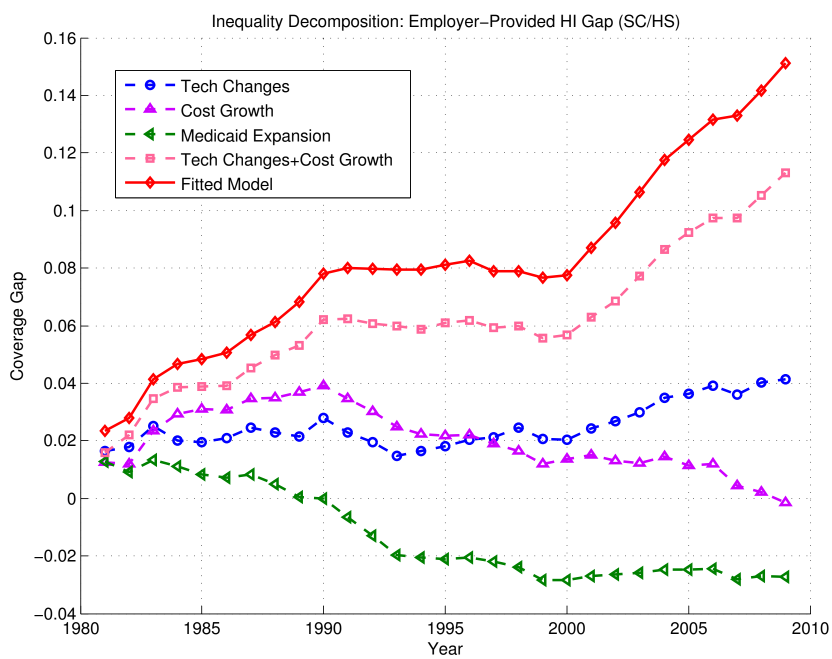


FIGURE 10. MODEL FIT: HEATH DISTRIBUTION BY PREVIOUS CHOICES

Source: Data moments are from CPS 1995-2010. The calculation of model moments is restricted to the sample time period.



(a) Male



(b) Female

FIGURE 11. EMPLOYER-PROVIDED HI COVERAGE GAP (SC/HS)

TABLE 3—ESTIMATES OF PREFERENCE PARAMETERS ON HEALTH AND LEISURE

	Male		Female	
γ: risk aversion				
Type 1	2.24E-04	(4.65E-06)	2.99E-04	(4.82E-06)
Type 2	1.15E-04	(4.07E-06)	1.53E-04	N.A.
Type 3	2.95E-04	(8.30E-06)	3.94E-04	N.A.
ϕ_h: flow utility of good health	0.200	(0.0079)	0.175	(0.0068)
ϕ_{RE}: value of good health in $V_{A+1}(\cdot)$	0.113	(0.0966)	0.198	(0.0904)
ϕ_1: leisure $\times$ dep. children	-0.155	(0.0057)	0.091	(0.0041)
ϕ_2: leisure $\times$ (age-45) if age $>$ 45	0.015	(0.0005)	0.014	(0.0005)
ϕ_3: leisure $\times$ bad health	0.057	(0.0029)	0.047	(0.0033)
ϕ_4: leisure $\times$ some college	0.007	(0.0012)	0.016	(0.0022)
ϕ_5: leisure $\times$ 4-year college	0.003	(0.0006)	0.020	(0.0029)
ϕ_6: time trend linear	-0.002	(0.0001)	-0.010	(0.0003)
$\phi_7 \cdot 100$: time trend square	0.001	(0.0001)	0.011	(0.0004)
σ_l: s.d of shocks to leisure	0.029	(0.0020)	0.025	(0.0022)
ϕ_0: constant term, leisure				
type 1	0.176	(0.0076)	0.204	(0.0081)
type 2	0.042	(0.0023)	0.049	N.A.
type 3	0.399	(0.0110)	0.462	N.A.

Parameter restrictions: $\gamma_{\text{female},k} = \gamma_{\text{female},1} \cdot \frac{\gamma_{\text{male},k}}{\gamma_{\text{male},1}}$, $\phi_{0,\text{female},k} = \phi_{0,\text{female},1} \cdot \frac{\phi_{0,\text{male},k}}{\phi_{0,\text{male},1}}$.

Standard errors in parentheses

TABLE 4—MINIMUM CONSUMPTION FLOOR PARAMETERS

c_0^{min}: initial value of consumption floor	3549.729	(66.5834)
g^c: time trend	15.475	(1.1776)

Standard errors in parentheses

TABLE 5—HEALTH TRANSITION FUNCTION PARAMETERS

$\beta_{0,\text{gender},k}$: constant		
male, type 1	-0.215	(0.0142)
male, type 2	-0.645	(0.0234)
male, type 3	-0.676	(0.0442)
female, type 1	-0.192	(0.0171)
female, type 2	-0.622	N.A.
female, type 3	-0.653	N.A.
β_1: current health	1.668	(0.0254)
β_2: health insurance coverage	0.223	(0.0063)
β_3: some college	0.257	(0.0278)
β_4: 4-year college or more	0.723	(0.0301)
β_5: age	-0.024	(0.0006)
$\beta_6 \cdot 100$: age square	-0.011	(0.0023)

Parameter restrictions: $\beta_{0,\text{female},k} = \beta_{0,\text{female},1} + \beta_{0,\text{male},k} - \beta_{0,\text{male},1}$.
Standard errors in parentheses

TABLE 6—SKILL PRODUCTION FUNCTION PARAMETERS

	j=HS		j=SC		j=CG	
$\kappa^j_{0,\text{gender},k}$: constant						
male, type 1	0.000	N.A.	0.000	N.A.	0.000	N.A.
male, type 2	-0.919	(0.0273)	-1.263	(0.0206)	0.408	(0.0185)
male, type 3	-1.534	(0.0625)	0.759	(0.0421)	0.618	(0.0345)
female, type 1	-0.357	(0.0088)	-0.078	(0.0113)	-0.232	(0.0101)
female, type 2	-1.276	N.A.	-1.341	N.A.	0.177	N.A.
female, type 3	-1.890	N.A.	0.681	N.A.	0.386	N.A.
κ^j_1: health	0.083	(0.0067)	0.116	(0.0027)	0.167	(0.0072)
κ^j_2: experience	0.029	(0.0009)	0.033	(0.0013)	0.026	(0.0010)
$\kappa^j_3 \cdot 100$: exper. square	-0.052	(0.0019)	-0.036	(0.0029)	-0.057	(0.0027)
s.d of shocks	0.401	(0.0086)	0.331	(0.0113)	0.576	(0.0080)

Parameter restrictions: $\kappa_{0,\text{male},k} = 0$ and $\kappa_{0,\text{female},k} = \kappa_{0,\text{female},1} - \kappa_{0,\text{male},1}$ for $k = 2,3$.
Standard errors in parentheses

