

The Macroeconomic Implications of Rising Wage Inequality in the United States*

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Abstract

This paper explores the implications of the recent shifts in U.S. wage structure (rising skill premium, narrowing gender gap, increasing persistent and transitory residual wage dispersion) for the cross-sectional distributions of hours worked, consumption and earnings across U.S. households. We develop an incomplete-markets overlapping-generations model where individuals choose education and form households, and households choose consumption and labor supply of each spouse. The model is parameterized using micro data from PSID, CPS and CEX. With the changing wage structure as the only primitive force, the model can account for many of the key trends in cross-sectional U.S. data. The model allows to quantify the welfare consequences of the rise in wage inequality, and the role played by education, labor supply, and saving in providing insurance against the observed shocks.

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1 Introduction

The structure of relative wages in the U.S. economy has undergone a major transformation in the last three decades. Wage differentials between college-graduates and high-school graduates dropped in the 1970s, but have risen sharply since then (Katz and Autor, 1999). The wage gap between men and women has narrowed significantly (Goldin, 2003). Within narrow groups of workers defined by education, gender and age, the distribution of wages has become much more unequal. This increase in residual wage dispersion reflects increasing volatility in both persistent and transitory shocks (Juhn, Murphy and Pierce, 1992; Gottschalk and Moffitt, 1994).

Over the same period, the U.S. economy has experienced large shifts in the distribution labor supply, earnings, and consumption. Women's hours worked, relative to men's, have almost doubled since 1970. Conditional on working, the cross-sectional dispersion of hours remained stable for men, but narrowed markedly for women. The correlation between wages and hours increased sharply, especially for men. Finally, but perhaps most importantly, dispersion in measures of household consumption increased much less than dispersion in household earnings (Krueger and Perri, 2006; Attanasio, Battistin and Ichimura, 2007; Blundell, Pistaferri and Preston, 2008).¹

A vast literature has addressed the sources of changes in the wage structure (for surveys, see Acemoglu, 2002; Hornstein et al., 2006). However, much less research has been devoted to exploring whether this transformation has important macroeconomic and welfare implications. This paper first asks whether the well-documented shift in the wage structure, as the only primitive force, is quantitatively consonant with observed changes in the U.S. distributions of labor supply, earnings and consumption. The paper then addresses the welfare implications of structural change in labor markets, and investigates how welfare effects are mediated in equilibrium by changes in household behavior.

To answer these questions requires an economic model that delivers predictions for hours, earnings, consumption and welfare, given wages as inputs. The standard macroeconomic framework for studying distributional issues is the class of over-lapping-generations models with heterogeneous agents and incomplete markets developed by Bewley (1986), Imrohorglu (1989), Huggett (1993), Aiyagari (1994) and Rios-Rull (1995). Workers in these models are subject to uninsurable idiosyncratic labor market shocks, but can borrow and lend through a risk-free

¹All these facts will be documented in Section 2 based on data from the Consumers Expenditures Survey (CEX), the Current Population Survey (CPS), and the Panel Study of Income Dynamics (PSID).

bond to smooth consumption.

The prototypical incomplete markets model adopts the fiction of the “bachelor household”. However, the narrowing of the gender wage gap and the rise in female participation have potentially dramatic effects on inequality and welfare that can only be understood by explicitly modeling two-person households. Furthermore, wages and hours worked are characteristics recorded at the individual level, while consumption and welfare are typically measured at the level of the household. This presents an obvious challenge for the bachelor model as a lens for interpreting micro data. We therefore model households as comprising two potential earners, facing imperfectly correlated shocks. This model provides a mapping from individual wages to the within-household allocation of market hours, which in turn determines household-level income, consumption and, ultimately, welfare.

The life-cycle of individuals in the model is as follows. First they choose education, given an idiosyncratic cost of attending college. Then they form households comprising husbands and wives, where matching probabilities are functions of educational attainment. Couples move through the rest of the life-cycle together. During working age, the family chooses consumption, asset holdings and labor supply of both spouses. Retirement is financed through savings and a simple public pension system.

Another important feature of the model is that we posit an explicit production technology that aggregates capital and four types of labor input, defined by gender and educational attainment (as in Katz and Murphy, 1992; Heckman, Lochner and Taber, 1998). The prices of different types of labor input are equilibrium market-clearing outcomes, where both demand and supply change over time. Demand-side shifts favoring college relative to high-school graduates and men relative to women are modeled as time-varying weights in the aggregate production technology, which we label “skill-biased” and “gender-biased” technical change. Changes in the supply of different labor inputs reflect the cumulative effects of individuals’ optimal education choices and the household optimal choice of hours worked for both spouses.

The four distinct exogenous forces driving wage dynamics – skill and gender-biased technical change, and changes in the volatility of persistent and transitory individual-specific productivity shocks - are parameterized to reproduce, respectively, the observed rise in the skill premium, the observed decline in the gender wage gap, and the increases in the persistent and transitory components of residual wage dispersion estimated from the Panel Study of Income Dynamics (PSID) for 1967-2003.

The advantage of being explicit about the underlying technology is that the model can be used as a laboratory for two sets of counter-factual experiments. First, we activate our exoge-

nous forces one at the time, to shed light on the role played by each time-varying component of the wage structure in explaining the evolution of cross-sectional inequality. Second, by varying the set of choice variables for individuals (savings, labor supply, female participation, enrollment), we can isolate the roles of different behavioral responses on the supply side in mediating the welfare effects of these changes.

Overall, the quantitative experiment is successful, in that the calibrated model, coupled with the estimated changes in the wage structure, can account for many important trends in our cross-sectional data. Each of the four dimensions of structural change we emphasize plays an important role in explaining one or more of the key facts.

First, the model accounts for two thirds of the observed rise in relative hours worked for women. The key driving force is the narrowing gender wage gap (as in Jones, Manuelli and McGrattan, 2003). The model misses the rise in female hours in the period 1965-1975 where other important forces were at work, such as changes in social and cultural norms (Goldin and Katz, 2002; Fernandez and Fogli, 2007), increases in productivity in the home sector (Greenwood, Seshandri and Yorukoglu, 2005), and declines in childcare costs (Attanasio, Low and Sanchez, 2007).

Second, because of the modest individual labor supply elasticity, the model predicts little change in the dispersion of hours worked for men, as in the data. However, the model does not generate the observed decline in the variance of log hours worked for women. Conflicting forces are at work and offset each other: the rising volatility of shocks tends to increase dispersion, whereas the narrowing gender gap pulls dispersion down.

Third, the model successfully replicates observed dynamics in the correlation between individual wages and individual hours, for both men and women. Transitory shocks, which are largely self-insurable through savings, induce individuals to work more when wages are temporarily high. Thus the rise in the variance of transitory shocks pushes up the wage-hour correlation. Gender-biased technical change is an additional important driver of the large increase correlation for men. The reason is that as women's share of household earnings rises over time, shocks to male wages come to have a smaller impact on household consumption, implying smaller offsetting wealth effects on hours worked.

Fourth, the model generates a rise in household earnings and consumption dispersion in line with the U.S. evidence. Skill-biased and gender-biased technical change affect inequality in earnings and consumption symmetrically, since households do not adjust savings much in response to such permanent changes in the wage structure. In contrast, changes in the variance of wage risk have very different effects on earnings and consumption inequality due to self

insurance through labor supply, borrowing and saving. In the model, more volatile transitory shocks have very little effect on consumption dispersion, while bigger persistent shocks have roughly twice as much impact on earnings inequality as compared to consumption inequality.

Finally, the model can explain one third of the slowdown in aggregate labor productivity during the 1975-1985 period, and two thirds of the acceleration since 1995. These changes entirely reflect behavioral responses to changes in the wage structure. In the decade 1975-1985, thanks to gender-biased technical change, productivity declines as a large numbers of women enter the labor force. These women earn less per hour than the average working man, both because of the gender wage gap and because of a gender education gap during this period. In the 1995-2005 decade, productivity growth reflects a large inflow to the labor force of college graduates, whose relative wages are rising thanks to skill-biased technical change.

Given the remarkable performance in matching the data, we feel quite confident in using the structural model to address the key welfare question: what was the welfare cost from the changes in the wage structure for U.S. households?²

We find that welfare costs vary dramatically across cohorts, such that early cohorts entering the labor market in the 1970s and early 1980s lose up to 0.5 percent of permanent consumption relative to the 1965 cohort, while labor cohorts are in fact left better off, in expected terms, as a result of structural shifts in labor markets. Welfare losses are primarily due to bigger persistent shocks, while gender-biased and especially skill-biased technical change are welfare improving. The set of counter-factuals we run where we shut down various margins of adjustment to structural change shed further light on the source of welfare gains and losses. In particular, we find that U.S. households would have fared very poorly over the past thirty years had it not been possible to grasp at the opportunities presented by gender-biased and skill-biased technical change by increasing, respectively, female participation and college enrollment. By contrast, savings and labor supply are important adjustment margins in the face of larger persistent and transitory shocks.

The rest of the paper is organized as follows. Section 2 describes the stylized facts of interest. Section 3 presents the model, and defines the equilibrium. Section 4 describes the calibration and estimation strategy. Section 5 contains the main results on the macroeconomic and welfare

²There is a small but growing literature on the implications of rising inequality for the distribution of household consumption and welfare. The question was first addressed by the pioneering effort of Attanasio and Davis (1996) and, subsequently, with different methodologies, by Blundell and Preston (1998), Heckman, Lochner and Taber (1998), Krueger and Perri (2003, 2006), Blundell, Pistaferri and Preston (2007) and Guvenen and Kuruscu (2007). In the paper, we compare and contrast our methodology and results to the existing literature in detail.

consequences of the changing wage structure. Section 6 concludes. In the Appendixes, we summarize in great detail the construction of the CEX, CPS and PSID samples, the identification and estimation of the statistical wage process, and the numerical solution of the model's equilibrium transitional dynamics.

2 Stylized facts

This section describes the salient facts motivating our exercise. Statistics on wages, hours and earnings reported in this section are all computed from the Current Population Survey (CPS) March Files (1967-2005). Statistics on household consumption are based on Consumer Expenditure Survey (CEX) data (1980-2003). Enrollment data are taken from the U.S. Census Bureau. Our sample comprises of married households where the husband is 25-59 years old. Appendix A contains a detailed description of the underlying micro data, the handling of measurement issues, and a few other sample selection criteria.³

College premium and enrollment. Panel (A) of Figure 1 plots the evolution of college wage premium for men and women in the U.S. over the period 1967-2005. The male (female) college wage premium is defined as the ratio between the average hourly wage of men (women) with at least a college degree and the average hourly wage of men (women) without college degree. In the late 1960s, male college graduates earned around 45% more than the rest of the labor force. Over the 1970s, the college-high school wage differential declined to almost 30%. Since the late 1970s, the male college premium has been rising, levelling off around 90% after 2000.

The dynamics of the college wage premium for married women are qualitatively similar, with a more prolonged fall over the 1970s and a less steep rise over the last two decades. If in the late 1960s the level of the skill premium was almost identical across genders, now it is substantially lower for women (1.65 vs 1.90).

These magnitudes are consistent with those documented in the literature. For example, Katz and Autor (1999, Table 3) report that the college premium rose by around 30% for men, and by 23% for women from 1980 to 1995. Eckstein and Nagypal (2004, Figures 6-7) also report a sharper rise in the college premium for men.

³By focusing on continuously married couples, we exclude single households, and abstract from divorce and separations. On average, in our PSID sample, 75% of households where the head is 40-45 years old are composed by couples, with single and divorced households accounting equally for the rest, so the paper examines a vast majority of the U.S. population.

Panel (C) shows that college enrollment went up remarkably for both men and women over the same years. The fraction of women aged 25-29 with a college degree almost tripled over the period and in the mid 1990s women’s enrollment rates overtook men’s.⁴

The simultaneity of the increase in the relative supply of college graduates and in its relative price—the college wage premium—indicates that the U.S. economy witnessed an aggregate labor demand shift in favor of college graduates, i.e., what a vast literature on the subject has labeled “skill-biased technical change” (see Katz and Murphy, 1992; Krusell et al., 2000; Acemoglu, 2002).

Gender gap in wages and hours worked. Panel (B) depicts the dynamics of the gender wage gap, defined as the ratio of male to female wages. The gender gap stayed constant around 1.65 until the late 1970s and then declined rapidly, narrowing to 1.35 by 2003. The rise in the relative wage of women has coincided with a surge in the relative hours worked by women: panel (D) shows that in the late 1960s women worked 30% as much as men, while since the 1990s women’s market hours have been almost 60% of men’s.⁵ The trends in panels (B) and (C) are in line with existing estimates. Goldin (2006, Figure 6) and Blau and Kahn (2000, Figure 1) report virtually the same path as panel (B) for the gender wage gap and the calculations in Jones, Manuelli and McGrattan (2003, Figure 1) show a similar rise in relative hours worked for married women.

We interpret these trends using a supply-demand logic similar to that of movements in relative prices and quantities of skilled and unskilled labor: since relative wages and relative labor supply of women rose at the same time, a labor demand shift in favor of women operated in the U.S. economy in this period. We label this shift “gender-biased technical change.”⁶

Wage inequality. Panel (A) of Figure 2 plots the variance of log hourly wages for men and women over the 1967-2005 period.⁷ Interestingly, the increase is quite similar across genders,

⁴Men’s college enrollment shows a slower upward trend, and a large deviation above trend around the mid 1970s which is hard to explain through price movements. Some authors attribute this temporary surge in college enrollment to the incentives provided by 1) the Vietnam War draft deferment rules for male college students and 2) the GI Bill benefits for war veterans who took on college training programs (e.g., Card and Lemieux, 2001).

⁵As common in the literature (e.g., Blau and Kahn, 2000), we report the full-time gender gap, where full-time work is defined to be above 2000 hours per year. This is done because women are more likely to be employed part-time, and part-time work carries a well known wage penalty (see, e.g., Manning and Petrongolo, 2007)

⁶Goldin (2006) discusses in detail the sources of the labor demand shift that has occurred since the 1960s – what she calls the “quiet revolution”. She enumerates, for example, the impact of WWII in showing employers that women could be profitable and reliable workers; the role of contraceptives in allowing women to plan their careers and become viable candidates for high-paid jobs like lawyers or managers; the structural shift towards the service sector with its more flexible work schedule; and, finally, the role of anti-discrimination legislation.

⁷All the cross-sectional moments plotted in Figure 2 are demeaned in order to visualize differences in trends.

around 0.20 log points over the entire period. This rise in cross-sectional wage inequality has been well documented in the literature. Moreover, also Katz and Autor (1999, Table 4B) document a similar increase for men and women: around 0.15 from 1970 to 1995.

As seen above, the skill premium (or between-educational-group inequality) accounts for a sizeable part (around 1/3) of the rise, but residual (or within-group) inequality explains the bulk of the trend. This fact is well known at least since the seminal work of Juhn, Murphy and Pierce (1993). Changes in the skill premium are, by definition, a permanent shock once the education decision is made. However, as first pointed out by Gottschalk and Moffitt (1994), the rise in residual inequality can have either a persistent or a transitory nature. In Section 4.1, the panel dimension of PSID is used to estimate a statistical model for cross-sectional residual male wage dispersion in order to distinguish the persistent from the transitory components. This decomposition for residual inequality is a key input of our exercise.

Labor-supply inequality. Panel (B) of Figure 2 plots the variance of log hours worked by gender.⁸ Here, in contrast with skill premia and wage inequality, both the levels and the trends are rather different between men and women. Hours inequality is much lower for men, and it is basically flat over the period. For women, hours inequality declines throughout the 1970s, 1980s and 1990s, albeit at a decreasing rate.

Panel (C) reports the cross-sectional correlation between log wages and log hours by gender. This correlation rises until the late 1980s. The rise for men is more pronounced, by around 0.25 log points vs 0.15 for women. In the 1990s and beyond, the correlation is stable for men, while it declines somewhat for women. Surprisingly, these two dimensions of labor supply inequality have received much less attention in the literature relative to the facts on wage and consumption dispersion.

Household earnings and consumption inequality. The variances of household log earnings and equivalized log consumption are plotted in panel (D) of Figure 2.⁹ Household earnings inequality rose by 0.23 log points over the period, following a steady trend: this trend is a combination of factors which positively contribute to the rise such as the increase in wage

Means are reported in square brackets in the legend. Moreover, due to measurement error, often the levels of variances and correlations are not very informative. We explicitly deal with measurement error in Section 4.1.

⁸By construction, this statistics excludes women who do not participate. We define an individual as non-participants if he/she works less than 260 hours in the market, i.e. a quarter of part-time work. None of the key trends in hours is sensitive to this threshold: however, the lower the threshold the higher is the variance.

⁹We have followed Krueger and Perri (2006) in using the Census scale to construct adult equivalent measures of household consumption. It is unimportant whether or not earnings are equivalized: the increase in the variance of household log equivalized earnings is 0.20, i.e. only 0.03 points lower than our benchmark series.

inequality and in the wage-hours correlation, and factors which contribute little or negatively, such as the constant variance of male hours worked and the decline in females hours dispersion.¹⁰

The second line in this plot is the variance of log household equivalized consumption. The CEX data, assembled by Krueger and Perri (2006), are consistently available only since 1980. We use the same definition of consumption as Krueger and Perri: expenditures on nondurable goods, services and small durables, such as household appliances, plus services from housing and vehicles (this variable is labelled ND+). As previously documented by Cutler and Katz (1991) and Johnson and Shipp (1997), consumption inequality tracks quite closely earnings inequality in the 1980s. Krueger and Perri (2006) uncovered the surprising disjuncture between the two series in the 1990s evident from panel (D).

Overall, during 1980-2003, household log earnings dispersion rises more than twice as much as log consumption dispersion: 0.17 vs 0.07 log points. Comparable results on trends in U.S. consumption inequality for the 1990s were found by Attanasio, Battistin and Ichimura (2007) and by Blundell, Pistaferri and Preston (2008), in spite of different methodologies used to construct the data.

The facts just described are the basis of the quantitative analysis of our paper. Some facts serve as *inputs* to the model, and others as *targets* of the model.

The college-high school wage differential and the enrollment rate allow to infer the time-path of skill-biased technical change. Similarly, the male-female wage and hours differential allows to derive the time path of gender-biased technical change. As explained, the time paths of the variance of persistent and transitory wage shocks are estimated using PSID data. Changes in these four key components of individual labor productivity, and wages, (education-specific, gender-specific, persistent and transitory components) over the last three decades are the driving forces of our experiment, i.e. the inputs of the model.

The aim of the thought experiment is that of assessing how much this transformation of the wage structure can explain of the observed changes in the distribution of male and female hours worked (e.g., gender differentials in average hours, variances of hours, and wage-hours correlations), in household earnings inequality and, finally, in household consumption inequality. These moments are our targets.

¹⁰Evidence on the within-household correlation between male and female wages is mixed. CPS shows an increase concentrated in the 1980s, while PSID data display some swings, but no clear trend over the sample period. See Appendix A for a short discussion, and Figure A-4 for a plot of this moment in both data sets. We return on this point in Section 4.1 when discussing the assumptions on the female wage process.

3 Economic model

We begin by describing the model’s demographic structure, preferences, production technology, government policies, and financial markets. Next, we outline in detail the life cycle of the individuals who inhabit our economy. We conclude this section by defining a competitive equilibrium.

3.1 Preliminaries

Time Time is discrete, indexed by $t = 0, 1, \dots$ and continues forever.

Demographics The economy is populated by a continuum of individuals, equally many females and males. Gender is indexed by $g \in \{m, f\}$. We denote an individual’s age by $j \in \mathcal{J} \equiv \{1, 2, \dots, J\}$. Prior to age J , individuals survive from age j to $j + 1$ with age-dependent probability ζ^j . At each date a new cohort of measure one of each gender enters the economy. Since the size of the entering cohort and survival probabilities are time-invariant, the model age distribution is stationary.

Life-cycle The life cycle of individuals is comprised of four stages: education, matching, work, and retirement. In the first two stages, the decision unit is the individual. In the second two stages the decision unit is the household, i.e. a pair of spouses. Since our focus is mostly on labor market risk, we simplify the first two stages of the life cycle by letting both education and matching take place sequentially in a unique pre-labor market period of life labeled “age zero”. Thus agents enter the labor market as married adults at age $j = 1$, retire at age $j = j^R$, and die with certainty when they reach age $j = J$.

Preferences We let $u(c_t, x_t)$ be the period utility function defined over market consumption c_t and a non-market (or home) good x_t . Both c_t and x_t are public goods for the household. The public good assumption means that we do not need to distinguish between utility at the level of the individual spouse versus utility at the level of the household, or between unitary versus collective models of household behavior. Furthermore, viewing the family as a unitary decision maker enjoying utility from public goods represents the smallest deviation from the standard single-agent “bachelor” model that predominates in the life-cycle consumption-savings literature. The non-market good x_t is jointly produced with male and female non-market hours according to the constant-returns to scale technology $x(1 - n_t^m, 1 - n_t^f)$, where $n_t^g \in [0, 1]$ denotes hours worked in the market by the spouse of gender g .¹¹

¹¹Following Greenwood and Hercowitz (1991), we do not distinguish explicitly between time devoted to leisure

Technology There is one final market good produced by a representative firm using aggregate capital K_t and aggregate labor input H_t according to a Cobb-Douglas production technology $Z_t K_t^\alpha H_t^{1-\alpha}$ where α is capital's share of output, and Z_t is a time-varying scaling factor. Output can be used for household consumption C_t , government consumption G_t , investment I_t , or net exports NX_t . Capital depreciates at rate δ .

We follow Katz and Murphy (1992) and Heckman, Lochner and Taber (1998) in modelling aggregate labor H_t as a CES aggregator of four types of labor input, $H_t^{g,e}$, indexed by gender g and education level $e \in \mathcal{E} \equiv \{h, l\}$, where h denotes high education and l low education:

$$H_t = \left[\lambda_t^S \left(\lambda_t^G H_t^{m,h} + (1 - \lambda_t^G) H_t^{f,h} \right)^{\frac{\theta-1}{\theta}} + (1 - \lambda_t^S) \left(\lambda_t^G H_t^{m,l} + (1 - \lambda_t^G) H_t^{f,l} \right)^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}. \quad (1)$$

According to this specification, male and female efficiency units of labor, conditional on sharing the same education level, are perfect substitutes, while the elasticity of substitution between the two different education groups is θ .

The technological parameters λ_t^S and λ_t^G capture skill-biased and gender-biased technical change, i.e. shifts over time in the relative demand for high-educated labor and in the relative demand for male labor.¹²

Government The government taxes labor and asset income at flat rates (τ^n, τ^a) and pays out a fixed pension benefit b to retirees. The government budget is balanced every period: once the pension system has been financed, any excess tax revenues are spent on non-valued government consumption G_t .

Commodities, assets and markets At each date t , there are five traded commodities: a final good and four types of labor services, as described above. As in İmrohoroğlu (1989), Huggett (1993), Aiyagari (1994) and Ríos-Rull (1995), financial markets are incomplete in the sense that agents trade risk-free bonds, subject to a borrowing constraint, but do not have access to state-contingent insurance against individual labor-income risk. The interest rate on the bonds is set internationally and is assumed to be constant and equal to r . Agents do have access to annuities – insurance against the risk of surviving. An intermediary pools savings

and home-production. In many instances, the distinction between the two is fuzzy (e.g., in the case of childcare, cooking, gardening, shopping). Greenwood and Hercowitz's view is that "time [...] has no intrinsic worth on its own [...], but instead derives its value from what can be done with it." (page 1192).

¹²The term $(1 - \lambda_t^G) / \lambda_t^G$ creates a time-varying wedge between the wages of a man and a woman with the same human capital. Jones, Manuelli and McGrattan (2003) chose to model this wedge as a "tax" on the female wage in the household budget constraint. It is easy to see that, from the viewpoint of an individual agent, these alternative modelling choices are equivalent.

at the end of each period, and returns pooled savings proportionately to individuals who are still alive at the start of the next period, at actuarially-fair rates. All markets are perfectly competitive.

3.2 Life cycle

We now describe the four stages of the life-cycle in detail.

3.2.1 Education

At the start of life (age zero) individuals make a discrete education choice between pursuing a college degree ($e = h$) or a lower schooling degree ($e = l$). The utility cost of attending college κ is idiosyncratic, and is drawn from the gender-specific distribution F^g . This cost captures, in reduced form, cross-sectional variability in scholastic talent, parental background, access to credit, and tuition fees.