TABLE 7—EFFECT OF HEALTH CARE POLICIES ON EMPLOYMENT, HEALTH AND HEALTH INSURANCE COVERAGE

	Baseline	Medicaid	Mandates	Medicaid+Mandates
		All Male		
Employment				
HS	0.70	0.74	0.68	0.72
SC	0.81	0.83	0.79	0.83
CG	0.89	0.89	0.88	0.89
Health				
HS	0.50	0.52	0.50	0.52
SC	0.62	0.63	0.62	0.64
CG	0.74	0.74	0.74	0.74
HI Coverage				
HS	0.28	0.57	0.30	0.62
SC	0.37	0.58	0.39	0.62
CG	0.45	0.56	0.46	0.58
		All Female		
Employment				
HS	0.48	0.55	0.45	0.55
SC	0.65	0.70	0.63	0.70
CG	0.74	0.75	0.73	0.75
Health				
HS	0.47	0.50	0.47	0.50
SC	0.60	0.62	0.60	0.63
CG	0.74	0.76	0.75	0.76
HI Coverage				
HS	0.29	0.76	0.31	0.80
SC	0.42	0.77	0.45	0.80
CG	0.46	0.72	0.48	0.75

TABLE 8—EFFECT OF HEALTH CARE POLICIES AMONG THE EMPLOYED

	Baseline	Medicaid	Mandates	Medicaid+Mandates
		Employed Male		
Health				
HS	0.57	0.57	0.58	0.57
SC	0.68	0.68	0.69	0.68
CG	0.77	0.77	0.77	0.77
HI Coverage				
HS	0.29	0.42	0.32	0.47
SC	0.43	0.50	0.46	0.54
CG	0.49	0.50	0.52	0.53
EHI Coverage				
HS	0.29	0.27	0.32	0.30
SC	0.43	0.41	0.46	0.44
CG	0.49	0.50	0.52	0.52
Wages				
HS	16.12	15.32	15.73	14.80
SC	21.31	20.77	21.04	20.18
CG	33.39	33.52	32.86	33.00
		Employed Female		
Health				
HS	0.60	0.57	0.61	0.57
SC	0.69	0.67	0.69	0.67
CG	0.80	0.80	0.80	0.80
HI Coverage				
HS	0.36	0.56	0.42	0.63
SC	0.58	0.68	0.63	0.72
CG	0.61	0.63	0.64	0.67
EHI Coverage				
HS	0.35	0.30	0.41	0.33
SC	0.58	0.54	0.63	0.57
CG	0.61	0.61	0.64	0.63
Wages				
HS	11.69	10.69	11.36	10.02
SC	16.70	15.82	16.62	15.35
CG	24.00	23.90	23.64	23.43

TABLE 9— EFFECTS ON HEALTH INSURANCE AND WAGE INEQUALITY

	Baseline	Medicaid	Mandates	Medicaid+Mandates
	Employed Male			
Health Gap				
SC/HS	0.11	0.11	0.11	0.11
CG/HS	0.20	0.20	0.19	0.20
HI Gap				
SC/HS	0.14	0.08	0.14	0.06
CG/HS	0.21	0.09	0.19	0.06
EHI Gap				
SC/HS	0.14	0.15	0.14	0.14
CG/HS	0.21	0.23	0.20	0.22
Log Wage Ratio				
SC/HS	0.28	0.30	0.29	0.31
CG/HS	0.73	0.78	0.74	0.80
	Employed Female			
Health Gap				
SC/HS	0.09	0.10	0.08	0.10
CG/HS	0.20	0.23	0.19	0.23
HI Gap				
SC/HS	0.23	0.12	0.22	0.09
CG/HS	0.25	0.07	0.22	0.03
EHI Gap				
SC/HS	0.23	0.24	0.22	0.23
CG/HS	0.26	0.30	0.23	0.30
Log Wage Ratio				
SC/HS	0.36	0.39	0.38	0.43
CG/HS	0.72	0.80	0.73	0.85

TABLE 10— HEALTH CARE POLICIES EXPERIMENTS: % CHANGES IN WELFARE

	Medicaid	Mandates	Medicaid+Mandates
		Male	
HS	1.36	-1.06	0.66
SC	1.31	-0.68	0.85
CG	0.15	-0.14	0.07
		Female	
HS	2.94	-0.82	2.26
SC	2.30	-0.61	1.85
CG	0.34	-0.13	0.32

For Online Publication

DATA

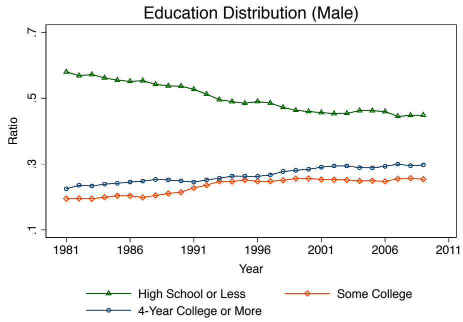
A1. March Current Population Survey (March CPS)

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 annual earnings divided by hours worked.[38] 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). Individuals' self-reported health status is available starting from survey year 1995.[39] I define an individual to be healthy (in good health) if the individual reported to be in excellent or very good health status. Calculations are weighted by CPS sampling weights and are deflated using the 2005 GDP deflator.

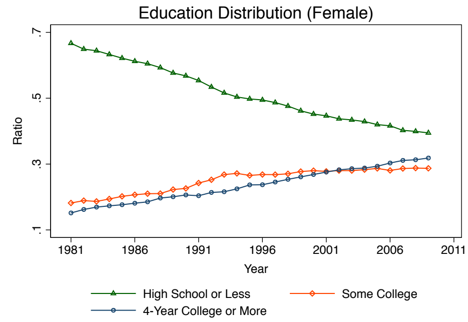
Figure A1 presents the educational distribution over years in the CPS sample. The proportion of the age 25-65 population who were college graduates grew steadily throughout the sample period, especially for women. 4-year college graduates comprised about 22% of males in 1981 and 30% by 2009. 15% of women had a 4-year college degree in 1981, and this ratio grew to 32% in 2009. Table A1 reports summary statistics for the CPS sample across all years.

[38]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.

[39]March CPS does not collect individuals' health status information in the earning year.



(a) Male



(b) Female

FIGURE A1. EDUCATION DISTRIBUTION OVER TIME

Source: March Current Population Survey 1982-2010.

TABLE A1— SUMMARY STATISTICS (CPS 1982-2010)

	mean	N
Age	42.18	2,166,231
Female	0.53	2,166,231
Some college	0.25	2,166,231
4-year college or more	0.25	2,166,231
Employed without EHI	0.13	2,166,231
Employed with EHI	0.59	2,166,231
Not employed	0.29	2,166,231
Hourly Wage	18.97	1,550,523
Medicaid	0.06	2,166,231
Healthy	0.62	1,284,022

A2. *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 the 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 in the SIPP 1996 panel are interviewed once every 4 months from 1996 to 2000. SIPP has detailed information on individuals' labor market activity, health insurance coverage, Medicaid coverage, and number of children. In addition, the 1996 SIPP collects information on individuals' health and medical usage once a year, and on their work history. I only include individuals aged 25 to 64 in the sample.[40] Table A2 reports summary statistics for SIPP sample.