When individuals decide whether or not going to college they factor in their draw for the cost, κ , the college wage premium they will command in the labor market, and the value of being highly educated when entering the matching stage: with positive assortative matching, acquiring college education increases the probability of meeting a college-educated – and thus high-earning – spouse. Let $\mathbb{M}_t^g(e)$ be the expected value, upon entering the matching stage at date t , for an individual of gender g who has chosen education level e . The optimal education choice for an individual with gender g and education cost κ is

$$e_t^g(\kappa) = \begin{cases} h & \text{if } \mathbb{M}_t^g(h) - \kappa \geq \mathbb{M}_t^g(l) \\ l & \text{otherwise} \end{cases} \quad (2)$$

where $e_t^g(\cdot)$ denotes the gender-specific education decision rule.¹³ Let q_t^g be the fraction of individuals of gender g choosing to attend college in period t . Then

$$q_t^g = F^g(\mathbb{M}_t^g(h) - \mathbb{M}_t^g(l)) \in [0, 1]. \quad (3)$$

¹³Our simple model for education acquisition is consistent with the key empirical patterns: (i) a positive correlation between education and scholastic ability/parental background (i.e. low κ), (ii) a positive correlation between education and wages, and, therefore, (iii) a positive correlation between measures of ability/background and wages. In the model, κ does not have a direct effect on earnings, it impacts earnings only through education. The debate on whether there are returns to ability above and beyond education is ongoing. For example, in a recent paper, Cawley, Heckman and Vytlačil (2001) argue that measures of cognitive ability and schooling are so strongly correlated that one cannot separate their effects on labor market outcomes without imposing arbitrary parametric structures in estimation (e.g., log-linearity and separability) which, when tested, are usually rejected.

3.2.2 Matching

Upon entering the matching stage, individuals are characterized by two states: gender and education (g, e) . Following Fernández and Rogerson (2001), matching (or marriage) is modelled as a mechanical process: individuals of opposite gender are exogenously paired based on their educational level. Let $\pi_t^m(e^m, e^f) \in [0, 1]$ be the fraction of men in education group e^m who marry a woman belonging to educational group e^f at time t . Symmetrically for women, we have probabilities $\pi_t^f(e^f, e^m)$.

The expected values upon entering the matching stage for men of high and low education levels can be written, respectively, as:

$$\begin{aligned} \mathbb{M}_t^m(h) &= \pi_t^m(h, h) \mathbb{V}_t^0(h, h) + \pi_t^m(h, l) \mathbb{V}_t^0(h, l), \\ \mathbb{M}_t^m(l) &= \pi_t^m(l, l) \mathbb{V}_t^0(l, l) + \pi_t^m(l, h) \mathbb{V}_t^0(l, h), \end{aligned} \quad (4)$$

where $\mathbb{V}_t^0(e^m, e^f)$ is expected lifetime utility at date t for each member of a newly-married (age zero) couple comprising a male with education e^m and a female with education e^f . Similar expressions can be derived for the functions $\mathbb{M}_t^f(e)$.

The enrollment rates from the schooling stage, q_t^g , together with the matching probabilities, π_t^g , jointly determine the education composition of newly-formed households. For example, the fraction of matches of mixed type (h, l) at date t is given by

$$q_t^m \pi_t^m(h, l) = (1 - q_t^f) \pi_t^f(l, h), \quad (5)$$

where the equality is an aggregate consistency condition. Denote by ϱ_t the cross-sectional Pearson correlation coefficient between the education level of husband and wife. One can show that, in the model,

$$\varrho_t = \frac{q_t^m \pi_t^m(h, h) - q_t^m q_t^f}{\sqrt{q_t^m (1 - q_t^m) q_t^f (1 - q_t^f)}}. \quad (6)$$

The correlation ϱ_t measures the degree of assortative matching. We treat this correlation as a structural parameter of the economy.

Finally, since our focus is on labor market risk, we abstract from shocks to family composition. Thus matching takes place only once, and marital unions last until the couple dies together.¹⁴

¹⁴Calibrated equilibrium model of marriage and divorce have been developed to assess the determinants of intergenerational mobility (see e.g. Aiyagari, Greenwood, and Guner, 2000); and to assess the role of changes in family composition on macroeconomic magnitudes (Cubeddu and Ríos-Rull, 2003).

3.2.3 Work

Individuals start working at age $j = 1$ and retire at age j^R . During this phase of the life cycle, they allocate their time between market work and production of the non-market good x_t . Labor services supplied to the market are indexed by the gender-education pair (g, e) , and each labor input commands a type-specific competitive price $p_t^{g,e}$ per efficiency unit.

An individual's endowment of efficiency units per hour of market work (or individual labor productivity) depends on experience and on the individual's history of idiosyncratic labor productivity shocks. Thus, at time t the hourly wage for an individual of age j and type (g, e) is given by

$$\underbrace{p_t^{g,e}}_{\text{price per unit}} \times \underbrace{\exp(L(j) + y_t)}_{\text{efficiency units}}, \quad (7)$$

where $L(j)$ is a deterministic function of age, and y_t is the stochastic individual-specific component of (log) labor productivity.¹⁵

Men and women face the same experience profile and the same stochastic process for idiosyncratic productivity. We model y_t as the sum of two orthogonal components: a persistent autoregressive shock, and a transitory shock. More precisely,

$$\begin{aligned} y_t &= \eta_t + v_t, \\ \eta_t &= \rho\eta_{t-1} + \omega_t \end{aligned} \quad (8)$$

where v_t and ω_t are drawn from distributions with mean zero and variances λ_t^v and λ_t^ω , respectively. The sequences $\{\lambda_t^v, \lambda_t^\omega\}$ capture time variation in the dispersion of idiosyncratic transitory and persistent shocks. At age $j = 1$, the initial value for the persistent component is drawn from a time-invariant distribution with mean zero and variance λ^η . We allow shocks to be correlated across spouses within a household. All these assumptions are discussed in detail in Section 4.1, when we present the parametrization of the model. In what follows, for notational simplicity, we stack the two idiosyncratic components $\{\eta_t, v_t\}$ for an individual of gender g in the vector $\mathbf{y}_t^g \in \mathcal{Y}$, and denote her/his individual efficiency units $\varepsilon(j, \mathbf{y}_t^g)$.

Households trade a risk-free asset paying a constant pre-tax rate of return r , subject to a borrowing limit \underline{a} . Asset holdings are denoted $a_t \in \mathcal{A} \equiv [\underline{a}, \infty)$. One unit of savings delivers

¹⁵Our model assumes a return to *age* rather than to actual labor market experience. This choice is made out of convenience: accounting explicitly for the return to experience would add two continuous state variables to the problem, one for the husband and one for the wife, making it significantly harder to solve. This simplification is unlikely to matter for men's choices, since the vast majority participate throughout working life anyway. In the literature there are different views on the role of labor market experience for women's work decisions. Olivetti (2006) argues that increases in returns to experience had a large effect on women's hours worked in the last three decades. In contrast, Attanasio, Low and Sanchez (2008) find small effects.

$1/\zeta^j$ units of assets next period, reflecting the perfect-annuity survivors' premium (spouses in a couple die simultaneously).

The problem of the household can thus be written as follows

$$\begin{aligned}
\mathbb{V}_t \left(e^m, e^f, j, a_t, \mathbf{y}_t^m, \mathbf{y}_t^f \right) &= \max_{c_t, a_{t+1}, n_t^m, n_t^f} u(c_t, x_t) + \beta \zeta^j E_t \left[\mathbb{V}_{t+1} \left(e^m, e^f, j+1, a_{t+1}, \mathbf{y}_{t+1}^m, \mathbf{y}_{t+1}^f \right) \right] \\
&\text{subject to} \\
c_t + \zeta^j a_{t+1} &= [1 + (1 - \tau^a) r] a_t + (1 - \tau^n) \left[p_t^{m, e^m} \varepsilon(j, \mathbf{y}_t^m) n_t^m + p_t^{f, e^f} \varepsilon(j, \mathbf{y}_t^f) n_t^f \right] \\
x_t &= x \left(1 - n_t^m, 1 - n_t^f \right) \\
a_{t+1} &\geq \underline{a}, \quad c_t \geq 0, \quad n_t^m, n_t^f \in [0, 1]
\end{aligned} \tag{9}$$

where the value function \mathbb{V}_t defines expected lifetime utility at time t , and takes as arguments the state variables for the household problem: the education pair (e^m, e^f) , age j , wealth a_t , and the vectors of components of male and female productivity $(\mathbf{y}_t^m, \mathbf{y}_t^f)$. Preferences and the asset market structure imply that there are neither voluntary nor accidental bequests.

The expected lifetime value for each spouse in a newly-formed household, \mathbb{V}_t^0 , is given by

$$\mathbb{V}_t^0(e^m, e^f) = E \left[\mathbb{V}_t \left(e^m, e^f, 1, 0, \mathbf{y}_t^m, \mathbf{y}_t^f \right) \right],$$

where the zero value for the fourth argument reflects the assumption that agents enter the working stage of the life cycle with zero wealth, and where the expectation is taken over the set of possible productivity shocks at age one.¹⁶

3.2.4 Retirement

Since retirees do not work, the only state variables for a retired household ($j \geq j^R$) are age and wealth. Retirees receive lump-sum social-security benefits b every period until death. Benefits are taxed at rate τ^n .

¹⁶The assumption of zero initial wealth is consistent with the absence of bequests in equilibrium. We analyzed the empirical distribution of financial wealth for individuals aged 23-25 in the U.S. from the 1992 Survey of Consumer Finances. We found that median wealth is negligible for this age group (\$2,000), with no significant differences across the two education groups. Details are available upon request.

The problem of a retired household is

$$\begin{aligned}
\mathbb{V}_t(j, a_t) &= \max_{c_t, a_{t+1}} u(c_t, x_t) + \beta \zeta^j \mathbb{V}_{t+1}(j+1, a_{t+1}) \\
&\text{subject to} \\
c_t + \zeta^j a_{t+1} &= [1 + (1 - \tau^a) r] a_t + (1 - \tau^n) b \\
x_t &= x(1, 1) \\
a_{t+1} &\geq \underline{a}, \quad c_t \geq 0, \quad a_{t+(J-j+1)} \geq 0
\end{aligned} \tag{10}$$

The home-production constraint clarifies that the entire time endowment of each spouse is devoted to the production of the non-market good x_t . The last inequality implies that agents cannot die in debt.¹⁷

3.3 Equilibrium

The economy is initially in a steady-state. Unexpectedly, agents discover that the economy will experience a period of structural change, with the changes being fully summarized by the sequences for SBTC, GBTC, and the variances of the stochastic wage components $\{\boldsymbol{\lambda}_t\} \equiv \{\lambda_t^S, \lambda_t^G, \lambda_t^v, \lambda_t^\omega\}$. Agents have perfect foresight over the future evolution of these sequences.

Let \mathcal{B}_A and \mathcal{B}_Y be the Borel sigma-algebras of \mathcal{A} and \mathcal{Y} , and $P(\mathcal{E})$ and $P(\mathcal{J})$ be the power sets of \mathcal{E} and \mathcal{J} . The state space is denoted by $\mathcal{S} \equiv \mathcal{E}^2 \times \mathcal{J} \times \mathcal{A} \times \mathcal{Y}^2$. Let $\Sigma_{\mathcal{S}}$ be the sigma algebra on \mathcal{S} defined as $\Sigma_{\mathcal{S}} \equiv P(\mathcal{E}) \otimes P(\mathcal{E}) \otimes P(\mathcal{J}) \otimes \mathcal{B}_A \otimes \mathcal{B}_Y \otimes \mathcal{B}_Y$ and $(\mathcal{S}, \Sigma_{\mathcal{S}})$ be the corresponding measurable space. Denote the measure of households on $(\mathcal{S}, \Sigma_{\mathcal{S}})$ in period t as μ_t and the initial stationary distribution as μ_* .

Given μ_* , $\{Z_t\}$, $\{\varrho_t\}$ and a sequence of wage-structure parameters $\{\boldsymbol{\lambda}_t\}$, a *competitive equilibrium* is a sequence of discounted values $\{\mathbb{M}_t^g(e)\}$; decision rules for education, consumption, hours worked and savings $\{e_t^g(\kappa), c_t(s), n_t^g(s), a_{t+1}(s)\}$; value functions $\{\mathbb{V}_t(s)\}$; firm choices $\{H_t^{g,e}, K_t\}$; prices $\{p_t^{g,e}\}$; government expenditures $\{G_t, b\}$; individual college graduation rates by gender and cohort $\{q_t^g\}$; matching probabilities $\{\pi_t^g\}$; and measures of households $\{\mu_t\}$ such that, for all t :

1. The education decision rule $e_t^g(\kappa)$ solves the individual problem (2) and q_t^g is the fraction of college graduates of gender g determined by (3).

¹⁷With a slight abuse of notation, we are only writing a subset of the states as arguments of \mathbb{V}_t in the retiree's problem, since during retirement the remaining state variables are irrelevant.

2. The matching probabilities π_t^g satisfy equation (6) and the consistency conditions

$$\begin{aligned} q_t^m \pi_t^m(h, h) &= q_t^f \pi_t^f(h, h) & (1 - q_t^m) \pi_t^m(l, h) &= q_t^f \pi_t^f(h, l) \\ q_t^m \pi_t^m(h, l) &= (1 - q_t^f) \pi_t^f(l, h) & (1 - q_t^m) \pi_t^m(l, l) &= (1 - q_t^f) \pi_t^f(l, l) \end{aligned} \quad (11)$$

Moreover, $\mathbb{M}_t^g(e)$ defined in (4) are the individual discounted utilities associated with this stage.

3. The household decision rules $c_t(s), n_t^g(s), a_{t+1}(s)$ solve the household problem (9) during the work stage, and (10) during retirement, with $\mathbb{V}_t(s)$ being the associated value functions.
4. The representative firm chooses its capital and its labor inputs optimally, i.e., K_t and $H_t^{g,e}$ satisfy;

$$\begin{aligned} r = \alpha Z_t \left(\frac{H_t}{K_t} \right)^{1-\alpha} - \delta & \quad p_t^{m,h} = \Omega_t^h \lambda_t^S \lambda_t^G & \quad p_t^{m,l} = \Omega_t^l (1 - \lambda_t^S) \lambda_t^G \\ p_t^{f,h} = \Omega_t^h \lambda_t^S (1 - \lambda_t^G) & \quad p_t^{f,l} = \Omega_t^l (1 - \lambda_t^S) (1 - \lambda_t^G) \end{aligned} \quad (12)$$

where $\Omega_t^e \equiv (1 - \alpha) Z_t \left(\frac{K_t}{H_t} \right)^\alpha H_t^{\frac{1}{1-\alpha}} \left(\lambda_t^G H_t^{m,e} + (1 - \lambda_t^G) H_t^{f,e} \right)^{-\frac{1}{\theta}}$ and H_t is given by (1).

5. The domestic labor markets clear, i.e. for all (g, e) pairs, $H_t^{g,e} = \int_{\mathcal{S}, e^g=e} \varepsilon(j, \mathbf{y}_t^m) n_t^g(s) d\mu_t$.
6. The domestic good market clears, $C_t + K_{t+1} - (1 - \delta)K_t + G_t + NX_t = Z_t K_t^\alpha H_t^{1-\alpha}$, where $C_t = \int_{\mathcal{S}} c_t(s) d\mu_t$ is aggregate consumption.
7. The world asset market clears. Let $A_{t+1} = \int_{\mathcal{S}} a_{t+1}(s) d\mu_t$ define aggregate domestically-owned capital at $t + 1$. Asset market clearing requires that the change in the country's net foreign asset position between t and $t + 1$ is equal to the year t current account: $(A_{t+1} - K_{t+1}) - (A_t - K_t) = NX_t + r(A_t - K_t)$
8. The government budget is balanced: $G_t + (1 - \tau^n) b \int_{\mathcal{S}, j \geq j^R} d\mu_t = \tau^a r A_t + \tau^n \sum_{g,e} p_t^{g,e} H_t^{g,e}$
9. For all $s \equiv (e^m, e^f, j, a_t, \mathbf{y}_t^m, \mathbf{y}_t^f) \in \mathcal{S}$, and $\mathbf{S} \equiv (\mathbf{E}^m \times \mathbf{E}^f \times \mathbf{J} \times \mathbf{A} \times \mathbf{Y}^m \times \mathbf{Y}^f) \in \Sigma_{\mathcal{S}}$, where $\{1\} \notin \mathbf{J}$, the measures μ_t satisfy $\mu_{t+1}(\mathbf{S}) = \int_{\mathcal{S}} Q_t(s, \mathbf{S}) d\mu_t$ with

$$Q_t(s, \mathbf{S}) = I_{\{e^m \in \mathbf{E}^m, e^f \in \mathbf{E}^f, j+1 \in \mathbf{J}, a_{t+1}(s) \in \mathbf{A}\}} \Pr \left\{ \mathbf{y}_{t+1}^m \in \mathbf{Y}^m, \mathbf{y}_{t+1}^f \in \mathbf{Y}^f \mid \mathbf{y}_t^m, \mathbf{y}_t^f \right\} \zeta^j.$$

The initial measure at age $j = 1$, for example for the (h, h) type, is obtained as

$$\mu_t(\{\{h\}, \{h\}, \{1\}, \{0\}, \mathbf{Y}^m, \mathbf{Y}^f\}) = q_t^m \pi_t^m(h, h) \Pr \left\{ \mathbf{y}_t^m \in \mathbf{Y}^m, \mathbf{y}_t^f \in \mathbf{Y}^f \mid j = 1 \right\},$$

and so on for all other education pairs.

4 The computational experiment

Experiment design The first objective of the paper is to study the implications of transformations in the wage structure for the dynamics of cross-sectional inequality in individuals' and households' earnings, consumption, and labor supply. In particular, we want to assess the ability of our model to reproduce the observed changes in a set of cross-sectional moments of interest, with changes in the wage structure parameters, i.e. the sequence $\{\boldsymbol{\lambda}_t\} \equiv \{\lambda_t^S, \lambda_t^G, \lambda_t^v, \lambda_t^\omega\}$, as the only time-varying input. Thus the sequence $\{\boldsymbol{\lambda}_t\}$ is parameterized so that it reproduces, respectively, the rise in the skill premium, the narrowing of the gender gap, and the increase in transitory and persistent residual wage inequality.

In addition, we calibrate the distributions for education costs so that the model broadly replicates empirical time paths for college enrollment by gender $\{q_t^g\}$. This ensures that when applying the matching probabilities $\{\pi_t^g\}$ from equation (11), the model will replicate the cross-sectional composition of households by education observed in the data.

To summarize, our strategy is to *calibrate* the model in order to match medium to low frequency trends in the wage structure and in the educational attainment of the population. We then *evaluate* the model by comparing the model-generated changes in the cross-sectional second moments of the joint equilibrium distribution of earnings, hours and consumption to their empirical counterparts, over the sample period.

Finally, we set the path for the aggregate scaling factor Z_t so that, in the absence of any behavioral response (i.e., assuming no changes in total effective hours for each type of labor input), the dynamics of $\boldsymbol{\lambda}_t$ would leave average output and labor productivity (output per hour) constant at the initial steady state level. We make this choice because we want to remain agnostic about the precise microfoundations underlying the dynamics in the components of $\boldsymbol{\lambda}_t$, and thus we want to avoid hard-wiring productivity changes in a particular direction into the design of the experiment. Of course it is quite possible that some of the much talked-about forces that have propelled the observed dynamics in $\boldsymbol{\lambda}_t$ –e.g., the weakening of unions, trade liberalization, or the fall in the price of ITC capital– have also directly increased economy-wide TFP. Any such increases should be added to the behavior-induced productivity (and welfare) effects that we quantify below.

We now turn to the parametrization of the model.

4.1 Parameterization

Some parameters are set outside the model, while others are estimated within the model and require solving for equilibrium allocations. The parameter values are summarized in Table 1.

4.1.1 Parameters set externally

Demographics The model period is one year. After the schooling choice and household formation, individuals enter the labor market at age 25, the median age of first marriage for males in the midpoint of our sample, 1982. They work for 35 years, and retire on their 60th birthday, thus $j^R = 35$. The age range of individuals in the model is the same as the range of our PSID, CPS and CEX samples. The maximum possible age is assumed to be 100, hence $J = 75$. Mortality probabilities $\{\zeta^j\}$ are taken from the U.S. Life Tables of the National Center for Health Statistics (1992).

Production technology The capital share parameter α is set to 0.33 and the depreciation rate δ to 0.06 (see Cooley, 1995). The constant world pre-tax interest rate r is set to 0.05. These parameter choices imply a capital-to-output ratio $K/Y = \alpha/(r + \delta) = 3$, a reasonable value for the United States. We follow Katz and Murphy (1992) in setting the parameter θ measuring the elasticity of substitution between education groups to 1.43.

Tax rates Following Domeij and Heathcote (2004), the tax rates on labor and capital income are set to $\tau^n = 0.27$ and $\tau^a = 0.40$, which implies an after-tax return to saving of 3%.

Matching probabilities The correlation between husbands' and wives' education level is constant, and set ϱ to 0.517, which is the average in our PSID sample for newly-formed households (i.e., aged 25-35). Given the model equilibrium enrollment rates and the target education correlation ϱ , equation (6) identifies the conditional probability $\pi_t^m(h, h)$. The remaining three matching probabilities follow from equations (11). The observed rise in educational attainment implies substantial changes in the matching probabilities. For example, across steady-states $\pi_t^m(h, h)$ rises from 0.43 to 0.79.

Productivity shocks The mapping between observed individual hourly wages and individual labor productivity is not immediate in our model, for two reasons. First, there are four different types of labor in the model, and over time their relative prices move in different ways. These dynamics induce changes in observed wages that do not correspond to changes in the number of efficiency units of labor supplied per unit of time. In particular, as is clear from

equation (7), one needs to filter out movements in the price component $p_t^{g,e}$ in order to isolate changes in efficiency units.

The second complication is that an individual's wage is observed in the data only if she/he works sufficiently to qualify for inclusion in our sample (260 hours per year). This selection problem is acute for women, especially in the first part of the sample period. Since in the model males and females are assumed to be subject to the same stochastic process for labor productivity shocks, this process can be estimated using only wage data for males, for whom selection issues are relatively minor given strong labor force attachment.¹⁸

Let $w_{i,j,t}$ be the hourly wage of individual i of age j at time t . Using PSID data, we therefore run an OLS regression of male hourly wages on a time dummy, a time dummy interacted with a college education dummy (e_i), and a cubic polynomial in potential experience (age minus years of education minus five) $L(j_{i,t})$:

$$\ln w_{i,j,t} = \beta_t^0 + \beta_t^1 e_i + L(j_{i,t}) + y_{i,j,t} \quad (13)$$

This specification is consistent with the wage equation (7) in the structural model. We find that the estimated polynomial function L peaks after 29 years of labor market experience at around twice the initial wage, and then declines by roughly 1% per year until retirement (which occurs after 35 years of experience). The residuals of equation (13) are a consistent estimate of the stochastic labor productivity component, since education is predetermined with respect to the realizations of $y_{i,j,t}$.

As described in equation (8), $y_{i,j,t}$ is modelled as the sum of a transitory plus a persistent component with time-varying variances. The choice of this statistical model was guided by three considerations. First, the typical autocovariance function for wages (across ages) shows a sharp drop between lag 0 and lag 1. This pattern suggests the presence of a purely transitory component which likely incorporates classical measurement error in wages. Second, there are strong life-cycle effects in the unconditional variance of wages: in our sample, there is almost a two-fold increase in the variance between age 25 and age 59. This suggests the existence of a persistent autoregressive component in wages. This component is modelled as an AR(1) process. Third, the nonstationarity of the wage process is captured by indexing the distributions for productivity innovations by year rather than by cohort, following the bulk of the literature which argues that cohort effects are small compared to time effects in accounting for the rise

¹⁸Low, Meghir, Pistaferri (2007) provide evidence on this. Attanasio, Low and Sanchez (2008) make the same symmetry assumption and find that it implies the right magnitude for the female wage variance, under the model's selection mechanism. As we will document later, our model has the same implication.

in wage inequality in the U.S. (e.g., Juhn, Murphy and Pierce, 1993; Heathcote, Storesletten and Violante, 2005).

In Appendix B we discuss identification and estimation of the wage process in great detail. Our estimation method is designed to minimize the distance between model and data with respect to the variances and covariances of wage residuals across cells identified by year and overlapping ten-year age group. We use the Equally Weighted Minimum Distance estimator proposed by Altonji and Segal (1996) based on Chamberlain (1984), and frequently employed in this type of analysis. Since one cannot separately identify the variance of the genuine transitory shock from the variance of measurement error, we assume that the variance of measurement error is time-invariant and use an external estimate.¹⁹ Based on the PSID Validation Study for 1982 and 1986, French (2002) finds that the variance of measurement error in log hourly wages is on average 0.02 across the two surveys. Expressed as a percentage of the residual wage variance in our sample, measurement error accounts for 8.5% of the total.

Our findings are summarized in Figure 3 and Table 2. Panel (B) of Figure 3 shows that residual wage dispersion (i.e., within experience/education groups) increased steadily over this period, and that the estimated model provides an excellent fit to the data. Comparing this picture to panel (A) in Figure 2 one concludes that the rise in this residual component accounts for around 2/3 of the total change in wage dispersion—a fraction in line with existing estimates: Katz and Autor (1999) estimate this fraction to be close to 60%.

Panel (C) displays the variance of measurement error, the variance of genuine transitory shocks λ_t^v , and the cumulated variance of persistent shocks: these three components sum to the total residual variance in panel (B). The variance of transitory shocks grows steadily throughout the period, while the cumulated variance of the persistent component is flat until the mid 1970s, then grows sharply during the decade 1975-1985, and is then roughly constant again except for a spike towards the end of the sample period. Consistently with this pattern, panel (D) shows that the variance of persistent shocks λ_t^ω doubles during the 1975-1985 decade. The point estimate for the initial (age 1) variance of the persistent component λ^η is 0.124, and shocks to this component are very persistent: the estimated annual autocorrelation coefficient ρ is 0.973 (see Table 2). The table also reports bootstrapped standard errors for all our estimates. In general, standard errors are small and the trends significant. As inputs for the model, we use Hodrick-Prescott-filtered trends of the estimated sequences $\{\lambda_t^v, \lambda_t^\omega\}$, with the HP smoothing parameter equal to ten.

¹⁹The strategy of using independent estimates of measurement error to separate the two components is common in the literature (e.g., Meghir and Pistaferri, 2004).

The correlation structure for shocks within the household is the only remaining aspect of the wage process. The correlation in the initial persistent productivity draw between husband and wife (which is almost a fixed effect, given the high persistence) is set equal to the correlation of education levels, i.e., 0.517. Our preferred interpretation for this assumption is that when matching, agents sort positively with respect to wages, irrespective of whether wage differences reflect (observable) education or the (unobservable) initial draw for the persistent component.²⁰ The cross-spouse correlations for transitory shocks and for innovations to persistent shocks is set to a common and constant level that reproduces, in equilibrium, the average observed correlation between wage growth for husband and wife. This empirical correlation, corrected for measurement error, is 0.15, which the model replicates when we feed in, as a structural parameter, a shock correlation of 0.134.²¹

4.1.2 Parameters calibrated internally

Utility costs of education We impose that the gender-specific distributions F^g for the utility cost of attending college are log-normal, $\ln \kappa \sim N(\bar{\kappa}^g, v_\kappa^g)$, and we choose means $\bar{\kappa}^g$ and variances v_κ^g to match enrollment rates by gender in the initial and final steady-states. The empirical counterpart for the initial steady state is the fraction of 25-54 years old who were college graduates in 1967: 15.3% for men, and 8.5% for women. The empirical counterpart for the final steady state is an estimate of the fraction of 25-29 year old graduates between 2000 and 2006: 25.6% for men and 31.7% for women. Intuitively, $\bar{\kappa}^g$ determine average enrollment levels by gender, while v_κ^g regulate the gender-specific elasticities of enrollment rates to increases in the college wage premium. The fact that college enrollment has increased more for women than for men (recall panel (C) in Figure 1) implies less dispersion in the distribution of female enrollment costs relative to that for men (see Table 1).

When we simulate the economy, the model's enrollment rates at each date t are those determined in equilibrium by the calibrated time-invariant cost distribution together with equation (3). By construction, the implied enrollment rates fit the broad trends documented in panel (C) of Figure 1.²²

²⁰The initial persistent draw does not appear explicitly in our expressions for matching probabilities, but sorting in this dimension is implicit in expected match values.

²¹These two choices for within-household shock correlation, are supported by existing studies. Hyslop (2001, Table 3) estimates the correlation between husband and wife fixed effects (which includes education) to be 0.572, and estimates the correlation of persistent shocks to be 0.154 over the 1980-1985 period in a sample of married households. Attanasio, Low and Sanchez (2008) use the Hyslop estimate for the correlation of shocks within the household, and thus choose a value very similar to ours.

²²The model enrollment rates do not reproduce the spike in male enrollment in the mid 1970s (see panel

Preferences The period utility function for an individual i at date t is:

$$u(c_{i,t}, x_{i,t}) = \frac{c_{i,t}^{1-\gamma}}{1-\gamma} + \psi \frac{x_{i,t}^{1-\sigma}}{1-\sigma}, \quad (14)$$

and the production technology for the non-market good has the symmetric CES form:

$$x_{i,t} = \left[(1 - n_{i,t}^m)^{1-\sigma} + (1 - n_{i,t}^f)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \quad (15)$$

First note that, even though we do not explicitly model fixed costs of work or indivisibilities, our preference specification allows for labor supply adjustments along the extensive margin: if the market wage of an individual is sufficiently low compared to the one of her spouse, she will choose zero market labor supply and devote all her time to producing the non-market good.

The curvature parameter γ is the reciprocal of the intertemporal elasticity of substitution (IES). Estimates for γ between one and two are common in the empirical consumption literature (see Attanasio, 1999, for a survey), so we set $\gamma = 1.5$. The parameter ψ determines the utility weight of non-market time relative to market consumption. We set $\psi = 0.335$ to match average household hours worked in the market, estimated to be 30% of the time endowment (assumed to be $15 * 365 = 5475$ hours per year per individual) over the sample period.

Given our functional forms and parametric restrictions, σ serves two purposes. The intertemporal elasticity of substitution for individual non-market time (leisure) is exactly $1/\sigma$, hence σ regulates the Frisch elasticity of labor supply.²³ Moreover, $1/\sigma$ is the static elasticity of substitution between male and female time in producing the non-market good. Consequently, σ will determine the allocation of time within the household. To see this, note that optimality within household i implies

$$\ln \left(\frac{1 - n_{i,t}^f}{1 - n_{i,t}^m} \right) = \frac{1}{\sigma} \ln \left(\frac{w_{i,t}^m}{w_{i,t}^f} \right). \quad (16)$$

Intuitively, the extent to which within-household wage differentials translate into differences in market hours is increasing in $1/\sigma$.

We set $\sigma = 3$. This value satisfies three criteria. First, this choice exactly replicates the empirical ratio of average female to average male hours of 0.48 (averaged over the entire period).

(C) of Figure 1) which we discussed in Section 2. As an alternative, we could have let the cost distribution be time-varying and replicate the enrollment rates year by year. However, this strategy implies an extra dimension of nonstationarity beyond wages, whereas the focus of our paper is on changes in the wage structure. By making this choice we underestimate the relative supply of college graduates, and thus the rate of SBTC in the 1970s. However *skill prices* are correct by construction because they are obtained by matching the path for the empirical college premium year by year.

²³Recall that the Frisch elasticity of labor supply is $(1/\sigma) (1 - n_{i,t}^g) / n_{i,t}^g$.

Second, the implied mean Frisch elasticity of labor supply for men is 0.48 and the one for women is 1.46.²⁴ These values are well within the range of gender-specific micro estimates (see Blundell MaCurdy, 2005, for a survey of micro estimates, and Domeij and Flodén, 2006, for an argument based on liquidity constraints for why micro-estimates may be downward biased). Third, with this choice the model almost exactly replicates the empirical correlation of -0.11 between changes in male wages and changes in female hours worked over the sample period.²⁵

The first and second results indicate that it is possible to account for gender differences in average hours and in the sensitivity of hours to fluctuations in wages without introducing any asymmetries in how male and female non-market hours enter preferences, or in the process for individual productivity shocks. The third result provides an implicit empirical validation for the degree of within-household risk-sharing that the model delivers through the joint labor supply decision. We conclude that this simple two-parameter (σ, ψ) model for the non-market sector can account for a surprising number of salient features of time allocation within the household.²⁶

As emphasized by Storesletten, Telmer and Yaron (2004), agents must have a realistic amount of wealth for the model to feature the appropriate amount of self insurance through savings. In the 1992 Survey of Consumer Finances, the ratio of average wealth (when excluding the top 1% of wealth holders) to average pre-tax labor income was 3.94 (Díaz-Giménez, Quadrini, and Ríos-Rull, 1997, Tables 6 and 9). With $\beta = 0.969$ our model matches this ratio in 1992. This value for β implies that the model economy has, on average, a small negative net foreign asset position (in 1992 foreign-owned assets are 9.0% of the domestic capital stock).

Borrowing constraint The ad-hoc borrowing constraint \underline{a} is calibrated to match the

²⁴The elasticity for women in the model declines from 1.77 in 1967 to 1.23 in 2005. This is consistent with the findings of Blau and Kahn (2005) who document a decline in married women’s labor supply elasticities between 1980 and 2000.

²⁵The raw empirical correlation is -0.087 and when correcting for measurement error it is lowered to -0.11 . The correction assumes that 1) hourly wages inherit all measurement error from hours, and 2) the measurement error in hours is 0.02, as estimated by French (2002). The average correlation in the model over the same period is -0.10 .

²⁶Our separable specification between market and non-market goods implies that the static elasticity of substitution (SES) between the two goods varies across households, and our choices for γ and σ imply that this elasticity is generally less than one (derivations are available upon request). Real business cycle models with a representative stand-in household sometimes assume larger static elasticities in order to increase internal propagation (e.g., Benhabib, Rogerson and Wright, 1991). However, a large value for the SES at the micro level in our model would imply implausibly high volatility for individual market hours and an implausibly negative intra-household correlation. As the recent literature on the Frisch labor supply elasticity has emphasized (e.g., Chang and Kim, 2006) “small” values for elasticities at the micro level are not necessarily inconsistent with “large” equilibrium values at the aggregate level.

proportion of agents with negative or zero wealth. In 1983, this number was 15.5% (Table 1 in Wolff, 2000). The implied borrowing limit is 20% percent of mean annual individual after-tax earnings in the initial steady state.

Pension benefits The U.S. social security system pays old-age pension benefits based on a concave function of average earnings. Several authors have documented that the implied risk-sharing is significant (e.g., Storesletten et al., 2004). Explicitly including such a system in our model would be computationally expensive, since one new state variable (an index of accumulated earnings) would have to be added. Here, we adopt a simpler, stylized version which captures the redistribution embedded in the U.S. system. In particular, all workers receive the same lump-sum pension b , the value of which is such that the dispersion of discounted lifetime earnings plus pension income in the final steady state of our economy is the same as in an alternative economy featuring the actual U.S. Old-Age Insurance system. The implied value for b is 24.5% of mean individual after-tax earnings in the initial steady state.²⁷

Technical change We compute the pair of sequences $\{\lambda_t^S, \lambda_t^G\}$ defining SBTC and GBTC so that the model time paths for the equilibrium male college premium and the equilibrium gender gap exactly match the trends in their empirical counterparts, where these trends are defined by applying an HP filter with smoothing parameter equal to ten to the raw data (see Section 2). Panel (A) of Figure 3 shows that the implied paths for λ_t^S and λ_t^G qualitatively follow closely the skill premium and the (inverse of the) gender gap.

Table 1 summarizes calibration strategy and parameter values. Appendix C outlines the computational algorithm for solving and simulating the model economy.

²⁷Using the parameters for the final steady state and a guess for the desired lump-sum pension value b we simulate an artificial panel of 80,000 households. For both spouses within a particular household, we compute average monthly earnings throughout working life (AIME). The AIME value is the input for a formula that calculates social security benefits as follows: 90 percent of AIME up to a first threshold (bendpoint) equal to 38 percent of average individual earnings, plus 32 percent of AIME from this bendpoint to a higher bendpoint equal to 159% of average earnings, plus 15 percent of the remaining AIME exceeding this last bendpoint. These are the actual bendpoints of the U.S. social security system in 2007. Once we have calculated the monthly social security benefits of husband and wife within the couple, we compute household benefits b_i^{US} as the maximum between: a) the sum of the two benefits, and b) 1.5 times the highest of the two benefits. This rule is called the "spousal benefit rule" in the U.S. pension system. We assume pension benefits in the U.S. system are taxed at half the labor income tax rate, which is a reasonable approximation. We repeat this procedure for every household in the artificial panel and then compute the within cohort variance of the log of lifetime household earnings plus social security. Next, we perform a similar calculation given our alternative hypothetical pension system characterized by a lump-sum pension, b . The desired value for b is the value that equates the dispersion in discounted lifetime income across the two systems. Solving for this value is a fixed point problem, since each time the guess for b is updated, the model panel of earnings changes slightly.

5 Results

This section presents the results of our numerical simulations. First, we simulate the calibrated benchmark economy, in which each dimension of technology in the vector λ_t is time-varying. We compare the model-implied paths for the cross-sectional moments of interest to their data counterparts and study the welfare implications of the shift in the wage structure.

We perform a set of decomposition experiments where we change the components of λ_t one at a time, holding the other components fixed at initial steady-state levels. In this way we are able to assess the extent to which the predicted dynamics for the moments of interest, and for welfare, are primarily attributable to (i) skill-biased technical change (SBTC), (ii) gender-biased technical change (GBTC), (iii) changes in the variance of persistent shocks, or (iv) changes in the variance of transitory shocks.

In the last part of the section, we report results from a set of counterfactuals in which we assess the importance of the various decision margins households can use to respond to the shifts in the wage structure: education, individual labor supply, female participation, and self-insurance through borrowing and saving.

5.1 Macroeconomic implications

We compare the simulated model output to the corresponding empirical moment computed from the CPS (for wages, hours and earnings) and from the CEX (for consumption).²⁸

Even though the focus of the exercise is on changes in cross-sectional inequality over time, it is useful to check the performance of the model along the life-cycle dimension. Thus, we begin by reporting the life-cycle dynamics in the mean and variance of household earnings and consumption for the cohort which is 25-29 years old in 1980 –the initial year of the consumption sample– and we compare it to the 1980 cohort in the model (Figure 4). The model slightly overestimates the rise in mean household earnings after age 45, but it replicates the other life-cycle facts remarkably well. We now turn to the performance of the model along the time dimension.

Female college premium Panel (A) of Figure 5 describes the evolution of the female

²⁸Recall that to estimate the time-varying parameters $\{\mathbf{A}_t\}$ we instead used data from the PSID, since our identification scheme relies heavily on the panel dimension. We chose to use CPS data for the model evaluation because the CPS sample is much larger than the PSID and CEX samples (see Table A-1), and thus trends in empirical moments are more easily discerned. In Appendix A, we systematically compare the time-paths for all the moments of interest across the two datasets. Although there is much more noise in the PSID series, reflecting the smaller sample, lower frequency trends are generally very similar to those in the CPS.

college premium (conditional on participation) in model and data. Recall that the model is calibrated to replicate the path for the male college premium. Panel (A) indicates that the model is able to replicate the fact that the female college premium has grown somewhat less than the corresponding male premium over the sample period (see Figure 1). The reason for slower growth is that female college enrollment increases much more rapidly than male enrollment over this period. Thus toward the end of the sample, women college graduates tend to be younger than high school graduates, and this negative experience gap limits the rise in the female skill premium. Panel (C) indicates that, not surprisingly, the dynamics of the college premium are almost exclusively attributable to skill-biased technical change. Gender-biased technical change has a small positive effect on the skill premium, because women are disproportionately high-school graduates in the 1970s and 1980s, and thus increasing female labor force participation reduces the relative supply of skilled labor.

Relative hours worked Panel (B) of Figure 5 plots average female hours worked relative to average male hours worked. The model accounts for roughly two thirds of the increase in relative female hours over this period. The dynamics of relative hours are driven almost entirely by the narrowing of the gender gap, i.e. by gender-biased technical change, see panel (D).

We find evidence of positive selection in the model, such that the gender gap for average observed wages is smaller than for offered wages, because low-wage women married to high-wage men tend not to work full time. Blau and Kahn (2006) provide empirical support for this type of selection in the U.S. in the 1980s and 1990s, using a wage imputation procedure for women working few or zero hours. Over time, as GBTC pushes low wage women into work, the selection effect weakens in the model. The fact that the gap in offered wages narrows more rapidly than that for observed wages helps explain why the model is able to generate such a large reallocation of female time in favor of market work.

The finding that the model accounts for the bulk of the increase in female hours over the period, and essentially the entire increase after 1980, is important since it means that our framework can address the positive and welfare implications of the trend away from the traditional single-male-earner family and towards the current dual-earner prototype. Similarly, Jones, Manuelli and McGrattan (2003) concluded that the narrowing gender gap can account for a significant portion of rising female participation. At the same time, the fact that our model stops short of replicating the increase in female hours in the 1960s and 1970s suggests a role for alternative non-wage-based explanations –particularly strong during this period– such as changes in social and cultural norms (Goldin and Katz, 2002; Fernandez and Fogli, 2007), increases in productivity in the home sector (Greenwood, Seshandri and Yorukoglu, 2005), and

declines in childcare costs (Attanasio, Low and Sanchez, 2007).

Wage inequality Figure 6 plots the evolution of the cross-sectional variance of log wages for men and women. Model and data align well in both cases. For men, this result confirms that, when fed back into the model, our statistical decomposition of the wage process into components attributable to age, education and persistent and transitory effects aggregates back up to reproduce the time series for cross-sectional inequality.²⁹

For women, the close alignment between the model and data series for wage inequality offers ex-post support for our assumption that the processes for male and female wages are symmetric. The decompositions in panels (C) and (D) indicate that skill-biased technical change, persistent shocks and transitory shocks all play important roles in accounting for the dynamics of wage inequality over this period, whereas gender-biased technical change has virtually no effect.

Hours inequality Figure 7 describes the time paths for the variances of log male and female hours. The model successfully replicates the fact that the level of cross-sectional dispersion in female market hours is much higher than for male market hours, even though our preference specification and wage process treat male and female leisure symmetrically. The reason is that the Frisch elasticity for market hours is decreasing in average hours worked. Given the gender wage gap, the efficient allocation of market work within the household implies that women tend to work fewer hours than men, and thus that their market hours are more sensitive to wage changes.

Over time, the model generates a small rise in hours inequality for men, compared to an essentially flat empirical time profile. Panel (C) indicates that this rise is driven mostly by stronger transitory shocks. The model, however, fails to replicate the observed decline in hours inequality for women, and instead predicts a flat profile for the variance of female hours (panel B). This flat profile reflects the existence of several offsetting forces (see panel D). On the one hand, larger transitory, and to a less extent, persistent shocks drive up dispersion in female hours. At the same time, the narrowing gender gap increases female hours thereby reducing the Frisch elasticity for female labor supply and its variability. To better understand how a narrowing gender gap works to reduce inequality in female hours, note that if the gender wage gap were to vanish entirely in our symmetric model, the distribution for female market hours would become identical to that for males.³⁰

²⁹There are several reasons the match is not perfect: (i) the data plotted is from the CPS, while our process for residual wage dispersion is estimated from the PSID; (ii) the joint distributions over age and education in model and data do not perfectly align year by year; and (iii) the inputs for the wage process are smoothed to filter out high frequency fluctuations.

³⁰A closer examination of the CPS data indicates that, mechanically, the main reason for the decline in

Wage-hours correlation Figure 8 displays the cross-sectional correlation between the individual log wage and individual log hours. As documented in Section 2 there is a dramatic rise in the wage-hour correlation for men in the 1970s and 1980s. The model reproduces both the magnitude and the timing of this increase.³¹

Panel (C) of the figure indicates that each component of the wage process plays an important role in determining the overall evolution of the wage-hour correlation. Given our assumption on the IES ($\gamma > 1$), wealth effects mean that individual hours will move inversely with uninsurable wage changes, whereas hours will move in step with wage changes that can be insured either through saving or through intra-household time reallocation. In the context of our model, the secular upward trend in the college premium has been largely uninsurable (conditional on educational choice), and has reduced the wage-hour correlation. However, this effect is more than offset by the positive impact of more volatile transitory shocks – which are straightforward to insure through precautionary savings – and by the effect of gender-biased technical change. Gender-biased technical change drives up the correlation between male hours and male wages because the larger is the fraction of household income attributable to the female, the smaller is the impact of a male income shock on household consumption, and thus the smaller the wealth effect on male hours.

The path for the female wage-hour correlation is flatter than the correlation for men, both in the model and data. As women’s share of household earnings has risen, household consumption

women’s hours dispersion is the increased clustering at full-time work (i.e., 2000 hours per year). This decline could be artificially inflated by heaping (i.e., rounding-off) in hours reports, a typical bias of retrospective surveys. However, part of it is certainly genuine. One way to reproduce this trend would be to extend the model, either by allowing for a part-time penalty in offered wages, or by restricting the hours decision to, say, zero, part-time, or full-time. In such a model, women would tend to work either relatively few hours or full-time. A narrowing gender gap would then push more and more women into the full-time category.

³¹The average level of this correlation is positive in the model, but negative in the data. In large part, the low number in the data reflects measurement error (the “division bias”): if an individual’s report of hours worked is too high (low), their imputed hourly wage, computed as earnings divided by hours, is automatically too low (high). The CPS offers two alternative ways to estimate hours worked, based two different questions, one about “usual weekly hours worked this year”, and the other about “hours worked last week”. The first question should provide a more accurate estimate for total hours worked in the previous year, but it was only asked beginning with the 1976 survey. Because we want to measure hours in a consistent way across our entire sample period, we chose to use the first question. However, for the post-1976 period we computed moments both ways. Reassuringly, the implied trends in the wage-hours correlation are essentially identical, both for men and for women. However, consistent with the conjecture that the usual-weekly-hours variable is less subject to measurement error, we found that the sub-sample average wage-hour correlation increases by 0.18, when hours are computed this way. Moreover, measurement error remains even in the usual-weekly-hours measure. Assuming that earnings are measured perfectly, so all measurement error in wages comes from hours, and using our external estimate for measurement error in wages of 0.02 (see Section 4.1), implies a measurement-error-corrected wage-hour correlation equal to 0.10, which significantly narrows the gap between data and model.

has responded increasingly strongly to female wage shocks, and these larger wealth effects moderate the increase in the wage-hour correlation. This also explains why the wage-hour correlation for women is higher than for men, both in the model and the data: on average the wealth effects associated with wage changes are smaller for women.

The variance of individual earnings predicted by the model (not plotted) lines up closely with the data for both men and women. The rise in female earnings inequality in the model slightly exceeds the data because of the misalignment in the paths for hours dispersion. However, in both model and data the increase in male (female) earnings inequality is larger than (similar to) the increase in wage inequality, which mechanically reflects the dynamics of the wage-hour correlation.

Household earnings and consumption inequality Figure 9 shows the time paths for the variance of household earnings and household consumption. The variance of household earnings is one moment for which the CPS and the PSID are not in full agreement, particularly towards the end of the sample, where inequality rises more rapidly in the CPS.³² The increase in household earnings inequality generated by the model (14 log points) lies in between the CPS and PSID series, and is closer to the PSID, as might be expected given that we use that source to estimate time variation in the wage structure. The rise in household earnings inequality in our CEX sample also lies in between that observed in the CPS and the PSID.

The model-generated rise in household earnings inequality is smaller than the rise in individual wage and earnings inequality because increasing risk at the individual level is partially insured within the household. Furthermore the surge in female participation means that the extent of within-family insurance is rising over time. Panel (C) indicates that the dynamics of household earnings dispersion are primarily driven by increases over the sample in the variances of transitory and persistent shocks. Gender-biased technical change has a modest offsetting effect, reflecting rising within-family insurance. The role of skill-biased technical change is muted by the imperfect correlation of education within the household, and by the fact that SBTC drives down the wage-hour correlation (recall Figure 8).