TABLE A2— SUMMARY STATISTICS (SIPP 1996-2000)

	mean	N
Age	43.78	29,554
Female	0.53	29,554
Some college	0.28	29,554
4-year college or more	0.22	29,554
Employed without EHI	0.12	29,554
Employed with EHI	0.65	29,554
Not employed	0.23	29,554
Hourly Wage	17.88	22,499
Medicaid	0.05	29,554
Healthy	0.59	29,554
Experience	7.76	29,554

[40] Individuals who are in the military, institutionalized, self-employed, or working for unpaid jobs are excluded.

A3. Medical Expenditure Panel Survey (MEPS)

The Medical Expenditure Panel Survey (MEPS) data provides 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 was 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.[41] Table A3 reports summary statistics for MEPS sample.

TABLE A3— SUMMARY STATISTICS (MEPS 2005)

	mean	N
Age	43.45	13,887
Female	0.53	13,887
Some college	0.23	13,887
4-year college or more	0.30	13,887
Covered by HI	0.78	13,887
Healthy	0.41	13,887
Log total medical expenditure	7.20	11,228

A4. 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. Both series are from the Bureau of Labor Statistics (BLS). I first convert the ECI series - which provides changes over time - into dollars using the information

[41] 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.

from the ECEC survey 2005Q4.[42] I then 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.

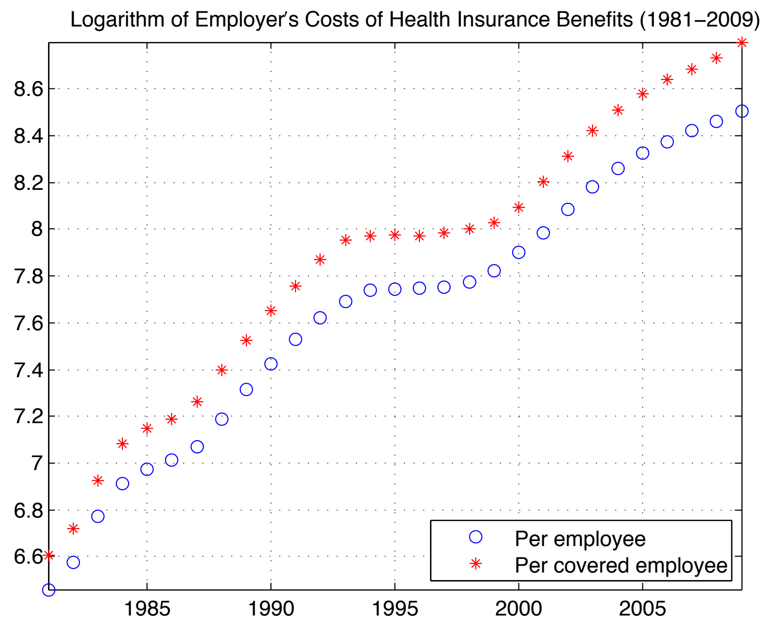


FIGURE A2. HEALTH INSURANCE COST

Source: Data are calculated using CPS 1982-2010 and ECI 1981-2009.

[42]The ECEC survey is based on the average employer cost presented in dollars 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, consistent with the annualized income calculation in CPS data.

MODEL PROOF

Proof of Proposition 1

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.

(B1) $$u_{1,0,a}(h_a, \varepsilon_a) = 1 - \exp(-\gamma \cdot \xi_{a,t}) + \phi_h h_a$$

(B2) $$u_{1,1,a}(h_a, \varepsilon_a) = 1 - \exp(-\gamma \cdot \widetilde{\mathscr{T}}(r_t^j s_a^j)) + \phi_h h_a$$

(B3) $$u_{2,a}(h_a, \varepsilon_a) = 1 - \exp(-\gamma \cdot \widetilde{\mathscr{T}}(r_t^j s_a^j - p_t)) + \phi_h h_a$$

(B4) $$u_{3,a}(h_a, \varepsilon_a) = 1 - \exp(-\gamma \cdot c_t^{min}) + \phi_h h_a + (\Gamma_a + \varepsilon_a^l)$$

where $\varepsilon_a = \{\varepsilon_a^l, \varepsilon_{a,0}^m, \varepsilon_a^j\}$ and $\xi_{a,t}$ is the certainty equivalent consumption value for the individual in the presence of risky medical expenditure.[43]

Therefore an individual's alternative-specific value functions are given by:

$$\begin{aligned} V_{1,a}(\Omega_{a,t}) =& (1 - I_{a,t}^{c,e}) u_{1,0,a}(h_a, \varepsilon_a) + I_{a,t}^{c,e} u_{1,1,a}(h_a, \varepsilon_a) + \delta \pi_{a+1}^s \mathbb{E}[V_{a+1} | \Omega_{a,t}, I_a = I_{a,t}^{c,e}, d_a^e = 1] \\ V_{2,a}(\Omega_{a,t}) =& u_{2,a}(h_a, \varepsilon_a) + \delta \pi_{a+1}^s \mathbb{E}[V_{a+1} | \Omega_{a,t}, I_a = 1, d_a^e = 1] \\ V_{3,a}(\Omega_{a,t}) =& u_{3,a}(h_a, \varepsilon_a) + \delta \pi_{a+1}^s \mathbb{E}[V_{a+1} | \Omega_{a,t}, I_a = d_{a,t}^c, d_a^e = 0] \end{aligned}$$

[43]For an individual with disposable income level $y_a^d = \widetilde{\mathscr{T}}(r_t^j s_a^j) > c_{min}$ and realized medical expenditure component $\overline{m}_{a,t} = p_t^m \exp(\mu_m(I_a, h_a, a, educ) + \sigma_m(h_a)\varepsilon_{a,0}^m)$, the certainty equivalent consumption $\xi_{a,t}$ is implicitly defined as below,

$$\exp(-\gamma \xi_{a,t}) = \mathbb{E}_{\varepsilon_{a,1}^m}[\exp(-\gamma \cdot \max\{y_a^d - \overline{m}_{a,t} \exp(\sigma_m(h_a)\varepsilon_{a,1}^m), c_t^{min}\})].$$

Notice that when there is no consumption floor, i.e., $c_t^{min} = -\infty$, then an individual's consumption equivalent is given by $\xi_{a,t} = y_a^d - \frac{1}{\gamma} \log\left(\mathbb{E}_{\varepsilon_{a,1}^m} \exp(\gamma \overline{m}_{a,t} \exp(\sigma_m(h_a)\varepsilon_{a,1}^m))\right)$.