Panel (B) describes the dynamics in the variance of household log consumption (ND+). The data show a modest increase in inequality over time. The model closely reproduces the growth in consumption inequality since 1980. The counter-factual experiments in which only one component of the wage process is time-varying shed light on the mapping from earnings inequality to consumption inequality. A comparison of panels (C) and (D) indicates that skill-

³²We discuss the source of this discrepancy in Appendix A.

biased technical change and gender-biased technical change impact inequality in earnings and consumption symmetrically. This reflects the fact that agents respond to SBTC and GBTC primarily by changing education choices and the allocation of market work within the household, rather than by adjusting savings. Similarly, Attanasio and Davis (1996) find that low-frequency changes in relative wages between educational groups led to changes in relative consumption expenditures of a similar magnitude.³³

By contrast, changes in the variance of wage risk have very different effects on earnings and consumption inequality. This is due to self insurance through savings: bigger transitory shocks account for a large fraction of the run up in earnings inequality, but have little impact on consumption inequality, since these shocks can be very well smoothed with the risk-free asset. Persistent shocks imply an increase in earnings inequality roughly twice that of consumption. In a recent paper, Blundell, Pistaferri and Preston (2007) merge PSID and CEX data to estimate the fraction of random-walk household earnings shocks that transmit to consumption. They find a partial-insurance coefficient of 40 percent, which is comparable to the fraction of persistent shocks that agents can insure within our model.

Krueger and Perri (2006, Figures 2 and 5) decompose the rise in consumption inequality into changes within and between groups. They document that half of the rise in consumption inequality was due to residual (within-group) inequality, and that the Huggett (1993) version of the standard incomplete markets model exaggerates this rise, whereas their debt-constrained economy underestimates it. They conclude that the amount of insurance available to households in the U.S. economy is somewhere in between the two models.

Our model – which has many more channels of self insurance than the Huggett model – generates an increase in residual consumption inequality that is precisely half of the total. However, in the data the rise of the within-group component occurs mostly in the 1980s, whereas in our model it grows smoothly throughout the 1990s as well. One possible interpretation of this finding is that households’ borrowing constraints were relaxed in the 1990s, which is the main argument of Krueger and Perri (2006).

Wealth inequality Our model does not capture the empirical level of wealth inequality. In 1992, the Gini coefficient of wealth for married households was 0.76 (Díaz-Giménez et al., 1997), compared to 0.56 in the model. The discrepancy is particularly large at the very top:

³³SBTC can induce a change in consumption inequality even though it is assumed to be foreseen (after 1965). This is because high-school graduates who are of working age when SBTC starts favoring college graduates cannot avoid low permanent income and consumption levels. Moreover, even when SBTC is foreseen, an individual who draws a very high schooling cost κ will *optimally* choose to remain unskilled and suffer low lifetime income.

the richest 1% of the population holds 5% of aggregate wealth in the model, compared to 30% in the U.S. data. This is a common shortcoming of incomplete-market models (see Castañeda, Díaz-Giménez, and Ríos-Rull, 2003, and Domeij and Heathcote, 2004, for alternative calibration strategies that generate realistic wealth inequality). Excluding the wealthiest one percent of households, the model replicates the stability of wealth concentration in the data over this period: the Gini coefficient for household-level net worth in the Survey of Consumer Finances increased by 0.018 between 1983 and 1998 (Wolff, 2000, Table 2) while over the same period our model predicts a decline of 0.007.

Labor productivity Panel (A) of Figure 10 shows the dynamics of aggregate labor productivity (output per hour) in the model relative to the detrended data.³⁴ Recall that our computational experiment is designed so that any changes in labor productivity come about only because of behavioral adjustments to the varying wage structure. The model generates a decline in labor productivity in the 1970s and a sharp rise after the mid 1990s –two key features of the actual U.S. data.

Panel (B) decomposes the productivity trend. GBTC reduces aggregate labor productivity since it shifts the pool of workers disproportionately in favor of women who, on average, earn less per hour than men. In contrast, SBTC shifts the pool in favor of college graduates who, on average, are more productive than high-school graduates. In the 1970s, when SBTC is weak, the first force dominates, then gradually the second force takes over.

There is also a sizable productivity gain coming from the rise in transitory uncertainty. Transitory shocks are substantially insurable through the risk-free asset, and since labor supply is flexible, households optimally time market hours to exploit (transitory) periods of high wages. The larger the Frisch elasticity, the larger the gain from a rise in transitory dispersion (see Heathcote, Storesletten and Violante, 2008, for a more thorough analysis of this point in a partial insurance model admitting closed-form solutions).

5.2 Welfare implications

The ability of the model to account for cross-sectional dynamics over the sample period encourages us to consider the welfare implications of the estimated changes in structural labor market parameters.

³⁴The data series is “Output Per Hour of All Persons: Nonfarm Business Sector”, series OPHNFB in FRED, <http://research.stlouisfed.org/fred2>. The data plotted in Figure 10 are deviations from a linear trend applied to the log of the original series from 1967 to 2005.

Methodology For households entering the labor market in year t , the average welfare loss associated with changes in the wage structure is defined as the percentage amount by which one would have to reduce average lifetime market consumption in a benchmark cohort in order for a household to be indifferent between being born in the the benchmark year versus being born in year t . Recall that the only reason welfare will differ across cohorts is because of time variation in λ_t . We also compute expected household welfare conditional on the educational composition of the household.

We take 1965 as the benchmark year for three reasons. First, this is the year when new information is revealed about the dynamics of the vector λ_t , so our welfare numbers are not affected by surprise effects concentrated in a short period of time. Second, absent surprise effects, average ex-post household welfare is equal to expected ex-ante welfare under the veil of ignorance. Third, using the 1965 cohort as the baseline for our welfare comparison rather than initial steady state cohorts (those entering the labor force in 1929 or earlier) will allow us to compare our welfare numbers with other estimates in the literature (see below). All our welfare calculations factor in education costs, which is important because enrollment increases over time in response to SBTC.

Let $\mathbb{U}_t^{e^m, e^f}(\mathbf{c}, \mathbf{x})$ be expected lifetime utility per member of a newly formed household of education composition (e^m, e^f) belonging to cohort t , where the expectation is over the set of possible equilibrium sequences for consumption of the market and non-market goods, $(\mathbf{c}, \mathbf{x}) \equiv \{c_t, x_t\}_t^{t+J-1}$. The welfare change for this type of household is defined, formally, as the value ϕ_t that solves:

$$2\mathbb{U}_t^{e^m, e^f}(\mathbf{c}, \mathbf{x}) - \sum_{g \in \{m, f\}} I_{\{e^g=h\}} \int_0^{\hat{\kappa}_t^g} \frac{\kappa dF^g}{q_t^g} = 2\mathbb{U}_{1965}^{e^m, e^f}((1 + \phi_t) \mathbf{c}, \mathbf{x}) - \sum_{g \in \{m, f\}} I_{\{e^g=h\}} \int_0^{\hat{\kappa}_{1965}^g} \frac{\kappa dF^g}{q_{1965}^g}. \quad (17)$$

The average education cost paid college graduates of gender g is the expected value for κ conditional on κ being less than the threshold $\hat{\kappa}_t^g \equiv \mathbb{M}_t^g(h) - \mathbb{M}_t^g(l)$ below which college is the optimal education choice.

The average welfare gain across all household types is defined by a similar equation where the terms involving lifetime utilities and education costs are now population-weighted sums across the different types. For example, values and expected schooling costs for type (h, l) in cohort t are weighted by $q_t^m \pi_t^m(h, l)$.

Attanasio and Davis (1996) and, similarly, Krueger and Perri (2003), estimate a stochastic process for consumption data from the CEX, and evaluate welfare effects of rising inequality with standard CRRA preferences. They report welfare losses between 1% and 2% of lifetime

consumption.

Their empirical approach has the advantage that no restrictive assumptions have to be made on the degree of market completeness, so it is less model-specific. However, it has two drawbacks, relative to our approach, which lead them to overestimate welfare losses. First, before computing changes in consumption variability in the data, they demean the time-series. This procedure excludes “level effects” on average productivity (and welfare) by construction. For example, as explained earlier, a rise in transitory (hence insurable) income volatility leads to higher productivity through modified labor supply decisions. Second, in their welfare calculations they average between education groups, but when comparing economies before and after the rise in inequality they hold fixed the weights on the two groups. By doing so, they exaggerate welfare losses because they do not account for the fact that infra-marginal agents are better off by paying a cost and switching from the low to the high education group.³⁵ Only with an explicit structural model can one quantify the level effects and calculate the average utility cost paid by all the individuals who switch into the college educated group, a key ingredient of the welfare calculation in equation (17). We now turn to our findings.

Average (ex-ante) welfare Panel (A) of Figure 11 plots the average welfare change for cohorts entering the labor market in years $t \geq 1965$. Cohorts entering until the early 1980s experience welfare losses up to 0.51% of lifetime consumption. After the mid 1980s, households start experiencing welfare gains which rise over time. For example, the cohort entering in 1990 enjoys a welfare gain, relative to the 1965 cohort, of 0.86% in terms of lifetime consumption.

The lower panel (B) of Figure 11 plots the contribution of each component of structural change (persistent and transitory shocks, GBTC and SBTC) to the overall welfare effect. Larger transitory shocks increase average labor productivity, as explained above, and thus induce small welfare gains. These welfare gains are enjoyed quite evenly by all cohorts, including the 1965 cohort, which is why the relative gains from transitory uncertainty for subsequent cohorts relative to 1965 appear small.³⁶ The large increase in the variance of persistent shocks is the

³⁵To illustrate this point, consider the following example. Suppose there are two groups in the population, low-skilled and high-skilled, with equal weights, and suppose that average consumption of the two groups becomes more unequal between t and $t + 1$. Then, from an ex-ante viewpoint, we would observe a welfare loss between t and $t + 1$. Loosely speaking, this is the logic behind the results of Attanasio and Davis, and Krueger and Perri. However, if households can switch from the low to the high skill group by paying a cost, then the right welfare comparison would put different weights on the two groups at t and $t + 1$ and, at the same time, would subtract the average incurred cost from the utility of the high-skill group. Because individuals will only switch groups if it is optimal for them to do so, this latter welfare calculation will imply a smaller welfare loss than the former.

³⁶Precisely, relative to a cohort spending its working years entirely in the initial steady state (i.e., entering the labor market in 1929), the 1965 cohort enjoys an expected welfare gain of 0.69% of which 0.26% derives

main source of welfare losses for the typical U.S. household. Since these shocks are so durable, buffer-stock savings are of limited use as an insurance device. If one were to focus only on the welfare effects of the rise in residual wage variability (transitory plus persistent shocks), one would conclude that changes in the wage structure led to welfare losses of around 2% of consumption.³⁷

Turning to GBTC, we identify two opposing forces at work. First, recall that in sharp contrast to SBTC, GBTC reduces average labor productivity in the market sector because it increases hours worked by women who earn less than men, on average. Second, GBTC induces a more even allocation of time within the household, which effectively increases productivity in the home sector, and also makes household market income less susceptible to individual level shocks. Overall, GBTC is welfare-improving: the welfare gain for the 1990 cohort is equivalent to 0.74% .of consumption.

Panel (B) indicates that skill-biased technical change was the source of sizeable welfare gains for the average U.S. household. Note that while both SBTC (an increase in λ_t^S) and bigger persistent shocks (an increase in λ_t^ω) increase cross-sectional consumption inequality in a similar fashion, the two phenomena have opposite implications for welfare. This asymmetry arises because in response to SBTC agents have the opportunity to avoid the low wage outcome through a behavioral response: inframarginal agents respond by changing their education decision, relative to the initial steady state, in favor of college. The dramatic rise in college enrollment witnessed in the U.S. (and replicated in the model) indicates that many households took advantage of this opportunity. Mechanically, in the calculation of average welfare, the weight on households with at least one college-graduate spouse rises in each successive cohort, with positive and sizable implications for average labor productivity and welfare.

It is important to emphasize that our estimates of the welfare gains from SBTC depend on the size of equilibrium education costs. In particular, welfare gains from SBTC will be smaller the larger are education costs on average, and the more rapidly costs per student rise with enrollment. In our economy, education is the first decision individuals make, and thus the calibrated values for education cost parameters depend on our modelling choices for subsequent stages in the life-cycle. We assume that education costs are paid at the individual level before

from larger transitory shocks.

³⁷This was, in fact, the conclusion we reached in Heathcote, Storesletten and Violante (2004). There the wage process also included a fixed individual effect and, as a result, the persistent component had lower durability: the autoregression coefficient ρ was 0.94. The 2% welfare loss obtained in our early draft was the result of both components (time-varying fixed effects and persistent shocks). Here, we have abstracted from fixed effects and, not surprisingly, the estimated AR(1) component is more persistent: $\rho = 0.97$.

household formation, while market consumption is a public good within the family. Thus equilibrium education costs paid are lower than they would be in alternative models in which either some part of the cost of college was shared within the household, or some part of the return to college was private. At the same time, however, we assume that households have perfect foresight regarding the widening of the college premium, which means that education costs must rise rapidly for marginal agents to avoid a counter-factual surge in enrollment. Taking these two points together, we conclude that it is unclear whether our modeling choices lead to over- or under-estimating the welfare gains associated with SBTC.³⁸

Conditional welfare Panel (C) shows welfare changes conditional on household type. Here, we see that as long as the household has at least one college educated member, it is significantly better off in expected terms, relative to the 1965 cohort. By contrast, the high school-high school households –accounting for 65% of all households in 1990– experience a remarkable welfare loss of 3.74% of lifetime consumption. As shown in panel (D), the welfare losses for these low skill households, relative to other household types, are attributable to SBTC.³⁹

5.3 Insurance and opportunities

The observed changes in the U.S. wage structure have amplified the risks households face in the labor market, but they have also offered new economic opportunities by raising the relative wages of women and of individuals who obtain a college education. In this section, we use our model to study how U.S. households have modified their economic choices to mitigate the adverse effects of rising uncertainty and to take advantage of these new opportunities.

Four distinct channels of behavioral response are considered: savings, flexible labor supply, female participation, and college enrollment. In the counterfactuals, we simulate the economy under the same parametrization but we “freeze” each margin of adjustment, one at the time.

Savings: We begin by solving the economy under the restriction that household asset

³⁸We conducted two simple experiments to get a sense of how sensitive our welfare numbers are to the distribution for education costs within the context of our model. First, we assumed that all additional college-goers during the transition have the same utility cost of going to college, where this cost is equal to the average cost in the initial steady state - this is an upper bound to the gains from SBTC. Second, we assumed that costs rise over time such that every additional college-goer is exactly indifferent between going to college or not - this constitutes a lower bound for the gains from SBTC. We found that average welfare gains in our model lie roughly midway between these two bounds: for example the bounds for average welfare for the 1990 cohort are –1.30% and 2.85%, while the model value is 0.86%.

³⁹In contrast to SBTC, GBTC benefits every household in the model, because we focus on married couples. If we had single men in the model, they would unambiguously lose from GBTC.

holdings are zero in every period, and compare the outcomes to the benchmark economy with access to credit markets.⁴⁰ The results are displayed in Figure 12. Agents now use labor supply as a substitute for savings to respond to wage shocks and to smooth consumption, lowering (raising) market hours in response to higher (lower) wages. This strategy translates into a substantially lower wage-hour correlation and lower earnings dispersion than in the baseline economy (see panels (A) and (C) in Figure 12). Absent savings, cross-sectional dispersion in household consumption must equal dispersion in household earnings. Thus the no-savings economy features both a higher *level* of consumption inequality and a slightly larger *increase* in consumption inequality [CHECK] than the benchmark economy (panel (B)). Households entering the labor market after the mid 1980s suffer a welfare loss in the no-savings economy that is 2-3 percent of lifetime consumption [CHECK] larger than in the baseline (panel (D)).

Labor supply: We then compare the benchmark economy to one without a flexible choice of hours - at each date men and women are forced to work their respective average hours in the initial steady state of the benchmark model. Fixing hours worked has little effect on the level of earnings inequality, because empirically the wage-hour correlation is close to zero anyway. At the same time, fixing hours increases the *level* of consumption inequality by shutting down wealth effects that reduce (increase) hours and thus earnings for high (low) consumption households. The additional welfare losses, relative to the baseline model, are about the same as for the savings channel, indicating that labor supply and savings are equally valuable adjustment margins. In the rigid labor supply economy, the median wealth-income ratio is $XYZ\%$ [CHECK] larger than in the benchmark model, as households rely more heavily on precautionary savings to smooth shocks.⁴¹

Female labor force participation: In our next alternative economy we constrain women's hours to be zero in every period, while allowing men to choose hours freely. Absent female participation, the shift in the wage structure would be detrimental: from the 1985 cohort and onwards, the welfare gain would be [UPDATE]4-5 percent lower than in the benchmark economy. The main reason why this experiment leads to large welfare losses is that the shrinking gender wage gap makes it very costly to exclude women from the labor market. In addition, ruling out female participation reduces the extent to which more volatile shocks can be self-insured via intra-household reallocation of time.

Interestingly, this alternative economy still generates about half the observed increase in

⁴⁰In this counterfactual economy, the entire aggregate demand for capital is satisfied by foreign assets.

⁴¹The quantitative study by Pijoan-Mas (2006) also finds that households make ample use of work effort as a self-insurance mechanism in order to mitigate the welfare costs of market incompleteness.

female college enrollment since 1970, even though women’s earnings are always zero by assumption. The reason is that education increases the probability of matching with a college-educated partner. Rising relative wages for college-educated men therefore increase the return to education for women through the “marriage market”.

Education choice: To examine the role of education choice as a means for exploiting the new opportunities offered by a rising skill premium, we consider an economy in which the fraction of college graduates is fixed at the initial steady state level. In our benchmark economy, the supply of college-educated workers rises in response to skill-biased technical change (SBTC) and this increased supply mitigates the effect of SBTC on the equilibrium college premium. The no-education-choice economy assumes away any such supply responses, implying a larger increase in the college premium after 1985.[UPDATE FOOTNOTE NUMBERS]⁴² The model reveals a dramatic worsening of welfare when agents cannot adjust their education choices: the welfare loss from changes in the wage structure would be [UPDATE]10 percent for the cohorts born in the 1990’s, relative to a gain of [UPDATE]1 percent in the benchmark economy. This is due to three forces. First, the rise in college attendance in the baseline model has large general-equilibrium effects in mitigating SBTC. Without this powerful force at work, consumption inequality doubles (see panel (B)). Second, in the economy with no schooling choice, the individuals who would optimally change decisions in favor of college in the benchmark economy miss out on the opportunities offered by the higher college premium. Third, as enrollment rises, the quality of the pool in the matching market improves, which constitutes an externality in the context of our model in which education costs are paid at the individual level. Precluding a rise in enrollment means increasing the welfare losses for later cohorts associated with this externality.

Summarizing, the four channels of adjustment explored here – savings, flexible hours, female participation, and schooling choice – are all quantitatively important. In terms of alleviating the adverse effects of rising consumption inequality, the four channels appear to be roughly equally important: closing any one of them would imply about twice as large an increase in consumption inequality as compared to the baseline model. However, in terms of overall welfare, female participation and college choice matter much more than saving and flexible labor supply, since they allow individuals to take advantage of the opportunities created by the dynamics of gender and skill-biased technical change.

⁴²According to the model, the rise in the college premium would be twice as large in absence of increased college enrollment: an increase from 1.3 to 2.6 between 1977 and 2000, compared to an increase from 1.3 to 1.9 in the data and in the benchmark economy.

6 Conclusion

In the last three decades, the U.S. economy has experienced a dramatic change in the wage structure along three dimensions. First, the college premium doubled. Second, the gender gap halved. Third, “residual” individual wage variability increased substantially due to a rise in the variance of persistent shocks - concentrated primarily in the 1980s - and a steady increase in the variance of transitory shocks.

In this paper, we have studied the macroeconomic and welfare implications of all these changes through the lens of a version of the neoclassical growth model with incomplete markets and overlapping-generations.

Our model extends the prototypical incomplete markets framework in several dimensions, adding an education choice, a marriage technology, a model of the family in which husband and wife face imperfectly correlated persistent and transitory shocks to wages, and an explicit production technology incorporating labor inputs differentiated by gender and education. The payoff from adding all this detail is twofold. First, we can deliver a detailed model of structural labor market change, explicitly addressing several key trends including a widening college premium and a narrowing gender gap, in addition to the rise in residual dispersion. Second, we can address the roles of key insurance mechanisms and responses to structural change, including college enrollment, female participation and flexibility in hours worked, in addition to the more widely-studied role of precautionary savings.

We argued that the model can account for most of the key trends in cross-sectional U.S. data on hours, earnings and consumption. Each dimension of the wage structure plays an important role. Rising transitory wage instability is a key determinant of the rise in wage-hour correlation and in household earnings. Persistent wage shocks and the skill premium account for the bulk of the dynamics in consumption inequality. The narrowing gender gap explains most of the rise in relative hours worked by women, and also drives convergence across men and women in higher moments for individual hours

When we calculated the welfare effects of the observed changes in the wage structure, we found that couples comprising two high-school graduates were hit very harshly. For this type of family, the cohort who entered the labor market in 1990 is 3.5 percent worse off than the 1965 cohort in terms of lifetime consumption. However, every other family type experiences welfare gains, and on average the 1990 cohort is better off than the 1965 cohort by 0.90 percentage points. This welfare gain contrasts with the conventional view that rising inequality led to welfare losses (e.g., Attanasio and Davis, 1996; Krueger and Perri, 2003). Our welfare

estimates are rosier because they are derived in the context of a structural equilibrium model that incorporates behavioral adjustment in response to labor market change.

In extending the standard incomplete markets model, we have generally opted for the simplest modeling choices, in part because solving for equilibrium transitional dynamics is numerically challenging. However, the model invites refinement in various dimensions to address a large set of issues that are not the focus of the present paper.

First, one could pursue alternative models of the family. We assumed that market and non-market goods are public goods within the family, because this constitutes the smallest deviation from the standard bachelor-household model, and because we found that this effectively unitary model of the household can successfully replicate key features of time allocation within the household.⁴³ By contrast, recently developed models of the family based on the "collective" paradigm or on cooperative bargaining emphasize how the distribution of control of resources within the household can influence the distribution of private consumption and leisure. For example, Lise and Seitz (2007) find evidence that, in the U.K., the closing of the gender gap induced a decline in intra-family consumption inequality, with positive implications for welfare.

Second, our model of household formation is fairly rudimentary. Moreover, to avoid incorporating an additional source of time-variation in the model, we have abstracted from the changes in the intra-household correlation between education levels of the two spouses over the sample period. Panel (C) of Figure A-4 shows that this correlation follows qualitatively the time path of the college premium, suggesting that the latter may be an important determinant of household formation patterns. This issue invites further research.

Third, we have made some stark assumptions on the information set of the agents. We have assumed that agents have no advanced information on persistent and transitory shocks, but have perfect foresight over the dynamics of the skill premium and the gender gap. Interestingly, relaxing either assumption should lead to more favorable outcomes in terms of welfare (assuming perfect foresight regarding the skill premium implies marginal agents face high college costs during transition). The greater the fraction of wage fluctuations that is foreseen, the smaller should be the impact of rising residual wage dispersion on consumption inequality (see, for example, Guvenen, 2007; Primiceri and van Rens, 2007). Our model generates realistic increases in consumption dispersion both over the life-cycle and over time, indicating that our information

⁴³Given our separable preference specification, we could have chosen to define individual utility over consumption and leisure, both private goods, and to represent the household utility function as an equally weighted average of each spouse's individual utility. Appropriately recalibrated, this alternative would imply identical allocations across the initial and final steady states, but because it would change the nature of the cost-benefit calculation in the education decision, welfare results would change.

set assumptions are broadly consistent with this sort of evidence.

Taking stock, we believe that the recent changes in the cross-sectional distribution of wages, hours worked, and household consumption expenditures offer a unique opportunity to improve our understanding of human capital accumulation, household formation and dissolution, labor supply, and risk sharing through markets, families and government— all key issues at the cross-road between macroeconomics and labor economics. In this paper we focused on a subset of facts and a subset of issues, leaving plenty of room for further research.

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Table 1: Summary of Parameterization

Parameter	Moment to match	Value
Parameters set externally		
$\{\zeta^j\}$	age-specific survival rates (U.S. Life Tables)	see text
γ	micro-estimates of intertemporal elasticity of substitution	1.50
ϱ	intra-family correlation of education at ages 25-35 (PSID)	0.517
α	capital share of output (NIPA)	0.33
δ	depreciation rate (NIPA)	0.06
θ	elasticity of substitution between college and high-school graduates	1.43
r	risk-free interest rate	0.03
τ^n, τ^a	labor income and capital income tax rates	0.27, 0.40
$L(j)$	male hourly wage life-cycle profile (PSID)	see text
$\{\lambda_t^\omega, \lambda_t^v\}, \lambda^\eta, \rho$	male hourly wage residuals dynamics (PSID)	see Table 2
Parameters calibrated internally		
$\bar{\kappa}^m, v_{\kappa}^m$	male college enrollment in initial and final steady-state	2.96, 0.88
$\bar{\kappa}^f, v_{\kappa}^f$	female college enrollment in initial and final steady-state	2.22, 0.31
β	ratio of average wealth (for poorest 99%) to average labor income	0.969
ψ	average household market hours	0.335
σ	ratio of average male to female market hours	3.0
b	redistribution (of lifetime earnings) through U.S. pension system	0.245
\underline{a}	15.5% of households have zero or negative wealth	-0.20
$\{\lambda_t^S\}$	ratio of average male college to high-school wages	see Figure 1
$\{\lambda_t^G\}$	ratio of average male to female wages, full-time workers	see Figure 1
$\{Z_t\}$	average post-tax earnings equal to one, absent behavioral response	see text

Table 2: Parameter Estimates of Wage Process

Persistent Component			Transitory Component		
	Estimate	S.E.		Estimate	S.E.
ρ	0.9733	(0.0066)			
λ^η	0.1242	(0.0067)			
λ_{1967}^ω	0.0076	(0.0024)	λ_{1967}^v	0.0389	(0.0121)
λ_{1968}^ω	0.0151	(0.0077)	λ_{1968}^v	0.0215	(0.0098)
λ_{1969}^ω	0.0079	(0.0039)	λ_{1969}^v	0.0321	(0.0110)
λ_{1970}^ω	0.0087	(0.0044)	λ_{1970}^v	0.0317	(0.0093)
λ_{1971}^ω	0.0074	(0.0043)	λ_{1971}^v	0.0328	(0.0096)
λ_{1972}^ω	0.0219	(0.0067)	λ_{1972}^v	0.0489	(0.0098)
λ_{1973}^ω	0.0065	(0.0038)	λ_{1973}^v	0.0375	(0.0092)
λ_{1974}^ω	0.0030	(0.0022)	λ_{1974}^v	0.0490	(0.0093)
λ_{1975}^ω	0.0094	(0.0050)	λ_{1975}^v	0.0371	(0.0086)
λ_{1976}^ω	0.0067	(0.0042)	λ_{1976}^v	0.0626	(0.0102)
λ_{1977}^ω	0.0083	(0.0038)	λ_{1977}^v	0.0472	(0.0099)
λ_{1978}^ω	0.0132	(0.0047)	λ_{1978}^v	0.0547	(0.0121)
λ_{1979}^ω	0.0075	(0.0039)	λ_{1979}^v	0.0580	(0.0117)
λ_{1980}^ω	0.0171	(0.0052)	λ_{1980}^v	0.0620	(0.0101)
λ_{1981}^ω	0.0118	(0.0052)	λ_{1981}^v	0.0566	(0.0113)
λ_{1982}^ω	0.0179	(0.0046)	λ_{1982}^v	0.0611	(0.0095)
λ_{1983}^ω	0.0180	(0.0066)	λ_{1983}^v	0.0663	(0.0102)
λ_{1984}^ω	0.0208	(0.0061)	λ_{1984}^v	0.0510	(0.0096)
λ_{1985}^ω	0.0158	(0.0058)	λ_{1985}^v	0.0511	(0.0096)
λ_{1986}^ω	0.0249	(0.0053)	λ_{1986}^v	0.0754	(0.0111)
λ_{1987}^ω	0.0045	(0.0039)	λ_{1987}^v	0.0683	(0.0109)
λ_{1988}^ω	0.0226	(0.0048)	λ_{1988}^v	0.0762	(0.0110)
λ_{1989}^ω	0.0144	(0.0055)	λ_{1989}^v	0.0606	(0.0104)
λ_{1990}^ω	0.0054	(0.0047)	λ_{1990}^v	0.0648	(0.0098)
λ_{1991}^ω	0.0182	(0.0058)	λ_{1991}^v	0.0703	(0.0103)
λ_{1992}^ω	0.0078	(0.0054)	λ_{1992}^v	0.0661	(0.0111)
λ_{1993}^ω	0.0303	(0.0072)	λ_{1993}^v	0.0734	(0.0100)
λ_{1994}^ω	0.0087	(0.0055)	λ_{1994}^v	0.0772	(0.0130)
λ_{1995}^ω	0.0114	(0.0063)	λ_{1995}^v	0.0681	(0.0110)
λ_{1996}^ω	0.0163	(0.0069)	λ_{1996}^v	0.0581	(0.0117)
λ_{1997}^ω	0.0190	(0.0049)	λ_{1997}^v	0.0714	(0.0115)
λ_{1998}^ω	0.0219	(0.0068)	λ_{1998}^v	0.0774	(0.0123)
λ_{1999}^ω	0.0216	(0.0049)	λ_{1999}^v	0.0787	(0.0111)
λ_{2000}^ω	0.0212	(0.0079)	λ_{2000}^v	0.0872	(0.0131)

Note: Minimum Distance estimates of the parameters of the wage process in equation (8). Standard Errors (S.E.) are obtained by block-bootstrap based on 500 replications. See Appendix B for details.

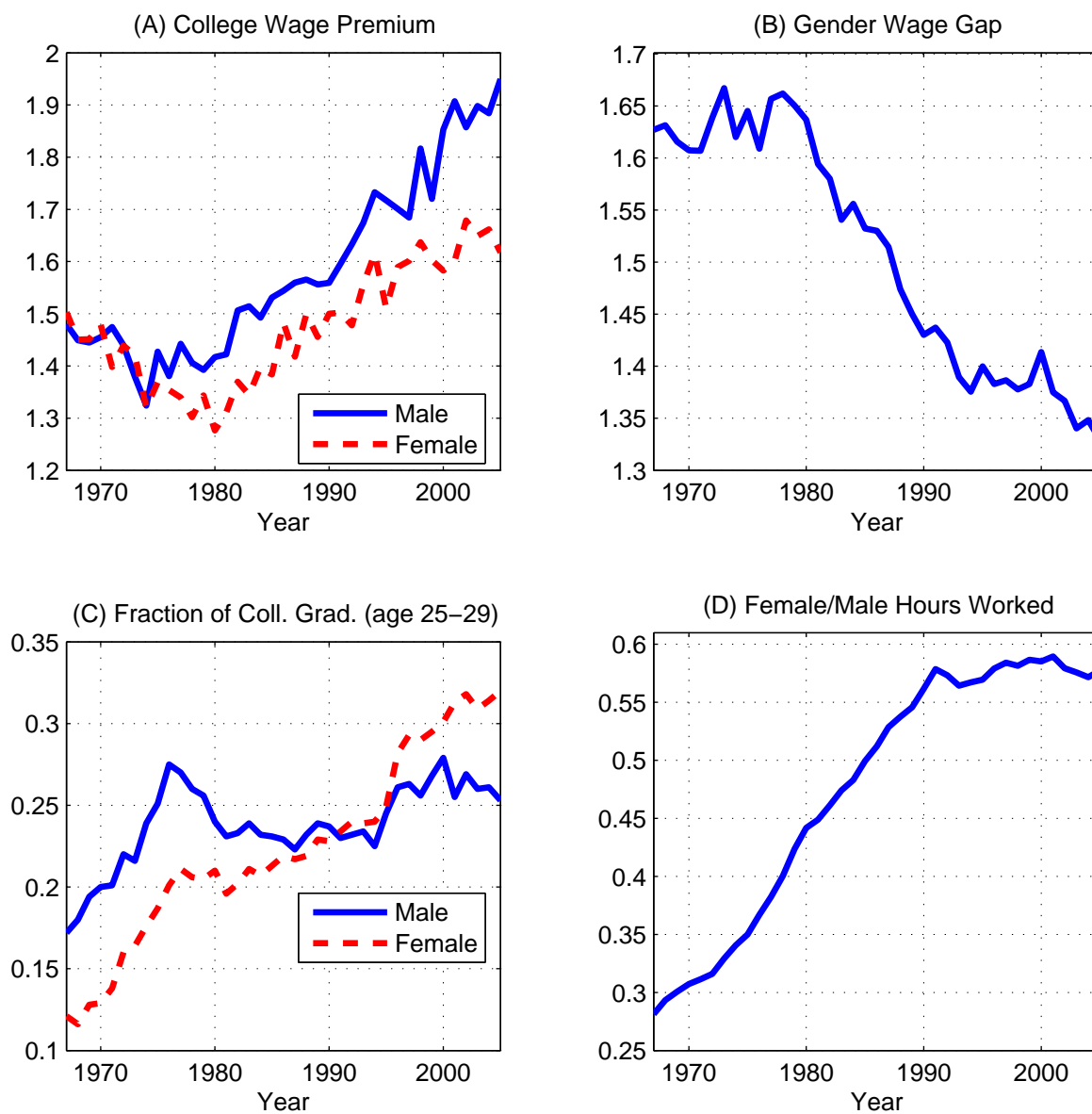


Figure 1: Cross-Sectional Facts. Sources: CPS for panels (A), (B), (D); U.S. Census Bureau for enrollment data in panel (C).

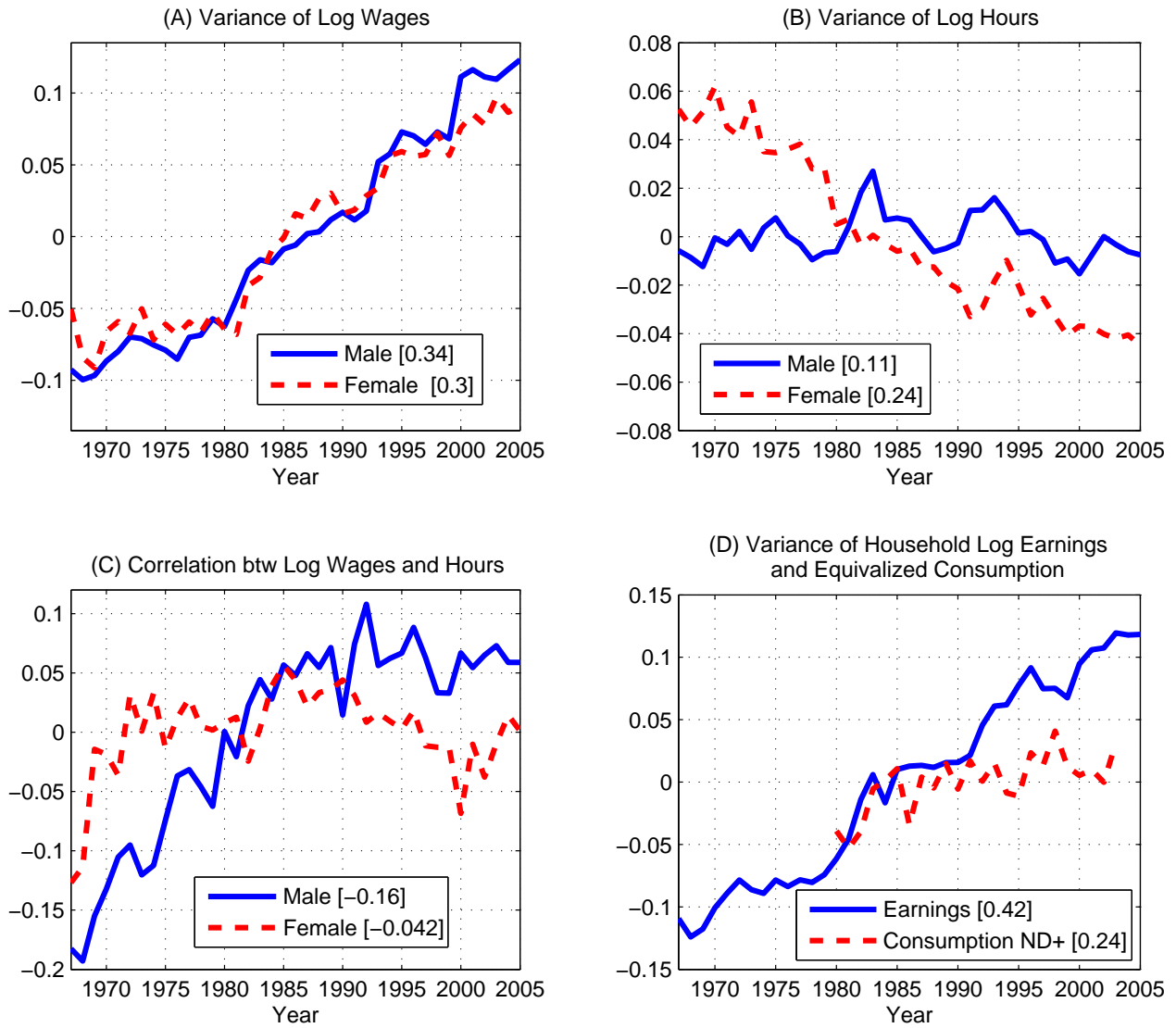


Figure 2: Cross-Sectional Facts. Sources: CPS for panels (A), (B), (C) and earnings data in panel (D); CEX for consumption data in panel (D). Household consumption expenditures are equivalized through the Census scale. Sample means in square brackets in the legend.

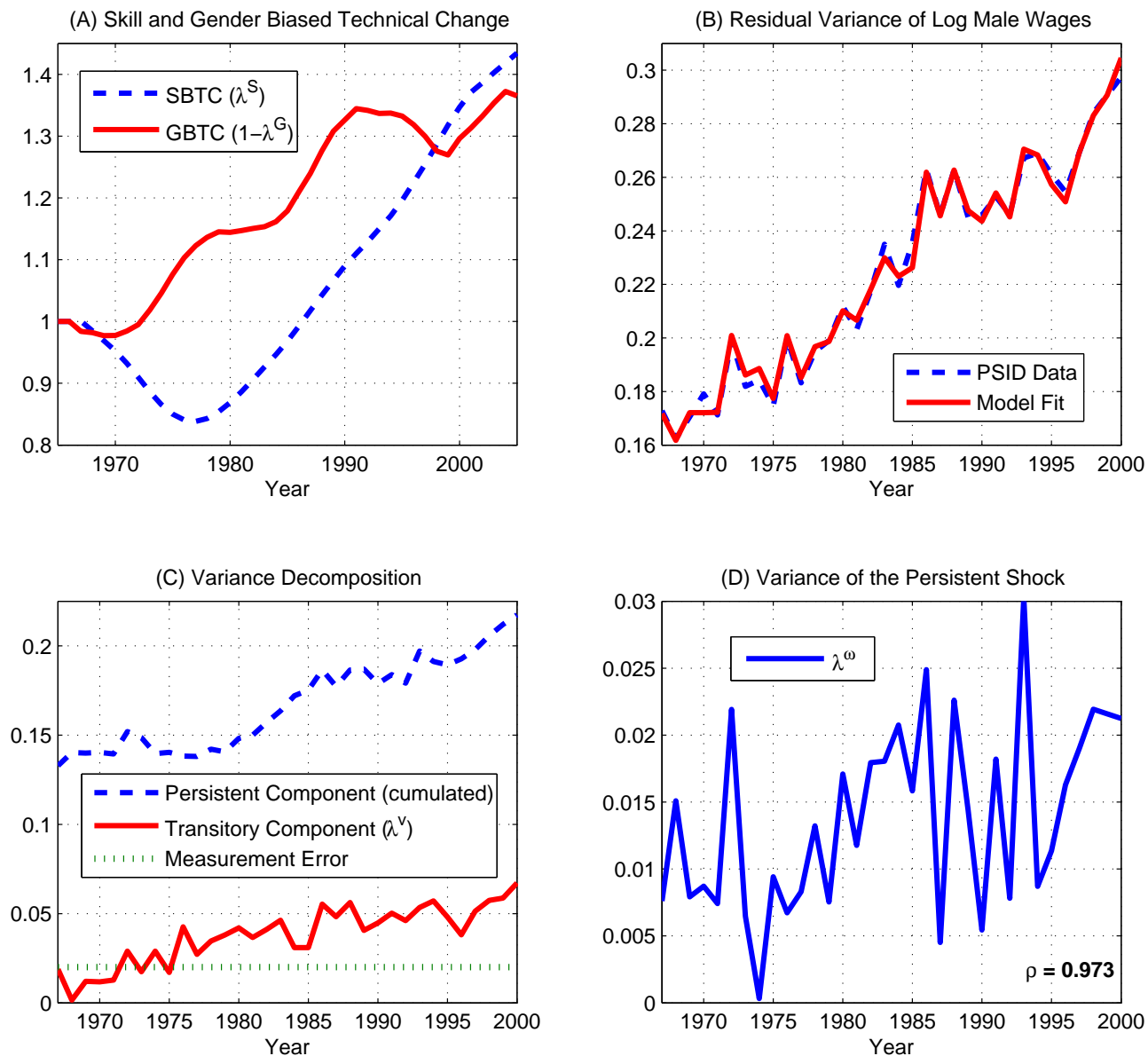


Figure 3: Panel (A): Results of the internal calibration for skill- and gender-biased technical change. Panels (B)-(D): Results of the estimation of the residual wage process in equation (8) from PSID data. The estimation method is discussed in Appendix B. See also Table 2 for the point estimates and the bootstrapped standard errors. This Figure displays all the four components of the $\{\lambda_t\}$ sequence.

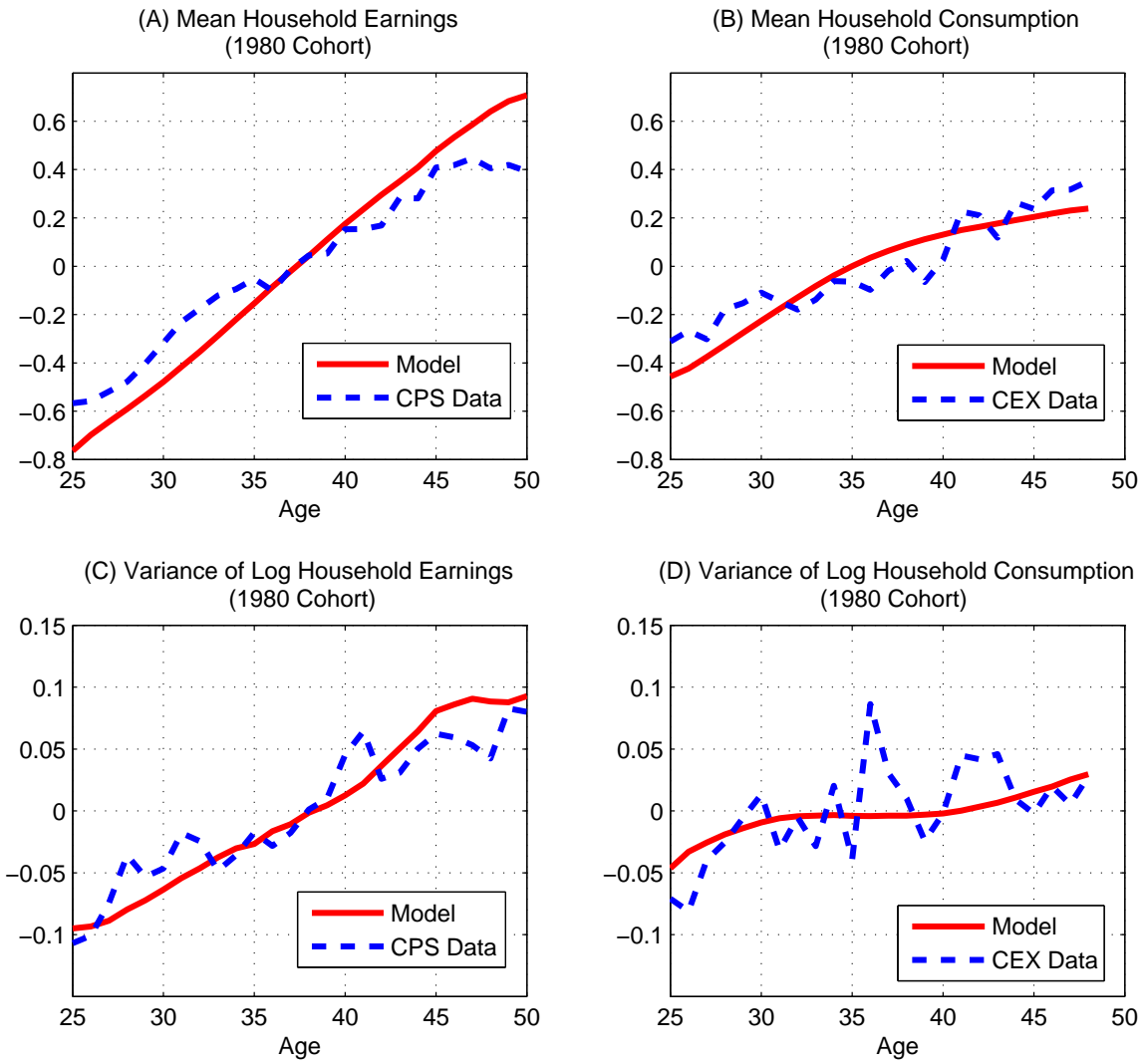


Figure 4: Model-data comparison. Evolution of household earnings and equivalized consumption (mean and variance of the logs) over the life cycle of the cohort which is 25-29 years old in 1980.

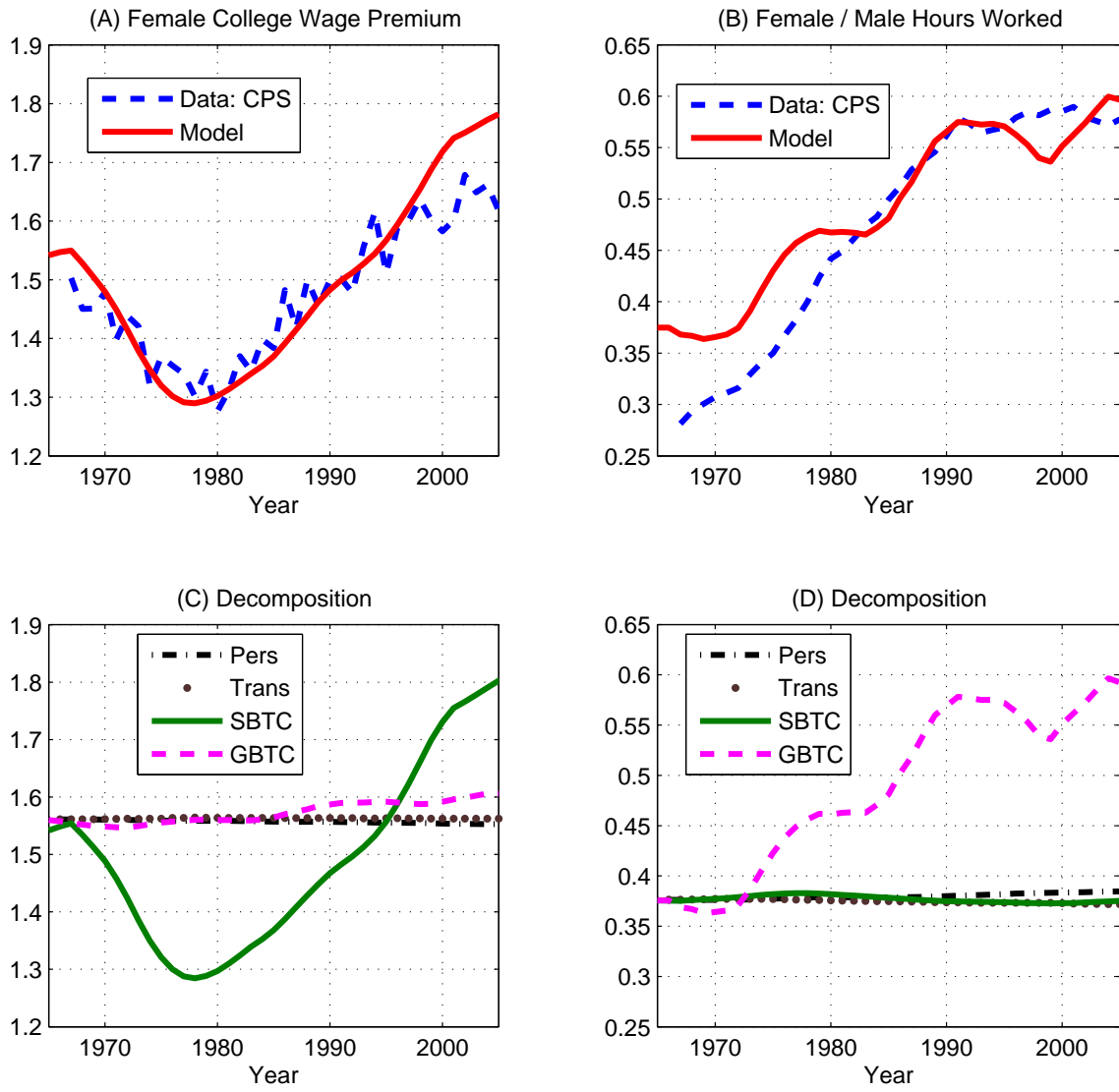


Figure 5: Model-data comparison and decomposition. Evolution of the female college wage premium and of female-male relative hours worked.