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

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

$$
\begin{aligned}
V_{1,a}(\Omega_{a,t}) =& u_{1,0,a}(h_a, \varepsilon_a) + \delta \pi^s_{a+1} \mathbb{E}[V_{a+1} | \Omega_{a,t}, I_a = 1, d^e_a = 1] \\
V_{2,a}(\Omega_{a,t}) =& u_{2,a}(h_a, \varepsilon_a) + \delta \pi^s_{a+1} \mathbb{E}[V_{a+1} | \Omega_{a,t}, I_a = 1, d^e_a = 1]
\end{aligned}
$$

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

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

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

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

if $\exp(-\gamma \widetilde{\mathscr{T}}(r^j_t s^j_a - p_t)) - \delta \pi^s_{a+1} \Delta CV_{a+1}(\Omega_{a,t}) > 0$, 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 $\xi^*_{a,t}$.

Model Solution Algorithm

The solution algorithm is an extension of the method developed by Lee and Wolpin (2006), introducing health insurance market equilibrium together with labor market equilibrium over time. In implementing the solution algorithm, I assume the economy begins in 1942 (t = 1). I simulate a large sample of individuals for each cohort aged 25 to 64 at every calendar year, starting with the cohort age 25 in 1942, and thus age 64 in 1981, and ending with the cohort age 25 in 2009. I simulate each individual's optimal decisions for given macroeconomic sequences and these individuals' expectations and calculate the aggregate implications of their behaviors; furthermore, I require that individuals' expectations are consistent with their aggregate behavior and macroeconomic processes. The details of the algorithm consists of the following steps:

Step 1: Choose a set of parameters that characterize individuals' forecasting of the equilibrium prices process $(\log r^{HS}_{t+1}, \log r^{SC}_{t+1}, \log r^{CG}_{t+1}, \log p_{t+1})$ and for the aggregate shock process $\log \zeta_t$.

Step 2: Solve the optimization problem at each age a and information set $\Omega_{a,t}$ from $t = 1$ through $t = T$. Individuals' value function, $V_a(\Omega_{a,t})$, can be solved using Bellman Equation 8 through backward recursion beginning with age $a = A$, for calendar year $t = 1$ to T.

Step 3: Guess an initial set of values for equilibrium prices $(r^j_1)^0$ and $(p_1)^0$. Given initial age distribution and distribution of state variables for all cohorts alive at that time, simulate a sample of agents and their labor market activities and outcomes, and calculate aggregate quantity of supply in each intermediate goods production. Solve the value of aggregate shock at that time using data on output.

Step 4: Update the initial guess for rental prices to be equal to the marginal products of aggregate quantity, say $(r^j_1)^1$ and $(p_1)^1$. Repeat steps 3, use $(r^j_1)^1$ and $(p_1)^1$ as initial guess in step 3, until the sequence of equilibrium prices and aggregate shocks converge, say to $(r^j_1)^*$ and $(p_1)^*$.

Specifically, $\log r^j_t$, $\log p_t$, $\log \zeta_t$ are updated using the five equations

$$\log r^j_t = \log C_t - log(D(S^{HS}_t, S^{SC}_t, S^{CG}_t)) + \log(z^j_t) + (\nu - 1)\log(S^j_t), \quad j \in \{HS, SC, CG\}$$

$$\log p_t = \log p^m_t + \log\left(\frac{\sum_a \sum_{i=1}^{L_{a,t}} \exp(\mu_m(I^e_{i,a}, h_{i,a}, a_i, j_i) + \sigma_m(h_{i,a}, a_i, j_i)\cdot \varepsilon^m_{i,a})\cdot I^e_{i,a}}{\sum_a \sum_{i=1}^{L_{a,t}} I^e_{i,a}}\right)$$

$$\log \zeta_t = \log C_t - (1/\nu) log(D(S^{HS}_t, S^{SC}_t, S^{CG}_t))$$

where $D(S_t^{HS}, S_t^{SC}, S_t^{CG}) = z_t^{HS}(S_t^{HS})^{\nu} + z_t^{SC}(S_t^{SC})^{\nu} + z_t^{CG}(S_t^{CG})^{\nu}$, C_t is the total value of workers' compensation at time t.[44] The gender index in medical expenditure function is suppressed here.

Step 5: Guess an initial set of values for period two equilibrium prices. Repeat step 3 for $t = 2$ to obtain equilibrium prices $(r_2^j)^*$ and $(p_2)^*$.

Step 6: Repeat step 5 for $t = 3, \ldots, T$.

Step 7: Using the calculated series of equilibrium prices and aggregate shocks, estimate the parameters that govern the process of equilibrium prices and the process of aggregate shocks.

Step 8: Use these estimates, repeat step 2-7 until the series of equilibrium prices and aggregate shocks converge.

ESTIMATION METHOD

D1. Estimation Method, Moment Conditions, and the Asymptotic Distribution of Parameter Estimates

I estimate a vector of parameters on preference, human capital accumulation, health transition, aggregate production function, and skill-biased technology change, θ, using the simulated method of moments (SMM). There are 86 parameters to be estimated in total. The estimate, $\hat{\theta}$, is the value of θ that minimizes the weighted distance between the estimated life cycle profiles for labor participation, health insurance coverage, wage, and health for different cohorts over the time period 1981 to 2009. Specifically, I match 1530 moment conditions. Table D1 lists all the moment conditions used in the estimation.

Let $G(\theta)$ denote the vector of moment conditions that is described above, and let

[44] In the estimation, I calculate the average health insurance cost per covered employee for a firm (λp_t) using data from CPS and ECI, and then use the health insurance market equilibrium condition to infer the underlying medical services price p_t^m per unit of service purchased by a working-age individual.

$\hat{G}(\theta)$ denote its sample analog. Denote $\hat{W}$ as the weighting matrix, then the SMM estimator θ is given by (see, also French and Jones (2011)),

$$\text{(D1)} \qquad \arg\min_{\theta} \frac{1}{1+\tilde{n}} \hat{G}(\theta)' \hat{W} \hat{G}(\theta)$$

where $\tilde{n}$ is the ratio of the number of observations to the number of simulated observations.

The asymptotical distribution of SMM estimator $\hat{\theta}$ is given by

$$\text{(D2)} \qquad \sqrt{L}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, \Sigma)$$

with the variance-covariance matrix Σ given by

$$\Sigma = (1+\tilde{n})(D'WD)^{-1} D'WSWD(D'WD)^{-1}$$

where S is the variance-covariance matrix of the data moments,

$$D = \frac{\partial G(\theta)}{\partial \theta'} \bigg|_{\theta=\theta_0}$$

I use a "diagonal" weighting matrix, as suggested by French and Jones (2011). The diagonal weighting scheme uses the inverse of the matrix that is the same as S along the diagonal and has zeros off the diagonal of the matrix. I estimate D with its sample analogs. Specifically, I calculate D as the Jacobian matrix of sample moments at the estimated parameter values: $\hat{D} = \frac{\partial \hat{G}(\theta)}{\partial \theta'} \Big|_{\theta=\hat{\theta}}$. Furthermore, I employed the Savitzky-Golay filter to calculate the numerical first-order derivative of $\hat{G}(\theta)$ to deal with the issue of potential non-smoothness in numerical derivation calculation.