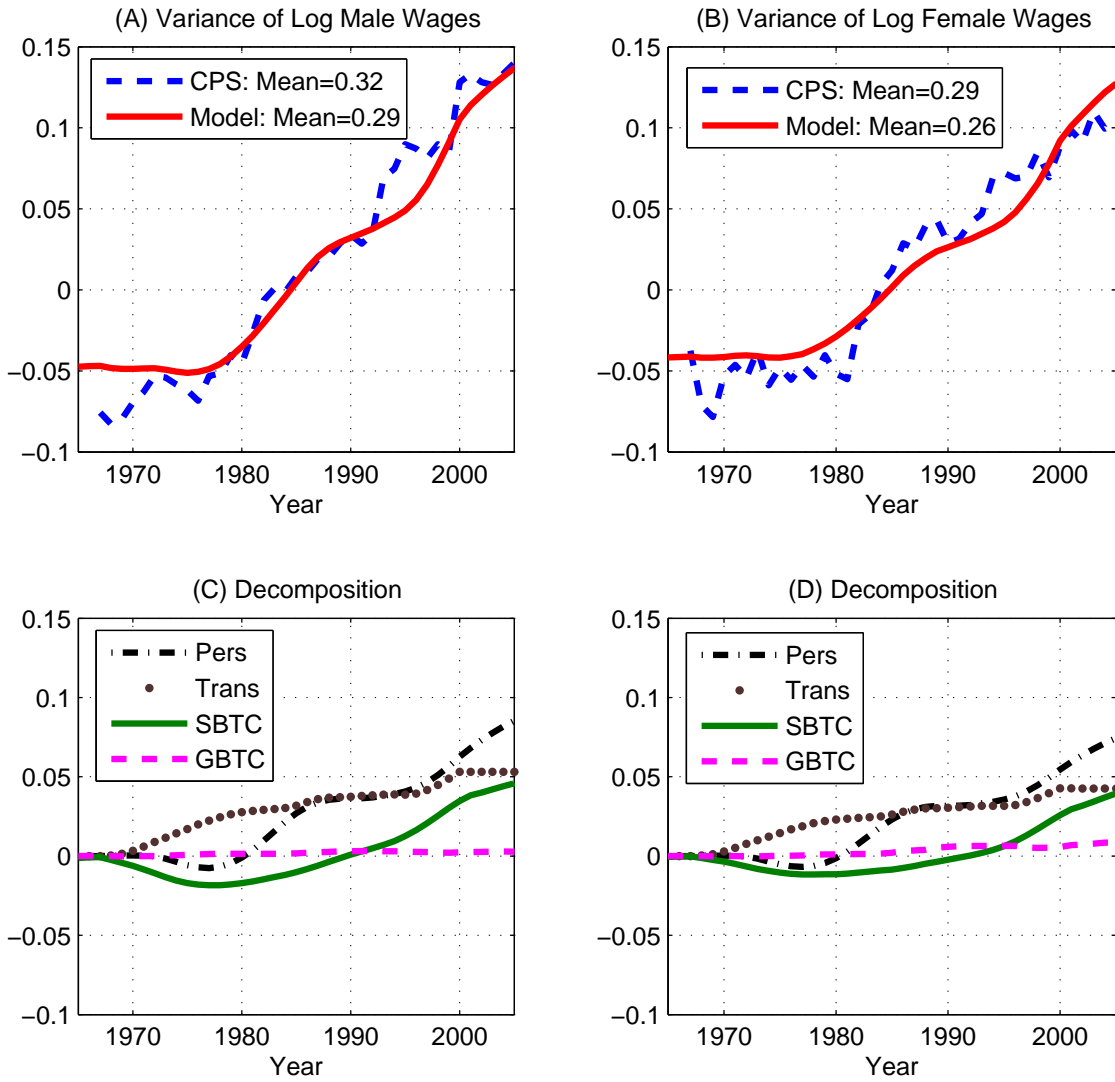


Figure 6: Model-data comparison and decomposition. Evolution of male and female log wage dispersion.

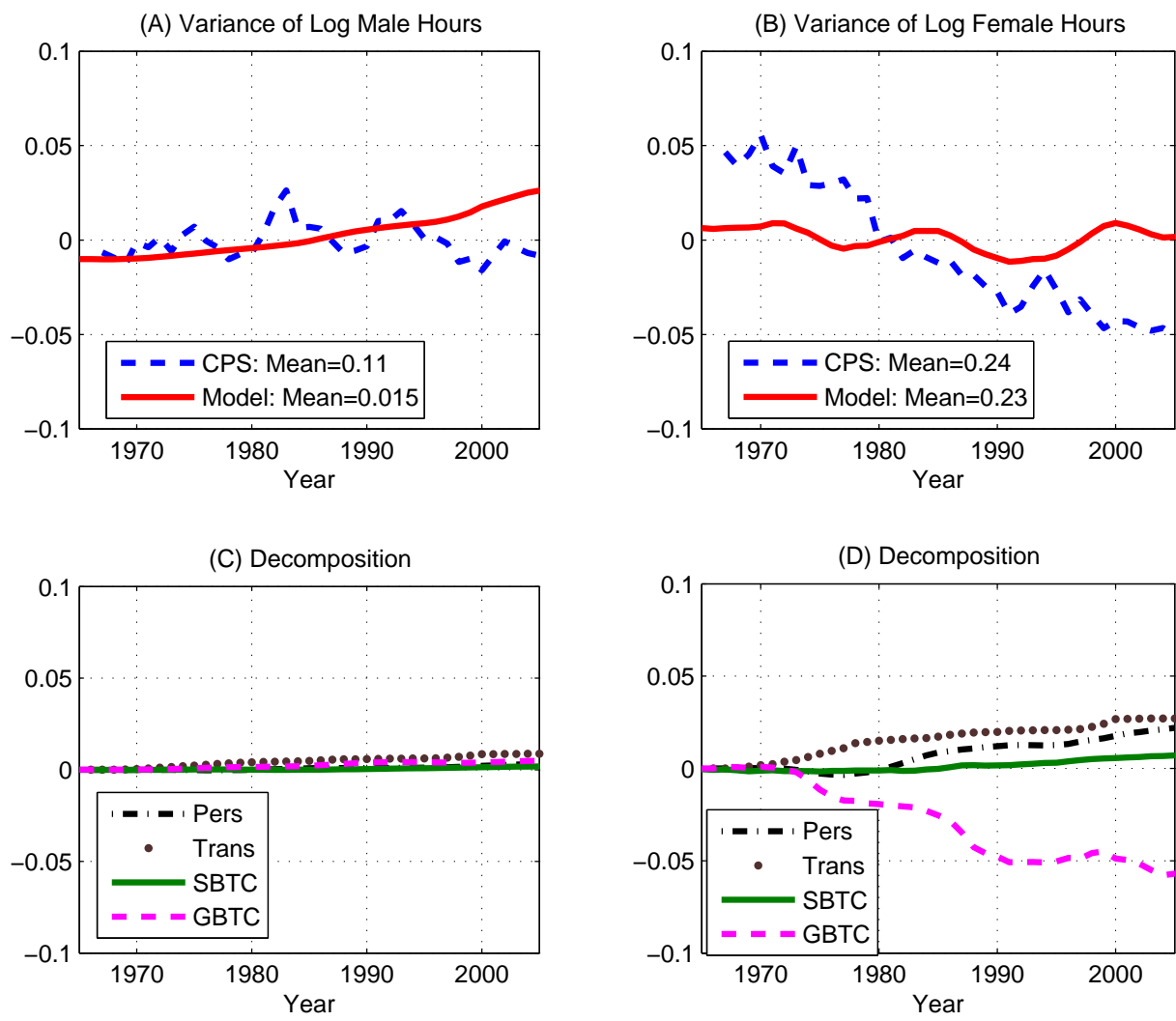


Figure 7: Model-data comparison and decomposition. Evolution of male and female log hours dispersion.

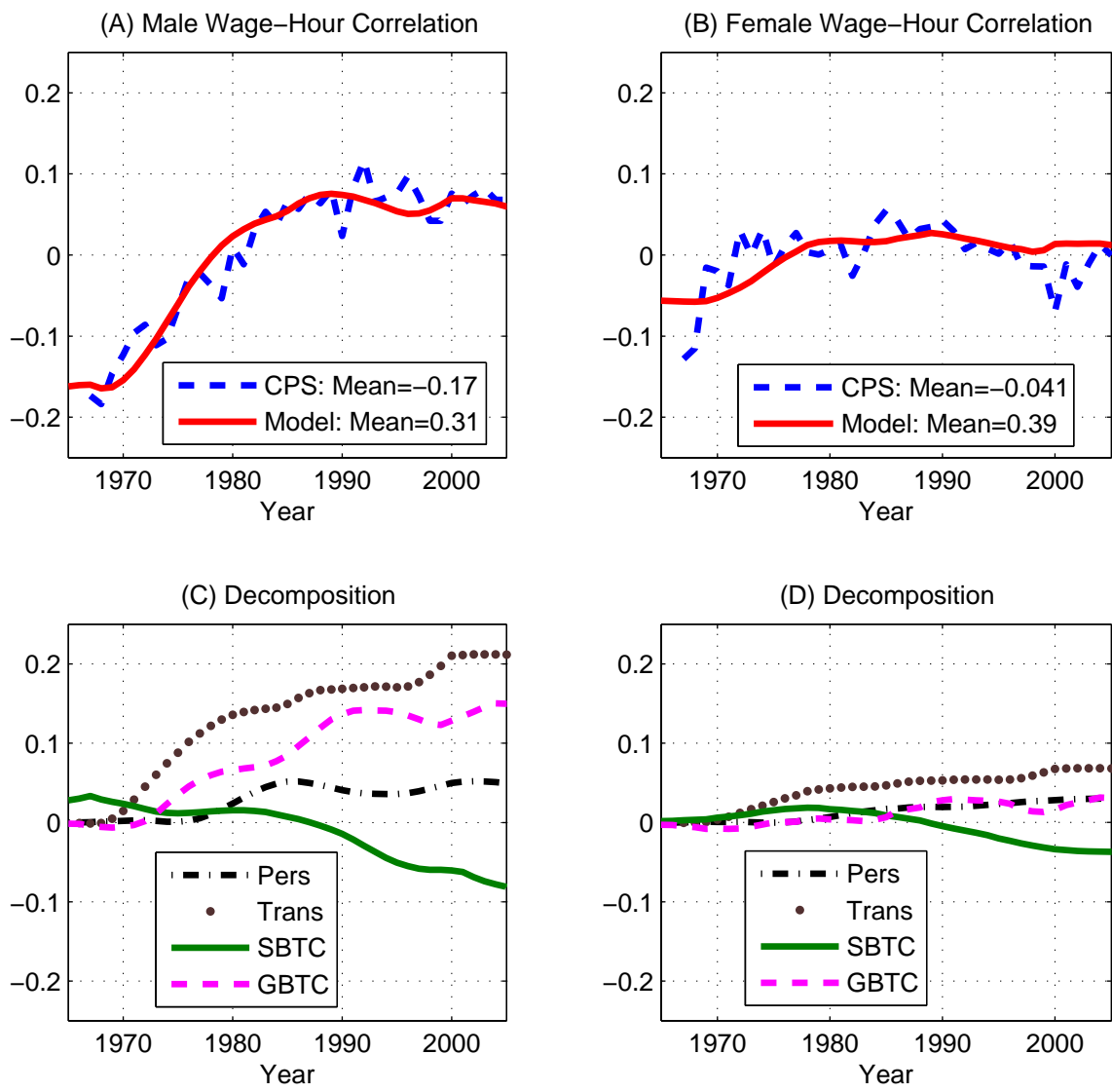


Figure 8: Model-data comparison and decomposition. Evolution of male and female correlation between log wages and log hours.

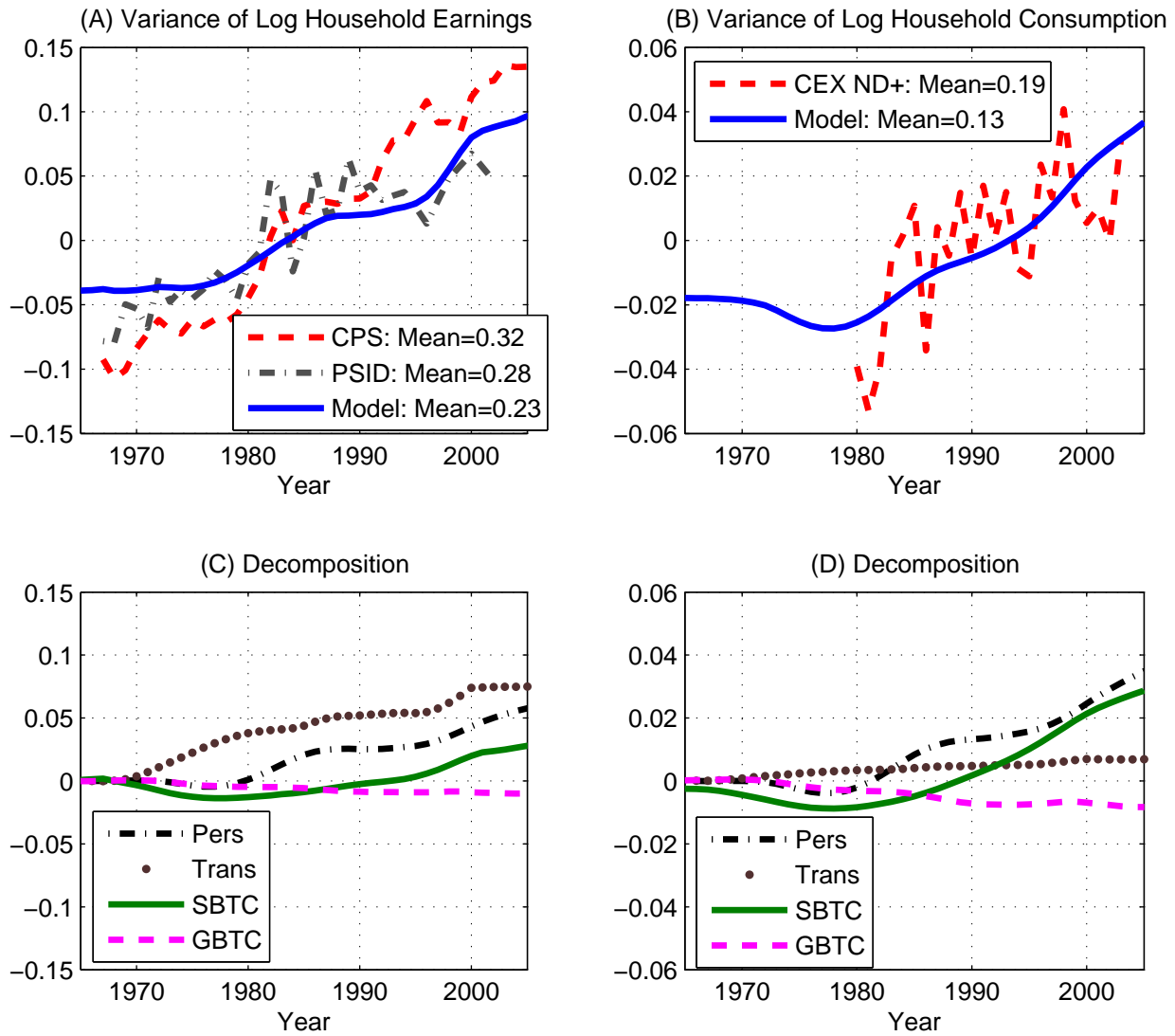


Figure 9: Model-data comparison and decomposition. Evolution of dispersion in households log earnings and log consumption.

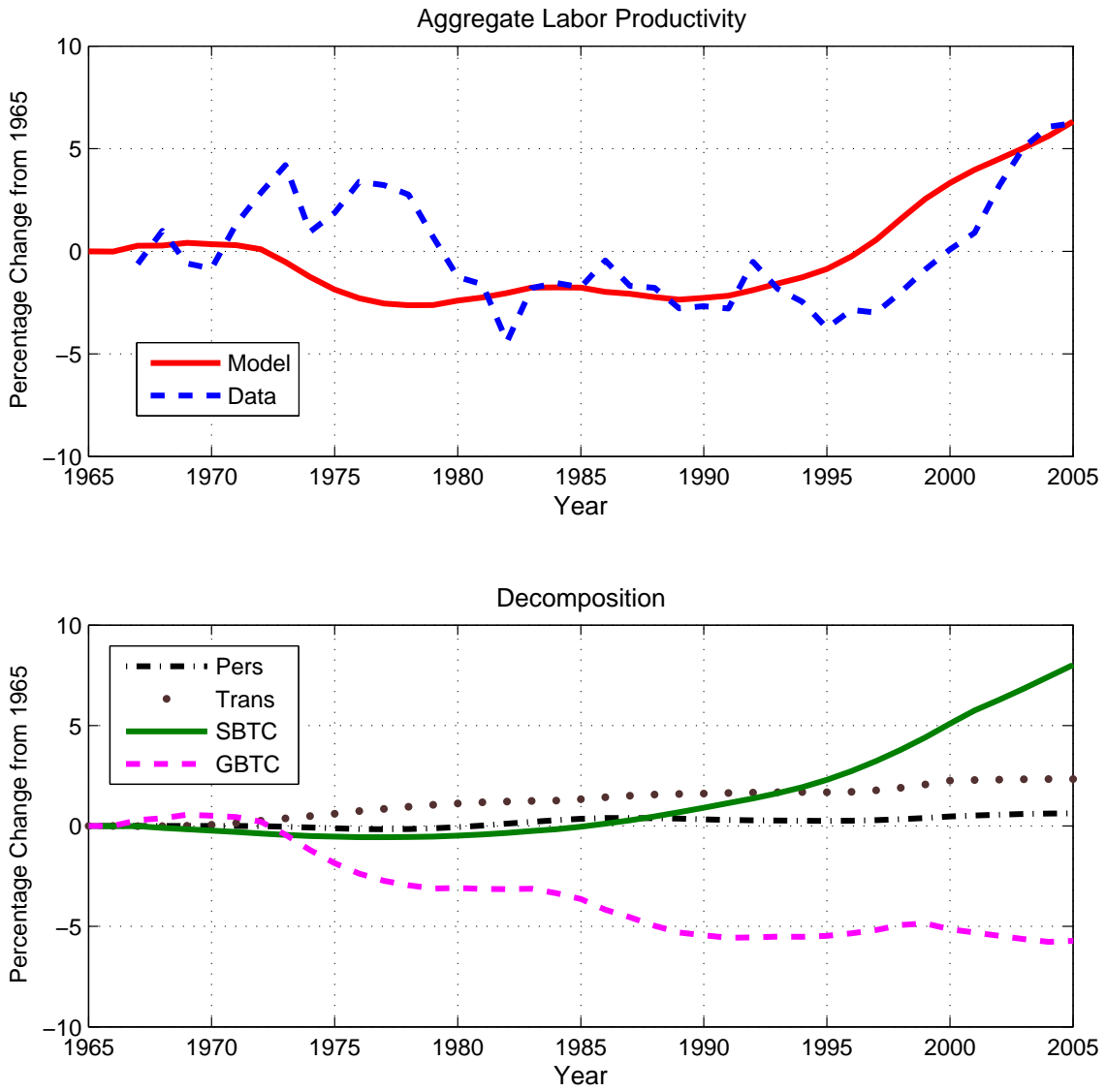


Figure 10: Model-data comparison and decomposition. The empirical series for aggregate labor productivity (output per hour) is constructed as log-deviations from a linear time trend.

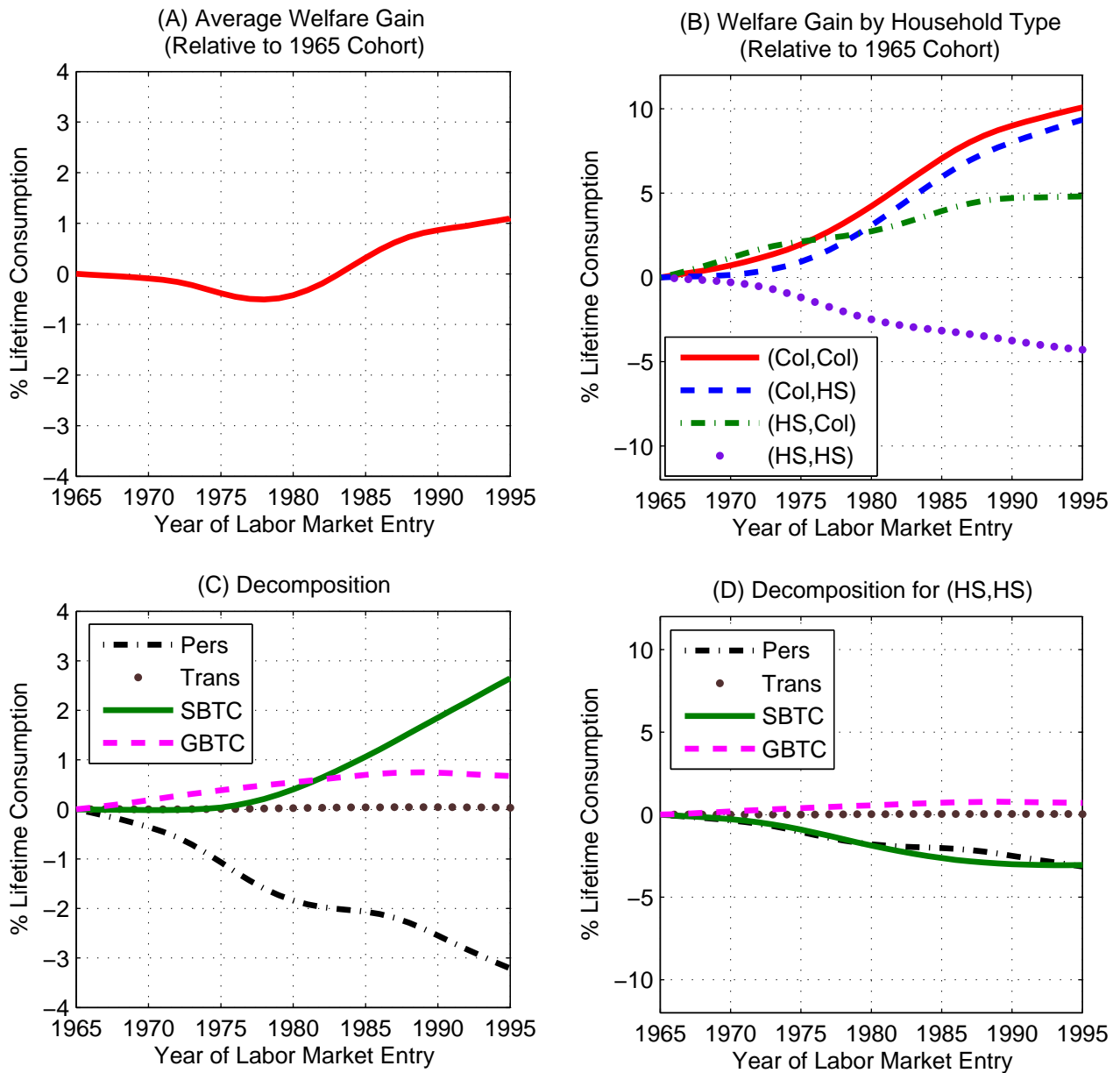


Figure 11: Panels (A)-(C): Average welfare gain and decomposition. Panel (B): Welfare gains by household type. Panel (D): Shock decomposition for families where both spouses are high-school graduates.

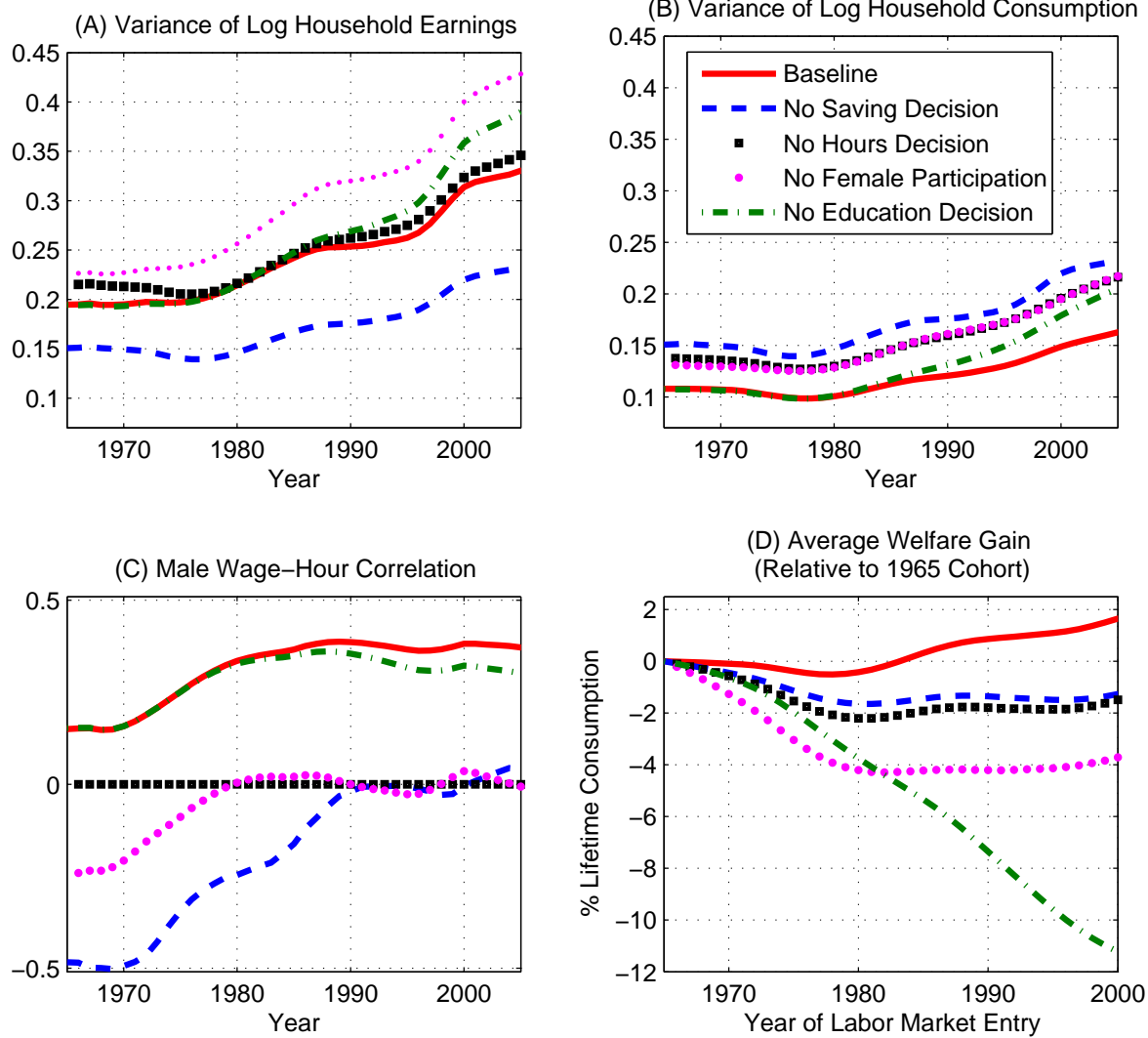


Figure 12: Counterfactual experiments to study the role of households' behavioral responses to the shift in the wage structure. The line labelled "Baseline" refers to the benchmark economy. "No Saving Decision": economy where household wealth is always zero. "No Hours Decision": economy where male and female labor supply is fixed. "No Female Participation": economy where women do not work. "No Education Decision": economy where the fraction of men and women with college degree is constant at the initial steady-state level.

A Data description

Our sources for individual and household level data are the Panel Study of Income Dynamics (PSID), the Current Population Survey (CPS), and the Consumer Expenditure Survey (CEX). Since all three data sets are widely used for microeconomic, and more recently, for quantitative macroeconomic research, we shall only briefly describe them here.

PSID: The PSID is a longitudinal study of a representative sample of U.S. individuals (men, women, and children) and the family units in which they reside. Approximately 5,000 households were interviewed in the first year of the survey, 1968. From 1968 to 1997, the PSID interviewed individuals from families in the sample every year, whether or not they were living in the same dwelling or with the same people. Adults have been followed as they have grown older, and children have been observed as they advance through childhood and into adulthood, forming family units of their own (the “split-offs”). This property makes it an unbalanced panel. Since 1997, PSID became biennial. The most recent year available, at the time of our analysis, is 2003. In 2003, the sample includes over 7,000 families. The PSID consists of various independent samples. We focus on the main and most commonly used, the so-called SRC sample, which does not require weights since it is representative of the U.S. population. Questions referring to income and labor supply are retrospective, e.g., those asked in the 1990 survey refer to calendar year 1989.

CPS: The CPS is a monthly survey of about 50,000 households conducted by the Bureau of the Census for the Bureau of Labor Statistics. The sample is selected to represent the civilian non-institutional population. Respondents are interviewed to obtain information about the employment status of each member of the household 16 years of age and older. The CPS is the primary source of information on the labor force characteristics of the U.S. population. Survey questions cover employment, unemployment, earnings, hours of work, and other indicators. A variety of demographic characteristics is available, including age, sex, race, marital status, and educational attainment.

In our investigation, we use the Annual Social and Economic Supplement (so-called March Files) in the format arranged by Unicon Research. Computer data files are only available starting from 1968, and the latest year available, at the time of our research, was 2006. In all our calculations, we use weights. As for PSID, questions referring to income and labor supply are retrospective.

CEX: The CEX is a survey collecting information on the buying habits of American consumers, including data on their expenditures, income, and consumer unit (household) characteristics. The data are collected by the Bureau of Labor Statistics and used primarily for revising the CPI. The data are collected in independent quarterly Interview and weekly Diary surveys of approximately 7,500 sample households (5,000 prior to 1999).

We use the data set constructed from the original CEX data by Krueger and Perri (2006) and available on the authors’ web sites. As common in most of the previous research, their data uses only the Interview survey which covers around 95% of total expenditures, with the exclusion of few frequently purchased items such as personal care products and housekeeping supplies which are only reported in the Diary survey. The period covered by their data is 1980-2003. CEX data before 1980 is not comparable to the later years. Households who are classified as incomplete income respondents by the CEX and have not completed the full set of five interviews are excluded. We refer to Krueger and Perri (2006) for additional details on the data construction.

Variables definitions: The calibration of the model and its evaluation are based on a set of cross-sectional first and second moments constructed from both PSID and CPS. The key variables of interest are: gross (i.e., before-tax) annual labor earnings, annual hours, hourly wages and household consumption. We always construct hourly wages as annual earnings divided by annual hours worked. Nominal wages, earnings and consumption are deflated with the CPI and expressed in 1992 dollars.

In PSID, gross annual earnings are defined as the sum of several labor income components including wages and salaries, bonuses, commissions, overtime, tips, etc. Annual hours are defined as “annual hours worked for money on all jobs including overtime”.

In CPS, gross annual earnings is defined as income from wages and salaries including pay for overtime, tips and commissions. Annual hours worked are constructed as the product of weeks worked last year and hours

worked last week. Until 1975, weeks worked are reported in intervals (0, 1-13, 14-26,...,50-52). To recode weeks worked for 1968-1975, Unicon grouped data in a few years after 1975 by intervals and computed within-interval means. These means from the later years were applied to the earlier years. The variable “hours worked last week at all jobs” is not ideal, but it is the only one continuously available since 1968 and comparable across years. Starting from the 1976 survey, CPS contains a question on “usual weekly hours worked this year”. As discussed in the paper, even though levels differ, trends in mean hours, in their variance and in the wage-hour correlation, which are the focus of our study, are virtually equivalent across the two definitions.

In CEX, gross annual earnings refer to the amount of wage and salary income before deductions received in past twelve months. Since we noticed that in the Krueger-Perri file there were some missing values for earnings, we merged earnings data from the CEX Public Release Member files (provided to us by Orazio Attanasio) into the Krueger-Perri file and use the former observations whenever earnings data were missing in the original Krueger-Perri file. Annual hours worked are defined as the product of “number of weeks worked full or part time by member in last 12 months” and “number of hours usually worked per week by member”.

Our benchmark definition for consumption is the same as Krueger and Perri, i.e. the sum of expenditures on nondurables, services, and small durables (such as household equipment) plus imputed services from owned housing and vehicles. Each expenditure component is deflated by an expenditure-specific, quarter-specific CPI. Household expenditures are equivalized through the Census scale. We label this variable ND+. In the paper, we also report statistics based on nondurable consumption only (variable ND in Krueger and Perri). See Krueger and Perri (2006) for further details.

Sample selection: The objective of our sample selection is to apply exactly the same restrictions to PSID, CPS and CEX. We select married households with non missing values for gender, age, and education where: 1) the husband is between 25 and 59 years old, 2) annual hours of the husband are at least 260, 3) conditional on working, the hourly wage (annual earnings divided by annual hours) is above half of the minimum wage for both spouses, and 4) income is not from self-employment.

The marital status restriction is needed in order to be consistent with the theoretical model. Restriction 1) is imposed to avoid severe sample selection in the hours and wage data due to early retirement. Restriction 2) is imposed since 260 hours per year (one quarter part-time) is our definition of labor force participation. Restriction 3) is imposed to reduce implausible outliers at the bottom of the wage distribution which is particularly important since we use the variance of log wages as a measure of dispersion (see Katz and Autor, 1999, for a discussion on the importance of trimming earnings data at the bottom). Restriction 4) is imposed since the presence of self-employment income makes it difficult to distinguish between the labor and the capital share, particularly in CPS and CEX, and to deal with negative labor income.

Table A-1 details the sample selection process in the three data sets, step by step. The final sample has 43,123 household/year observations in PSID, 600,326 household/year observations in CPS and 21,556 household/year observations in CEX.

Top-coding: After imposing our selection criteria, there are only 6 top-coded observations in the final PSID sample. Since we found that none of the statistics are affected by those few values, we did not make any correction for top-coded values. Roughly 2.1% of the earnings values in the final CPS sample are top-coded. Top coding of earnings in CPS changed substantially over the sample period. We follow Autor and Katz (1999) and multiply all top-coded observations by a factor equal to 1.5 up to 1996 and made no correction after 1996, when top-coded observations take on the average value of all top-coded observations, by demographic group, instead of the threshold value. We tried with other factors, for example 1.75 as suggested by Eckstein and Nagypal (2004), and our findings remain robust. In the final CEX sample there are 362 top-coded observations, i.e. around 1.7% of the total. Since the top-coding changes virtually in the same ways as in CPS, including the change of approach after 1996, we used the Autor-Katz strategy for CEX as well.

Comparison across PSID and CPS: Table A-2 shows that—over the period where they overlap (1980-2003)—the three samples are remarkably similar in their demographic and education structure by gender. Also means of wages, earnings and hours, by gender, are extremely similar in the three data sets. Finally, average food consumption expenditures in PSID are very comparable to the CEX estimate.

Figures A-1 to A-4 compare the time trends in the key moments of the joint distribution of hours, wages and earnings in CPS and PSID. The plots show deviations from the means, with means reported in the legend. A careful analysis of the four figures demonstrates that overall PSID and CPS data line up remarkably well along the vast majority of moments, in terms of both trends and levels. The PSID moments are more volatile, due to the much smaller (by over a factor of 15) sample size.

We find that some discrepancies arise towards the end of the sample, when the PSID data are still in “early release” format, for the trends in a couple of the moments involving women: the female college premium (Figure A-1, panel D), and the correlation between male and female log wages (Figure A-4, panel D). The trends for the moments involving men’s data are remarkably aligned across the two data sets.

Finally, the trend in household log earnings inequality (Figure A-4, panel B)—a crucial moment in our study—is somewhat flatter in PSID than CPS. Since the trends in male and female earnings dispersion broadly agree in CPS and PSID, the smaller increase in household earnings inequality in PSID should be attributed to the decline in the correlation between male and female wages in the 1990s vis-a-vis the small rise of this correlation in CPS over the same period. The trend of the variance of household log earnings in CEX lies somewhere in between PSID and CPS. For example, over the last two decades of available data (1984-2003), the CEX data show a rise of 0.08 log points vis-a-vis an increase of 0.12 in CPS and of 0.05 in PSID.

Enrollment data: The data on college enrollment that we use for the calibration of the model refer to the percentage of individuals 25-29 years of age who have completed college, by gender and year from 1940 to 2006. The source is Table A.2 of the Educational Attainment section on the U.S. Census Bureau web site, www.census.gov/population/www/socdemo.

B Identification and estimation of the wage process

B.1 Statistical model

As discussed in Section 3.2 of the main text, we posit the following statistical model of the log wage residuals for individual i of age j at time t . For all j, t

$$y_{i,j,t} = \eta_{i,j,t} + v_{i,j,t} + \tilde{v}_{i,j,t}$$

where $\tilde{v}_{i,j,t} \sim (0, \lambda^{\tilde{v}})$ is a transitory (i.e., uncorrelated over time) component capturing measurement error in hourly wages, $v_{i,j,t} \sim (0, \lambda_t^v)$ is a transitory component representing genuine individual productivity shock, and $\eta_{i,j,t}$ is the persistent component of labor productivity. In turn, this persistent component is modelled as follows. For all $j, t > 1$

$$\eta_{i,j,t} = \rho \eta_{i,j-1,t-1} + \omega_{i,j,t}$$

where $\omega_{i,j,t} \sim (0, \lambda_t^\omega)$. For all t , at age $j = 1$, $\eta_{i,1,t}$ is drawn from the time-invariant initial distribution with variance λ^η . We assume that $\omega_{i,j,t}$, $\tilde{v}_{i,j,t}$, $v_{i,j,t}$ and $\eta_{i,1,t}$ are orthogonal to each other, and i.i.d. across individuals in the population.

For all j , at $t = 1$ the distribution of labor productivity is assumed to be in its steady-state with variances $\{\lambda^{\tilde{v}}, \lambda_1^v, \lambda_1^\omega, \lambda^\eta\}$. This assumption is made to maintain consistency with the model’s solution and simulations. Note that some of the variances $\{\lambda_t^v, \lambda_t^\omega\}$ are time-varying while others $\{\lambda^{\tilde{v}}, \lambda^\eta\}$ are not. We restrict the variance of measurement error $\lambda^{\tilde{v}}$ to be constant for identification purposes and, as explained in the main text, we use an external estimate to identify its size.

B.2 Identification: an example

We now describe the identification procedure for the case where $t = 1, 2, 4$ and $j = 1, 2, 3$. This is a useful example to illustrate our case where, after a certain date, the PSID survey becomes biannual and data for

some intermediate years ($t = 3$ in the example) are missing. Let Υ denote the (1×10) parameter vector $\{\lambda_1^v, \lambda_2^v, \lambda_3^v, \lambda_4^v, \lambda_1^\omega, \lambda_2^\omega, \lambda_3^\omega, \lambda_4^\omega, \lambda^\eta, \rho\}$. The key challenge is to identify parameters at date $t = 3$.

Define the theoretical moment

$$m_{i,t,t+n}^j(\Upsilon) = E(y_{i,j,t} \cdot y_{i,j+n,t+n}). \quad (\text{B-1})$$

The expectation operator is defined over all individuals i of age j at time t present both at t and at $t + n$. In our simple example, we have a total of 12 such moments that we can construct from available data.

The covariance between period $t = 1$ and $t = 2$ for the entry cohort of age $j = 1$ at $t = 1$ is

$$m_{1,2}^1 = E[(\eta_{i,1,1} + v_{i,1,1})(\eta_{i,2,2} + v_{i,2,2})] = \rho\lambda^\eta,$$

and the same covariance between period $t = 2$ and $t = 4$ is

$$m_{2,4}^1 = E[(\eta_{i,1,2} + v_{i,1,2})(\eta_{i,3,4} + v_{i,3,4})] = \rho^2\lambda^\eta.$$

This pair of moments identifies (ρ, λ^η) .

At $t = 1$, the variance for the entry cohort

$$m_{1,1}^1 = E[(\eta_{i,1,1} + v_{i,1,1})^2] = \lambda^\eta + \lambda_1^v$$

identifies λ_1^v given knowledge of λ^η .

From variance of the age group $j = 2$ at time $t = 1$

$$m_{1,1}^2 = E[(\eta_{i,2,1} + v_{i,2,1})^2] = \rho^2\lambda^\eta + \lambda_1^\omega + \lambda_1^v,$$

we can identify λ_1^ω , given knowledge of the initial variance λ^η and of λ_1^v .

At $t = 2$, the two variances for age groups $j = 1, 2$

$$\begin{aligned} m_{2,2}^1 &= E[(\eta_{i,1,2} + v_{i,1,2})^2] = \lambda^\eta + \lambda_2^v \\ m_{2,2}^2 &= E[(\eta_{i,2,2} + v_{i,2,2})^2] = \rho^2\lambda^\eta + \lambda_2^\omega + \lambda_2^v \end{aligned}$$

identify λ_2^v and λ_2^ω .

At $t = 4$, we can construct the three variances

$$\begin{aligned} m_{4,4}^1 &= E[(\eta_{i,1,4} + v_{i,1,4})^2] = \lambda^\eta + \lambda_4^v \\ m_{4,4}^2 &= E[(\eta_{i,2,4} + v_{i,2,4})^2] = \rho^2\lambda^\eta + \lambda_4^\omega + \lambda_4^v \\ m_{4,4}^3 &= E[(\eta_{i,3,4} + v_{i,3,4})^2] = \rho^4\lambda^\eta + \rho^2\lambda_3^\omega + \lambda_4^\omega + \lambda_4^v. \end{aligned}$$

As usual, the variance of the entrant cohort identifies λ_4^v , given knowledge of the initial variance λ^η . Comparing the variance of new cohorts with the variance of age 2 cohorts identifies identify λ_4^ω , the variance of the current persistent shock. Finally, the variance of the age $j = 3$ cohort contains the variance of the persistent shock that hit at the previous date, and this allows identification of λ_3^ω .

Two remarks are in order. First, we can identify λ_3^ω in spite of lack of data for $t = 3$ because the ω shock hitting individuals at time $t = 3$ persists into $t = 4$, a date for which observations are available. Thus comparing wage dispersion between a new cohort and an old cohort at $t = 4$ allows to identify λ_3^ω since there are no cohort effects. Second, in general one cannot separately identify persistent and transitory shocks in the last year of the sample. Here, we can thanks, once again, to the assumption of no cohort effects in the initial variance λ^η .

The only parameter left to identify is λ_3^v . Transitory shocks at $t = 3$ do not show up in moments at any other t , and thus we need to impose a restriction to complete our identification. There are several possible

choices. We opt for assuming that the cross-sectional variance of wages in the population in the missing years is a weighted average of the variance in the year before and in the year after. In our specific example, if we let $\bar{m}_{t,t}$ be the cross-sectional variance of log wages at time t , then we assume that $\bar{m}_{3,3} = (\bar{m}_{2,2} + \bar{m}_{4,4})/2$. Given our knowledge of all the parameters $\{\rho, \lambda^\eta, \lambda_1^\omega, \lambda_2^\omega, \lambda_3^\omega\}$ one can reconstruct the cross-sectional variance component due to the cumulation of the persistent shocks up to $t = 3$. The difference between the total variance and the part due to persistent shocks identifies residually the transitory component λ_3^v .

B.3 Estimation

Parameter vector: We have available survey data for 1967-1996, 1998, 2000 and 2002. Even though, theoretically, the variance of the persistent shocks λ_t^ω is identified in the missing years, in practice the fact that the lack of data occurs towards the end of the sample substantially reduces the amount of information available to estimate such parameters. Moreover, as explained, identification in the missing years hinges on the no-cohort effects assumption. Therefore, we choose to take a cautious approach and estimate λ_t^ω only for those years when data are available. In simulating the model, we assume that the variance of the persistent shocks for the missing years is a weighted average of the two adjacent years.

Moreover, as we have explained above, separating the variances of persistent and transitory shock in the last year of the sample hinges also upon the, arguably restrictive, assumption of no cohort effects. Therefore, we choose not to estimate these two variances for 2002, but rather we use the 2002 survey only to improve our estimation of the structural variances up to 2000 (by constructing covariances between 2002 and the previous years). To sum up, we estimate ρ , λ^η , and $\{\lambda_{1967}^\omega, \dots, \lambda_{1996}^\omega, \lambda_{1998}^\omega, \lambda_{2000}^\omega; \lambda_{1967}^v, \dots, \lambda_{1996}^v, \lambda_{1998}^v, \lambda_{2000}^v\}$ for a total of $L = 66$ parameters. Denote by Υ the $(L \times 1)$ parameter vector.

Empirical moments: Every year t , we group individuals in the sample into 10-year adjacent age cells indexed by j , the first cell being age group “29” containing all workers between 25 and 34 years old, up until the last cell for age group “54” with individuals between 50 and 59. Our sample length and age grouping imply $T = 33$ and $J = 26$. Let $m_{t,t+n}^j(\Upsilon)$ be the theoretical covariance between wages in the two age-group/year cells determining the triple (j, t, n) , exactly as in (B-1). For every pair (j, t) , let $\bar{n}(j, t)$ be the maximum number of moments involving individuals of age j at time t that can be constructed from the sample (taking into account the fact that some years are missing).

The moment conditions used in the estimation are of the form

$$E(\iota_{i,j,t,n}) \left[\hat{y}_{i,j,t} \cdot \hat{y}_{i,j+n,t+n} - m_{t,t+n}^j(\Upsilon) \right] = 0,$$

where $\iota_{i,j,t,n}$ is an indicator function that equals 1 if individual i has observations in both periods/age groups determined by (j, t, n) and zero otherwise. The empirical counterpart of these moment conditions becomes

$$\hat{m}_{t,t+n}^j - m_{t,t+n}^j(\Upsilon) = 0,$$

where $\hat{m}_{t,t+n}^j = \frac{1}{I_{j,t,n}} \sum_{i=1}^{I_{j,t,n}} \hat{y}_{i,j,t} \cdot \hat{y}_{i,j+n,t+n}$ is the empirical covariance between wages for individuals of age j at time t and wages of the same individuals n periods later. Note that $I_{j,t,n} = \sum_{i=1}^I \iota_{i,j,t,n}$ since not all individuals contribute to each moment.

Estimator: The estimator we use is a minimum distance estimator that solves the following minimization problem

$$\min_{\Upsilon} [\hat{\mathbf{m}} - \mathbf{m}(\Upsilon)]' \mathcal{W} [\hat{\mathbf{m}} - \mathbf{m}(\Upsilon)], \quad (\text{B-2})$$

where $\hat{\mathbf{m}}$, and $\mathbf{m}(\Upsilon)$ are the vectors of the stacked empirical and theoretical covariances with dimension $N = \sum_{j=1}^J \sum_{t=1}^T \bar{n}(j, t)$, and \mathcal{W} is a $(N \times N)$ weighting matrix. In our estimation, $N = 9,634$.

To implement the estimator, we need a choice for \mathcal{W} . The bulk of the literature follows Altonji and Segal (1996) who found that in common applications there is a substantial small sample bias in the estimates of Υ , hence using the identity matrix for \mathcal{W} is a strategy superior to the use of the optimal weighting matrix

characterized by Chamberlain (1984). With this choice, the solution of equation (B-2) reduces to a nonlinear least square problem.