TABLE D1—TARGETED MOMENTS

Targeted Moments from CPS	# of Moments
Employed% by age, education and sex	$40 \times 3 \times 2$
EHI% by age, education and sex	$40 \times 3 \times 2$
Wage rate by age, education and sex	$40 \times 3 \times 2$
Employed% by year, education and sex	$29 \times 3 \times 2$
EHI% by year, education and sex	$29 \times 3 \times 2$
Wage rate by year, education and sex	$29 \times 3 \times 2$
Employed% by presence of dependent children and sex	2×2
Wage rate square by education and sex	3×2
Healthy% by age and sex[a]	40×2
Healthy% by education and sex	3×2
Targeted Moments from SIPP[b]	**# of Moments**
Healthy% by prev. health and sex	2×2
Healthy% by prev. health insurance coverage and sex	2×2
Healthy% by 4 age groups and sex[c]	4×2
Healthy% by education and sex	3×2
Employed% by 4 age groups , health and sex	$4 \times 2 \times 2$
EHI% by 4 age groups , health and sex	$4 \times 2 \times 2$
Employed% by education, health and sex	$3 \times 2 \times 2$
EHI% by education, health and sex	$3 \times 2 \times 2$
Wage rate by education, health, and sex	$3 \times 2 \times 2$
Wage rate by education, 4 experience groups, and sex	$3 \times 4 \times 2$
Prob. distribution of 4 experience groups by education and sex	$3 \times 3 \times 2$
Diagonal matrix of one-period choice transition prob by education and sex	$3 \times 3 \times 2$
Diagonal matrix of one-period choice transition prob by 4 age groups and sex	$3 \times 4 \times 2$
Diagonal matrix of one-period choice transition prob by health and sex	$3 \times 2 \times 2$
Product of current wage rate and prev. wage rate by education and sex	3×2

Note: All the moments are unconditional moments; wage rate is assigned to be zero for individuals who were not employed. EHI refers to employer-provided health insurance.

[a]CPS collects information on health status from 1996 onwards.

[b]SIPP data covers the 1996-2000 period, thus when matching moments from SIPP, I also restrict the model generated moments to the same time period.

[c]Due to the concern of small sample size, I calculate health distribution over 4 age groups for each gender: 25-34, 35-44, 45-54, 55-64.

D2. Discussion on MLE

This section discusses the possibility of estimating the model using maximum likelihood estimation and why it is not preferred.

Let ψ_t denote the aggregate-level state variable vector that is relevant for an individual's optimization problem, denoted by,

$$\psi_t \equiv \left\{ \begin{array}{l} t, \{\log z_t^j, \log z_{t+1}^j, \log r_t^j, \log r_{t-1}^j\}_{j=HS,SC,CG}, \log \zeta_t, \log \zeta_{t+1}, \\ \log p_t^m, \log p_{t+1}^m, \log p_t, \log p_{t-1} \end{array} \right\}$$

Let $\overline{\Omega}_a = \{\text{type}, \text{sex}, \text{educ}, h_a, \text{expr}_a, Z_a^{ch}\}$ denote the set of individual-level state variables net of the idiosyncratic shocks ($\varepsilon_a \equiv (\varepsilon_a^l, \varepsilon_{a,0}^m, \varepsilon_a^j)$). Therefore, an individual's information set is $\Omega_{a,t} = \{\psi_t, \overline{\Omega}_a, \varepsilon_a\}$.

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 ε_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 observed data and aggregate shocks is given by

$$\begin{aligned} & Pr[Y_{25,t}, \ldots, Y_{a,t+(a-25)}, \{\psi_t, \ldots, \psi_{t+(a-25)}\} | \overline{\Omega}_{25}] \\ = & \Pi_{\Delta a=1}^{a-25} Pr[Y_{25+\Delta a, t+\Delta a} | \{\overline{\Omega}_{25+\Delta a}, \psi_{t+\Delta a}\}] \\ & \cdot Pr(\overline{\Omega}_{25+\Delta a}, \psi_{t+\Delta a} | Y_{25+\Delta a-1, t+\Delta a-1}, \overline{\Omega}_{a+\Delta a-1}, \psi_{t+\Delta a-1}) \end{aligned}$$

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

There is no closed-form representation for the probability function, 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, we need to integrate over these aggregate variables in order to calculate the individual's choice probability. However, because 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.

The 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 simulated method of moments (SMM) as described in the previous section.

EXOGENOUS PARAMETER ESTIMATES

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 $\lambda = 0.8$.[45] 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.

[45] 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.

E1. 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 squared, and sex,

$$\text{Prob}_a(Z_a^{ch} = 1 | Z_{a-1}^{ch}, a, \text{educ}) = (1 + \exp(-X_a^{ch} \alpha_{ch}))^{-1}$$

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

Table E1 reports estimation result for the transition function regrading the presence of dependent children.

TABLE E1—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 squared/100	0.133**	(0.034)
Female	-0.026	(0.060)
Constant	3.209**	(0.631)
Observations	29554	

Standard errors in parentheses

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

E2. Approximating Progressive Labor Income Taxes

I assume the following functional form for labor income taxes,

$$\mathscr{T}(y) = \tau_0 + y - \tau_1 \frac{y^{\tau_2+1}}{\tau_2+1} \tag{E1}$$

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 $(\tau_1,\ \tau_2)$ I regress the 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 E1.[46] A regression of the actual tax liability on the predicted tax liability yields an R^2 of 0.93. Figure E1 plots the approximated labor income taxes along individuals' wage income.

E3. Approximating Medicaid Coverage Eligibility Rules

The income threshold at time t, y_t^{cat}, is obtained as a fraction of the Federal Poverty Level (FPL), which changes over time. The categorical standard of Medicaid eligibility is complex and it is difficult to incorporate all the factors that may impact the eligibility into the model.[47] I therefore approximate the categorical standard, $d_{a,t}^c$, as a function of model state variables such as age, employment status, presence of dependent children, year and education, separately for men and

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

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

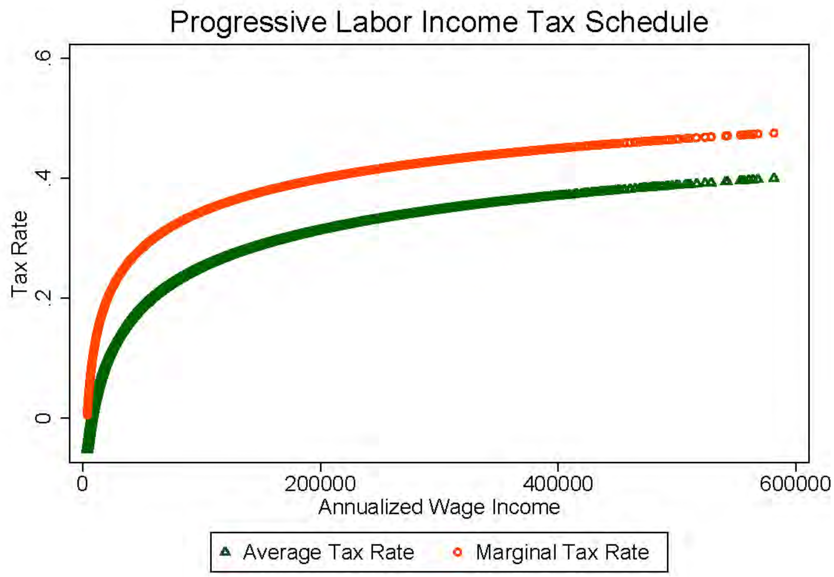


FIGURE E1. APPROXIMATED LABOR INCOME TAX SCHEDULE

women.[48]

Currently, Medicaid eligibility for adults is very limited in most states. In the median states, the income eligibility threshold for adults is 63% of the poverty level.[49] Individuals form an expectation on changes in the income threshold y_t^{cat} according to the following process,

$$\log y_{t+1}^{cat} - \log y_t^{cat} = g^{cat} + \varepsilon_{t+1}^{cat} \tag{E2}$$

Denote by FPL the poverty level for a 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

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

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

standard deviation of the logarithm of income threshold evolution process to be $g^{cat} = 0.0058$ and $\sigma^{cat} = 0.0118$. On average, FPL increases by 34% for each additional person. For example, in 2005, FPL for a 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 exceed the calculated Medicaid income threshold. In particular, I estimate a Probit model separately for men and women whose income is below the threshold:[50]

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

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 ($d^c_{a,t}$). The estimation results are reported in Table (E2).

[50]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 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.

TABLE E2—MEDICAID COVERAGE

	Male	Female
Age 30-34	0.123**	-0.119**
	(0.018)	(0.009)
Age 35-39	0.162**	-0.210**
	(0.018)	(0.010)
Age 40-44	0.169**	-0.253**
	(0.018)	(0.010)
Age 45-49	0.093**	-0.306**
	(0.018)	(0.011)
Age 50-54	-0.010	-0.350**
	(0.018)	(0.011)
Age 55-59	-0.213**	-0.415**
	(0.017)	(0.011)
Age 60-64	-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

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

E4. Medical Services Consumption

Recall from Equation (5) that health insurance coverage, health status, age, education, and gender affect the logarithm of medical services consumption through the mean shifter $\mu_m(\cdot)$; health status, age, education, and gender also impact the medical services consumption through the variance shifter $\sigma_m(\cdot)$. I assume that $\mu_m(\cdot)$ and $\sigma_m(\cdot)$ are linear functions of the following forms:

$$\begin{aligned}\mu_m(I_a, h_a, a, j, \text{female}) = {} & \alpha_{0,m} + \alpha_{1,m} I_a + \alpha_{2,m} h_a + \alpha_{3,m} a + \alpha_{4,m} \mathbf{1}(j = SC) \\ & + \alpha_{5,m} \mathbf{1}(j = CG) + \alpha_{6,m} \mathbf{1}(\text{female} = 1) + \alpha_{7,m} a \cdot \mathbf{1}(\text{female} = 1) \\ \sigma_m(h_a, a, j, \text{female}) = {} & \varsigma_{0,m} + \varsigma_{1,m} h_a + \varsigma_{2,m} a + \varsigma_{3,m} \mathbf{1}(j = SC) \\ & + \varsigma_{4,m} \mathbf{1}(j = CG) + \varsigma_{5,m} \mathbf{1}(\text{female} = 1) + \varsigma_{6,m} a \cdot \mathbf{1}(\text{female} = 1).\end{aligned}$$

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, 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. Thus, without loss of generality, I normalize $\alpha_{0,m} = 0$ and estimate the logarithm of medical services expenses ($p_t^m m_a$) for $t = 2005$ by maximum likelihood using the following model:

$$\text{(E3)} \qquad \log(p_t^m m_a) = \log p_t^m + \mu_m(I_a, h_a, a, j, \text{female}) + \sigma_m(h_a, a, j, \text{female}) \varepsilon_a^m$$

where $\varepsilon_a^m \sim N(0,1)$ and $\alpha_{0,m} = 0$.

Table E3 presents the estimation results for individuals' medical consumption expenses (Equation (E3)). The positive and significant coefficient for health insurance coverage implies that an individual's medical care consumption is higher when cov-

TABLE E3—MEDICAL SERVICES CONSUMPTION FUNCTION

$\mu_m(I_a, h_a, a, j, \text{female})$		
Covered by HI	0.680**	(0.036)
Healthy	-0.667**	(0.030)
Age	0.045**	(0.002)
Some college	0.211**	(0.036)
4-year college or more	0.262**	(0.035)
Female	0.965**	(0.122)
Age × female	-0.013**	(0.003)
$\sigma_m(h_a, a, j, \text{female})$		
Healthy	-0.158**	(0.021)
Age	-0.004**	(0.001)
Some college	-0.121**	(0.025)
4-year college or more	-0.158**	(0.024)
Female	0.173**	(0.087)
Age × female	-0.004**	(0.002)
Constant	1.812**	(0.070)
Observations	11228	

Standard errors in parentheses

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

ered 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 findings that higher educated individuals tend to utilize medical services more, other things being equal. The volatility of log medical care consumption is decreasing in health, age and education. I assume that $\varepsilon^m_{a,0}$ and $\varepsilon^m_{a,1}$ are independent, $\varepsilon^m_{a,0} \sim N(0, \sigma^2_{m,0})$, and $\varepsilon^m_{a,1} \sim N(0, \sigma^2_{m,0})$. Following French and Jones (2004), I set the variance of the transitory component of medical consumption to be $\sigma^2_{m,1} = 0.6668$. Therefore, $\sigma^2_{m,0} = 1 - \sigma^2_{m,1} = 0.3332$.

REST OF THE MODEL PARAMETER ESTIMATES

F1. Type Distribution Function

The conditional probability of being a particular type k is assumed to be given by the following Multinomial Logistic model:

$$Pr(\text{type}=k|\text{female}, j, h_{25}, \text{expr}_{25}, Z_{25}^{ch}) = \frac{\exp(\Pi^k)}{1+\exp(\Pi^1)+\exp(\Pi^2)}, \quad k=2,3$$

and $\sum_{k=1}^{3} \Pr(\text{type}=k) = 1$, where

$$\begin{aligned}\Pi^k =& \pi_0^k + \pi_1^k \mathbf{1}(\text{female}=1) + \pi_2^k \mathbf{1}(j=SC) + \pi_3^k \mathbf{1}(j=CG) \\ &+ \pi_4^k \mathbf{1}(\text{female}=1)\mathbf{1}(j=SC) + \pi_5^k \mathbf{1}(\text{female}=1)\mathbf{1}(j=CG) \\ &+ \pi_6^k h_{25} + \pi_7^k \text{expr}_{25} + \pi_8^k Z_{25}^{ch}.\end{aligned}$$

The parameter estimates are given in Table F1.

TABLE F1—TYPE PROBABILITY FUNCTION (MULTINOMIAL LOGIT MODEL)

	Type 2 ($k=2$)		Type 3 ($k=3$)	
π_0^k: constant	-1.024	(0.1404)	0.322	(0.0324)
π_1^k: female	-0.167	(0.0648)	0.181	(0.0393)
π_2^k: some college	-0.973	(0.0695)	-0.890	(0.0542)
π_3^k: 4-year college or more	-0.625	(0.1010)	-1.749	(0.0967)
π_4^k: female × some college	-0.048	(0.0875)	-0.041	(0.0364)
π_5^k: female × 4-year college	-0.325	(0.1279)	0.131	(0.0732)
π_6^k: health at age 25	0.494	(0.0712)	0.049	(0.0567)
π_7^k: work experience at age 25	-0.110	(0.0301)	-0.355	(0.0101)
π_8^k: presence of children at age 25	1.684	(0.1302)	1.745	(0.0223)

Standard errors in parentheses

F2. Equilibrium Forecasting Rules

I assume that the individuals' forecasting rule of changes in equilibrium prices can be approximated by the following system of equations:

$$\text{(F1)} \quad \log r^j_{t+1} - \log r^j_t = \rho^j_0 + \sum_l \rho^j_{1,l}(\log r^l_t - \log r^l_{t-1}) + \rho^j_2(\log p_t - \log p_{t-1}) + \rho^j_3(\log \zeta_{t+1} - \log \zeta_t) + \rho^j_4(\log p^m_{t+1} - \log p^m_t)$$

$$\text{(F2)} \quad \log p_{t+1} - \log p_t = \rho^p_0 + \sum_l \rho^p_{1,l}(\log r^l_t - \log r^l_{t-1}) + \rho^p_2(\log p_t - \log p_{t-1}) + \rho^p_3(\log \zeta_{t+1} - \log \zeta_t) + \rho^p_4(\log p^m_{t+1} - \log p^m_t)$$

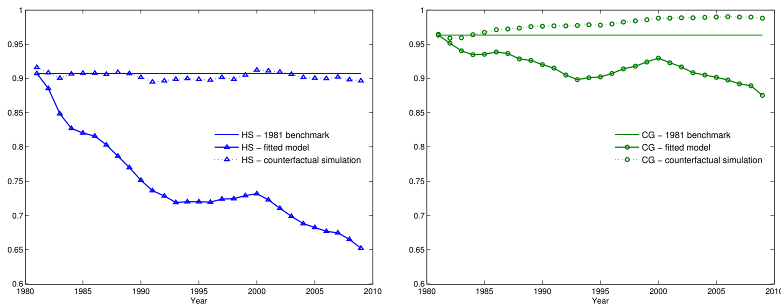
where ρ's are reduced form parameters that are consist with the model. Table F2 reports the estimated parameter values.

TABLE F2—EQUILIBRIUM FORECASTING RULES (ρ'S)

	$\Delta\log r^{HS}_{t+1}$	$\Delta\log r^{SC}_{t+1}$	$\Delta\log r^{CG}_{t+1}$	$\Delta\log p_{t+1}$
constant	0.027	0.035	0.038	0.008
$\Delta\log r^{HS}_t$	0.120	-0.070	0.018	-0.056
$\Delta\log r^{SC}_t$	-0.091	0.079	0.040	0.079
$\Delta\log r^{CG}_t$	0.086	-0.022	-0.099	-0.144
$\Delta\log p_t$	0.025	-0.119	0.032	0.011
$\Delta\log \zeta_{t+1}$	1.059	1.150	0.801	-0.063
$\Delta\log p^m_{t+1}$	0.001	0.065	-0.038	0.978

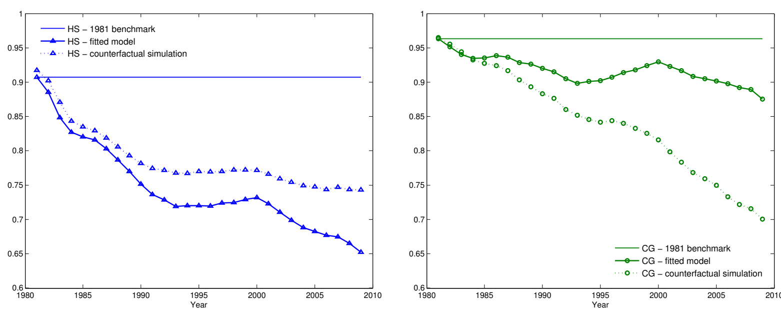
INEQUALITY DECOMPOSITION

Figures G4 and G5 plot log wage ratio under different simulations. As we can see, technological changes in the labor market is the primary factor in determining the wage inequality.



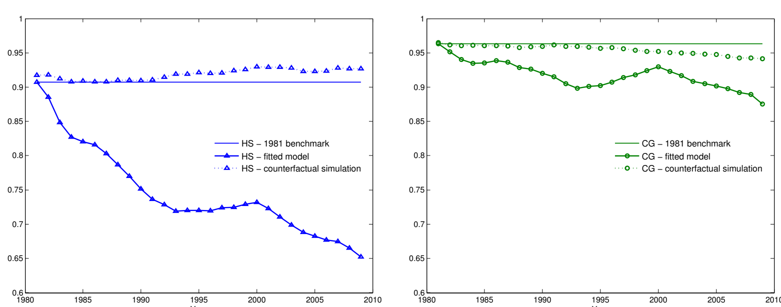
(a) Employer-Provided HI (HS) (b) Employer-Provided HI (CG)

FIGURE G1. IMPACT OF LABOR MARKET TECHNOLOGICAL CHANGES (EMPLOYED MALE)



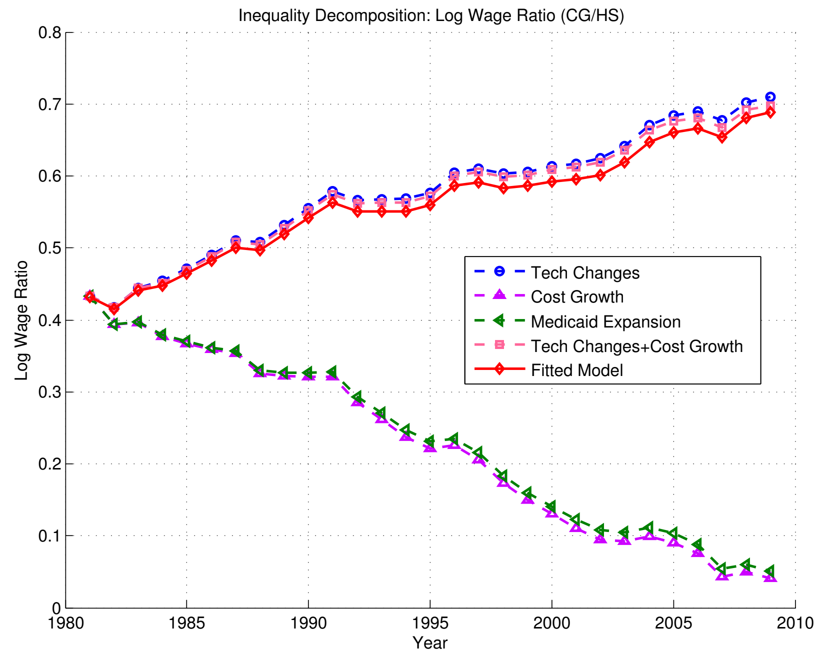
(a) Employer-Provided HI (HS) (b) Employer-Provided HI (CG)

FIGURE G2. IMPACT OF COST GROWTH (EMPLOYED MALE)

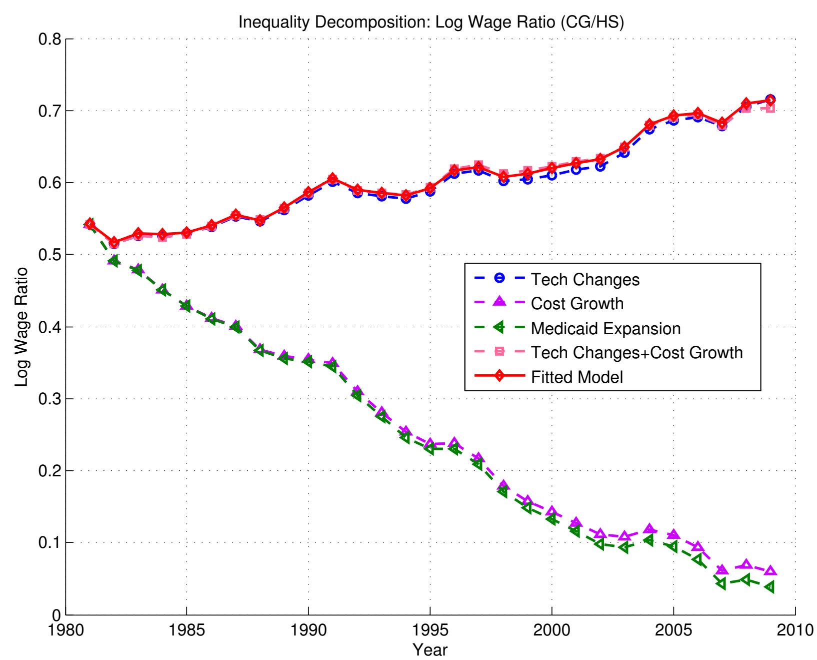


(a) Employer-Provided HI (HS) (b) Employer-Provided HI (CG)

FIGURE G3. IMPACT OF MEDICAID EXPANSION (EMPLOYED MALE)

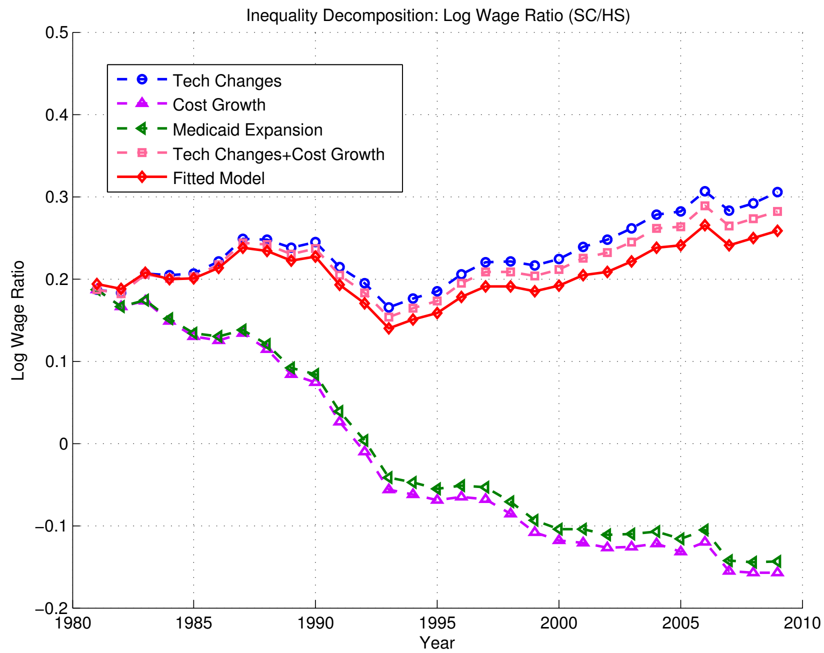


(a) Male

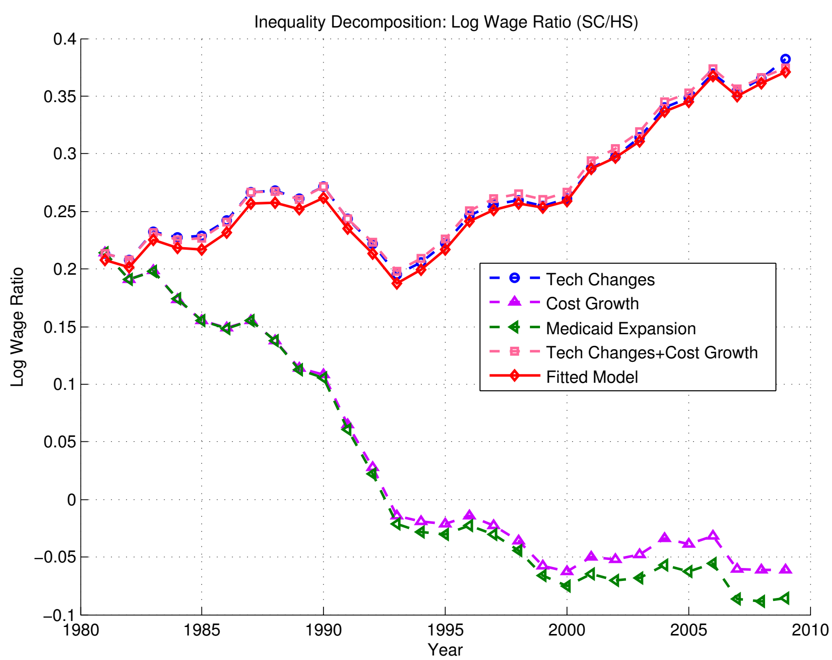


(b) Female

FIGURE G4. LOG WAGE RATIO (CG/HS)



(a) Male



(b) Female

FIGURE G5. LOG WAGE RATIO (SC/HS)