Standard errors are computed by block bootstrap, using 500 replications. Bootstrap samples are drawn at the household level with each sample containing the same number of households as the original sample. Resulting confidence intervals thus account for arbitrary serial dependence, heteroskedasticity and additional estimation error induced by the use of residuals from the first stage regressions.

Table 2 reports parameter estimates and standard errors. The results of the estimation are discussed in detail in Section 4.1.

C Numerical Algorithm

First we describe how we pick the sequence for the scaling variable Z_t . Then we review the details of the timing assumptions. Next we describe how we solve for decision rules, how we compute steady states and calibrate the parameters set endogenously. Lastly, we describe how we handle the transition phase in which the wage structure parameters λ_t and equilibrium prices $\mathbf{p}_t = \{p_t^{m,h}, p_t^{m,l}, p_t^{f,h}, p_t^{f,l}\}$ are time-varying. In what follows we denote initial (final) steady state variables by the subscript “*” (“**”).

C.1 Z sequence

The assumption that the economy is open and faces a constant pre-tax world interest rate r implies a constant capital-to-aggregate effective labor ratio, since

$$r = (\alpha Z_t K_t^{\alpha-1} H_t^{1-\alpha} - \delta) \Rightarrow \frac{K_t}{H_t} = Z_t^{\frac{1}{1-\alpha}} \left[\frac{1}{\alpha} (r + \delta) \right]^{\frac{1}{\alpha-1}}. \quad (\text{C-1})$$

Substituting the expression for K_t/H_t into the equilibrium expressions for prices \mathbf{p}_t defined in equation (12) it is clear that prices for different types of labor are functions of the technology parameters $\{Z_t, \lambda_t^S, \lambda_t^G\}$ and of the aggregate quantities of the different types of labor supplied $\mathbf{H}_t = \{H_t^{m,h}, H_t^{m,l}, H_t^{f,h}, H_t^{f,l}\}$. Denote these functions by $p(Z_t, \lambda_t^S, \lambda_t^G, \mathbf{H}_t)$.

Let $H(\lambda_t^S, \lambda_t^G, \mathbf{H}_t)$, as defined in (1), be the function defining aggregate effective labor supply. The path for Z_t is assumed such that, given the initial steady state quantities of labor input, \mathbf{H}_* , average individual after-tax earnings for agents of working age is equal to one at each date. This implies

$$\frac{1}{2 \int_{\mathcal{S}, j < j^R} d\mu_t} (1 - \tau^n)(1 - \alpha) Z_t^{\frac{\alpha}{1-\alpha}} \left(\frac{1}{\alpha} (r + \delta) \right)^{\frac{\alpha}{\alpha-1}} H(\lambda_t^S, \lambda_t^G, \mathbf{H}_*) = 1. \quad (\text{C-2})$$

C.2 Timing

Prior to 1965 we assume the economy is in an initial steady state in which parameters λ_* and prices \mathbf{p}_* are constant. In 1965 new information is revealed and agents revise expectations: instead of thinking that λ_* and \mathbf{p}_* will persist for ever, they now foresee the exact time-varying future paths for $\{\lambda_t\}_{t=1965}^{\infty}$ and $\{\mathbf{p}_t\}_{t=1965}^{\infty}$.

The first and last years for which we estimate $(\lambda_t^w, \lambda_t^v)$ using our PSID sample are 1967 and 2000 (see Appendix B) The path for λ_t is time-varying for $1967 \leq t \leq 2000$ in such a way that the wage structure in the model evolves precisely as in the data over this period. Prices are time-varying between 1965 and 1967, even though all technology parameters in λ_t are constant, because agents adjust their education and labor supply decisions in anticipation of future changes in the wage structure. This affects the relative supplies of different types of labor, and thus, relative prices.

We assume that by 2021, prices for the four types of labor have converged to their final steady state values, denoted \mathbf{p}_{**} . These prices are such that the model replicates the observed college premium and gender gap for 2002, the last year of our PSID sample. Adjustment to the final steady state is slow because it takes time for educational composition of the workforce to adjust to the final steady state values, and while this adjustment is taking place, the relative supplies of different types of labor are changing.

We need to make assumptions for the path for λ_t during the transition period. For $t > 2000$ we assume that the wage risk parameters $(\lambda_t^v, \lambda_t^\omega)$ are constant and equal to the estimated values for 2000, denoted $(\lambda_{**}^v, \lambda_{**}^\omega)$. We assume that the path for λ_t^S over the period $2000 < t < 2021$ is such that the relative price $p_t^{m,h}/p_t^{m,l}$ is constant at the value that replicates the observed male college premium in 2002. The path for λ_t^G is such that the model gender premium is equal at each date to that observed in 2002. Note that these assumptions imply that both $\{\lambda_t^S, \lambda_t^G\}$ and \mathbf{p}_t are time-varying between 2000 and 2021.

Recall that some parameters are calibrated internally, as described in Section 4.1. In addition to all these parameter values, agents need to know the sequences for equilibrium prices $\{\mathbf{p}_t\}$ in order to solve their problems. In practice, we proceed as follows. We first solve for initial and final steady states to set the internally calibrated time-invariant parameter values, the steady-state values for the technology parameters, and to solve for the associated steady-state prices. Given these parameters and prices, we then solve for the transition in order to fill in the sequence $\{Z_t, \lambda_t^S, \lambda_t^G\}_{t=1967}^{2020}$ and $\{\mathbf{p}_t\}_{t=1965}^{2020}$.

C.3 Decision rules

The household decision problems are standard finite horizon dynamic programming problems. We start in the last period of life, J , and work backwards by age. Solving for decision rules in the retirement stage of the life-cycle is relatively simple, since there is no labor market risk and the only decision for the household is how to divide income between consumption and savings. Solving for decisions in the working stage of the life-cycle is more challenging computationally, because the state space is large: for each household type and for each age we need to keep track of household wealth and of the persistent and transitory stochastic components of the wage for both the husband and the wife.

We assume that the transitory shocks and the innovations to the persistent component can each take two values, but we allow the cumulated value of the persistent component to be continuous. At each age, we approximate decision rules for consumption using piecewise tri-linear functions defined over wealth and the male and female persistent components (one function for each possible combination of age and mix of education and transitory shocks within the household). We make our grid finer at low levels of wealth, and allow the number of grid points for persistent shocks to increase with age, given that our estimates indicate a high value for the autoregressive coefficient ρ . We use the ‘‘endogenous grid’’ method for Euler equation iteration, as described by Carroll (2005). The key idea is that at each point in the state space, one considers a grid over current shocks and *next* period wealth, and then uses the inter-temporal first order condition to compute implied current wealth. This can be accomplished very quickly, because it avoids having to solve a non-linear equation (the Euler equation) numerically. The method is also well-suited to dealing with borrowing constraints: setting the value for next period assets at the constraint determines the ‘endogenous’ value for current assets below which the constraint must bind. As explained by and Barillas and Fernandez-Villaverde (2006), it is straightforward to extend this method to the case where labor supply is endogenous, as in our economy.

C.4 Steady states and internal calibration

It is useful to postpone determining $(\bar{\kappa}^m, \bar{\kappa}^f, v_\kappa^m, v_\kappa^f)$ and simply assume that there exist values for these parameters that deliver the target enrollment rates by gender in the two steady states, $(q_*^m, q_*^f, q_{**}^m, q_{**}^f)$. This way, in what follows, we can avoid solving for the education decisions.

We guess values for parameters $(Z_*, Z_{**}, \lambda_*^G, \lambda_{**}^G, \beta, \underline{a}, \psi, b)$ and equilibrium prices $(p_*^{m,h}, p_{**}^{m,h})$. Given

the production technology and the calibration strategy, these guesses are sufficient to construct the remaining steady state prices as follows.

First, since the selection issue for men is assumed to be minor, given guesses for $(p_*^{m,h}, p_{**}^{m,h})$ and the observed college premia in 1967 and 2002, we immediately have $(p_*^{m,l}, p_{**}^{m,l})$. For example, if Π_* is the ratio between the average wage of male college graduates relative to male high-school graduates at the start of the sample, we set

$$p_*^{m,l} = \frac{p_*^{m,h}}{\Pi_*}. \quad (\text{C-3})$$

Second, given the guesses for $(\lambda_*^G, \lambda_{**}^G)$, from (12) we can recover steady state prices for female labor. For example, in the first steady-state

$$\frac{p_*^{m,h}}{p_*^{f,h}} = \frac{p_*^{m,l}}{p_*^{f,l}} = \frac{\lambda_*^G}{1 - \lambda_*^G} \quad (\text{C-4})$$

In the initial steady-state, the solution to the household's problem delivers a set of decision rules, as well associated value functions \mathbb{V}_* and expected start-of-working-life values \mathbb{V}_*^0 . Then, we move to the matching stage. Given the enrollment rates (q_*^m, q_*^f) and the target degree of assortative matching ϱ , we can compute matching probabilities (π_*^m, π_*^f) using the equation defining the correlation between education levels within the household (6) and the consistency conditions of the form (5). The same logic applies to the final steady state.

At this point we can simulate the economy to compute cross-sectional moments. We do two simulations, one for each steady state, and compute the set of statistics that correspond to our target calibration moments and equilibrium conditions. Since technology parameters and equilibrium prices vary across steady states, so do household decisions and cross-sectional moments. We want to calibrate the model economy to replicate certain features of the U.S. economy (e.g., mean hours worked) on average across the sample period. We implement this by computing average empirical target statistics across the sample period, and searching for parameter values such that these are reproduced in the model when averaging across the two steady state simulations.

To verify that the guesses for prices $(p_*^{m,h}, p_{**}^{m,h})$ are in fact consistent with equilibrium requires knowledge of each argument of the equilibrium pricing functions, since we need to verify that $p_*^{m,h} = p(Z_*, \lambda_*^S, \lambda_*^G, \mathbf{H}_*)$. The vector of aggregate effective hours worked by each type of labor, \mathbf{H}_* , can be computed within the simulation. The technology parameters Z_* and λ_*^G are part of the guess. However, we still need to compute the implied value for λ_*^S . Since, absent selection, the observed skill premium Π_* is equal to the price ratio $p_*^{m,h}/p_*^{m,l}$, we can compute λ_*^S using the ratio of the expressions for the marginal products of male skilled and unskilled labor:

$$\Pi_* = \frac{p_*^{m,h}}{p_*^{m,l}} = \frac{\lambda_*^S}{1 - \lambda_*^S} \mathbf{c}_* \Rightarrow \lambda_*^S = \frac{\Pi_*}{\Pi_* + \mathbf{c}_*} \quad (\text{C-5})$$

where

$$\mathbf{c}_* = \left[\frac{\lambda_*^G H_*^{m,h} + (1 - \lambda_*^G) H_*^{f,h}}{\lambda_*^G H_*^{m,l} + (1 - \lambda_*^G) H_*^{f,l}} \right]^{-\frac{1}{\theta}}. \quad (\text{C-6})$$

To recap, we guess a vector $(Z_*, Z_{**}, \lambda_*^G, \lambda_{**}^G, \beta, \underline{a}, \psi, b, p_*^{m,h}, p_{**}^{m,h})$, solve the model, and check whether or not the corresponding eight target calibration moments (see Section 4.1) and two equilibrium conditions for prices are satisfied. If any of these conditions are not satisfied at the initial guess, we use multi-dimensional Newton-Raphson methods to update the guess. Then we resolve decision rules, and resimulate, iterating in this fashion to convergence.

The last step in the steady-state stage of the solution method is to compute the education cost distribution parameters $(\bar{\kappa}^m, \bar{\kappa}^f, v_{\kappa}^m, v_{\kappa}^f)$. We do this by first using equations (4) to compute expected values of education by household type in both steady-states. We then solve a simple set of four non-linear equations of the form

(3), one for each gender and for each steady-state, to compute the four utility cost parameters. This procedure allows us to perfectly replicate the target enrollment rates by gender in 1967 and 2002.

C.5 Transitional dynamics

Once all parameter values are known, it remains to solve for prices from 1965 (when information about future changes in the wage structure is revealed) to 2020 (the last year of transition).

We first guess sequences $\{p_t^{m,h}\}_{t=1965}^{2020}$, $\{p_t^{m,l}\}_{t=1965}^{1966}$, $\{\lambda_t^G\}_{t=1967}^{2020}$. Given these guesses, we can construct prices for each type of labor at each date as follows: (i) for $t < 1965$ prices are given by p_* , (ii) for $1965 \leq t < 1967$ prices for male labor are given by the guess $(p_t^{m,h}, p_t^{m,l})$, while prices for female labor can be determined given $\lambda_t^G = \lambda_*^G$ using the expression for the gender premium (C-4), (iii) for $1967 \leq t \leq 2020$, $p_t^{m,l}$ can be readily computed given the guess $p_t^{m,h}$ and the empirical college premium by applying (C-5), while prices for female labor are implied by the guess for λ_t^G and equation (C-4), (iv) for $t \geq 2021$, prices are given by p_{**} .

Given all the prices, we solve each cohort's problem, beginning with the cohort that enters the labor force in year $t = 1965 - j^R = 1929$, and ending with the cohort that enters the labor force in year 2021. We then compute cohort-specific expected values \mathbb{V}_t for each household type.

To compute cross-sectional moments, and aggregate effective hours for each type of labor, we need to know the education composition of the workforce at each date. For each cohort we therefore guess enrollment rates, (q_t^m, q_t^f) . Given these guesses and the target degree of assortative matching ϱ , we compute matching probabilities π_t^g . Given these probabilities and the values \mathbb{V}_t we can calculate expected education values \mathbb{M}_t^g . Finally we use the equilibrium schooling condition (3) to check whether the guessed enrollment rates are correct. Enrollment rates allow us to derive the household composition for each cohort.

Once we have decision rules and household composition for all cohorts, we can simulate the economy and compute time series for the model-implied gender premium and compare this to its empirical counterpart. This is the basis for updating the sequence $\{\lambda_t^G\}$.

To establish whether the guesses for prices are consistent with equilibrium, we need to check whether the guessed prices are equal to those implied by applying the functions $p(Z_t, \lambda_t^S, \lambda_t^G, \mathbf{H}_t)$. To check this we need the time series $\{Z_t\}$ and $\{\lambda_t^S\}$ in addition to aggregate effective hours for each type of labor, $\{\mathbf{H}_t\}$. We generate series for $\{\mathbf{H}_t\}$ by simulation, and use these series, along with the (guessed) sequences for $\{\lambda_t^G\}$, $\{p_t^{m,h}\}$ and $\{p_t^{m,l}\}$ to compute a time series $\{\lambda_t^S\}$ using the time t equivalent of equations (C-5). We then use equation (C-2) to construct a time series $\{Z_t\}$ such that in the hypothetical counter-factual that $\mathbf{H}_t = \mathbf{H}_*$ for all t , average individual earnings would be time-invariant. We are then in a position to compute the model-implied equilibrium price sequences.

After comparing the guessed price sequences to the model-implied price sequences, we update our guesses. We then resolve all cohorts problems, resimulate, and check again for market-clearing in all labor markets, and for the appropriate gender wage gap, iterating until convergence.

Table A-1: Sample Selection in PSID, CPS and CEX

	PSID (67-96, 98, 00, 02)		CPS (67-05)		CEX (80-03)	
	#dropped	# remain	#dropped	# remain	#dropped	# remain
Initial sample of married households	–	68,860	–	1,312,864	–	40,605
Age of husband 25-59	10,274	58,586	354,256	958,608	11,604	29,001
Hours worked of husband at least 260	1,927	56,659	138,269	820,339	1,430	27,571
Wage husband above half minimum wage	1,215	55,444	87,466	732,893	2,316	25,255
Wage wife above half minimum wage	1,723	53,721	32,021	700,872	902	24,353
Income husband not from self-employment	8,784	44,937	28,330	672,542	1,857	22,496
Income wife not from self-employment	1,814	43,123	12,216	660,326	940	21,556

Table A-2: Comparison Across PSID, CPS and CEX Samples

	PSID	CPS	CEX
Average age of men	39.15	40.94	41.26
Average age of women	37.0	38.62	39.2
Fraction of male college graduates	0.31	0.31	0.31
Fraction of female college graduates	0.24	0.24	0.24
Average earnings of men (1992 \$)	39,674	40,182	38,441
Average earnings of women (1992 \$)	15,097	14,199	15,570
Average hours worked by men	2,223	2,252	2,225
Average hours worked by women	1,258	1,227	1,286
Average hourly wage of men (1992 \$)	18.09	18.44	17.49
Average hourly wage of women (1992 \$)	9.55	9.33	9.83
Average household earnings (1992 \$)	54,772	54,381	54,011
Average food consumption (1992 \$)	4,626	–	4,082

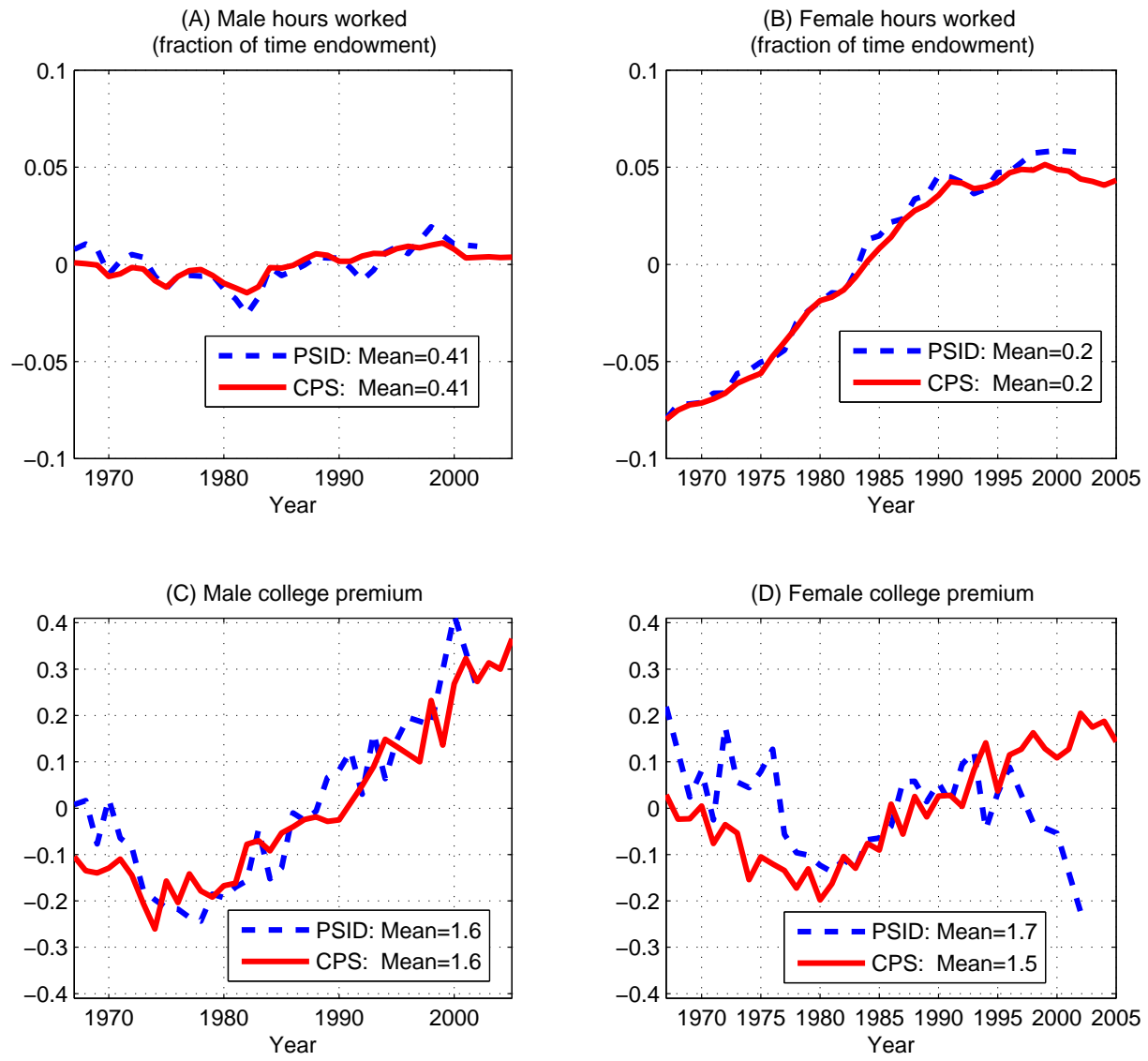


Figure A-1: Comparison between CPS and PSID Sample of Married Households

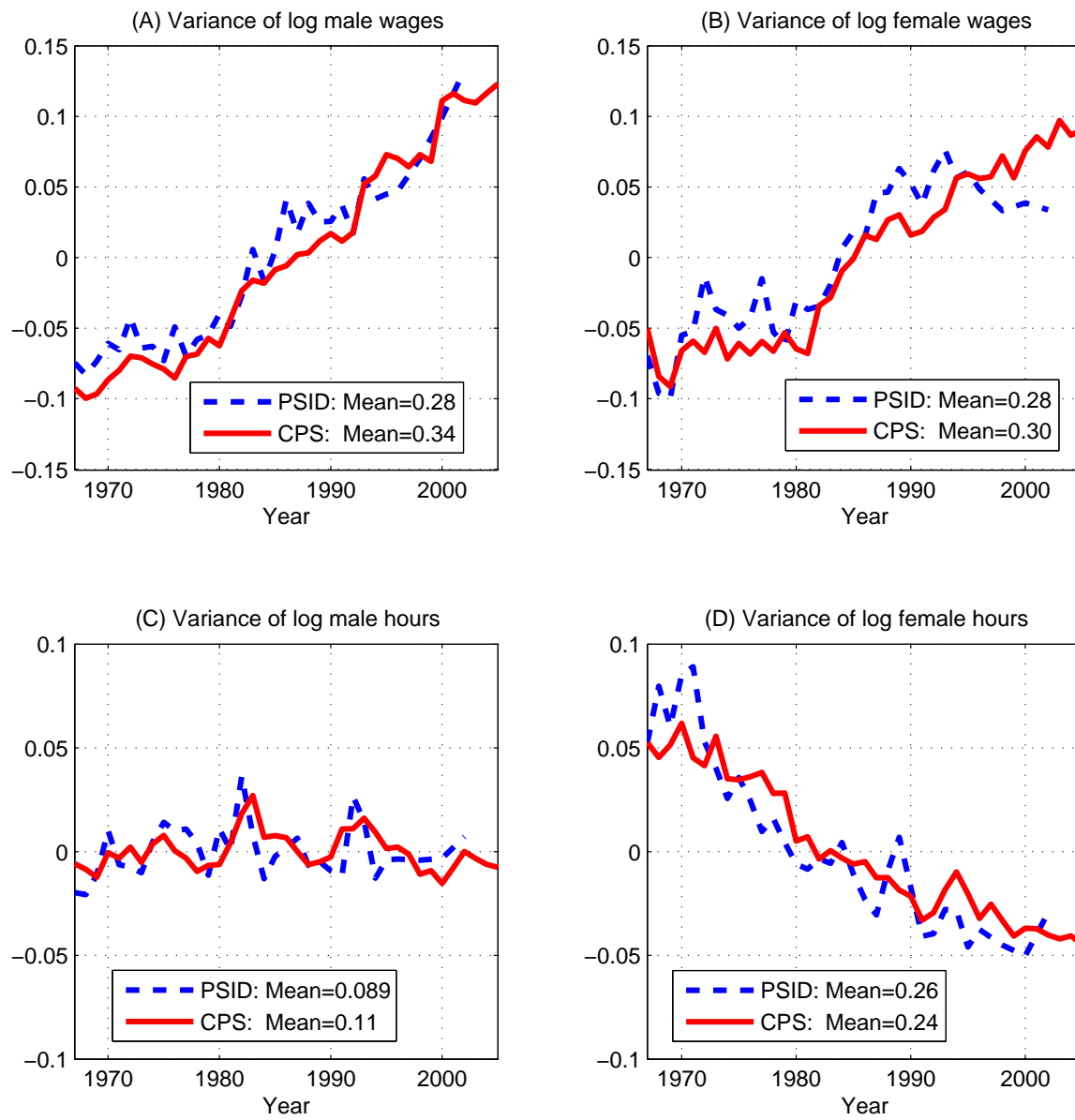


Figure A-2: Comparison between CPS and PSID Sample of Married Households

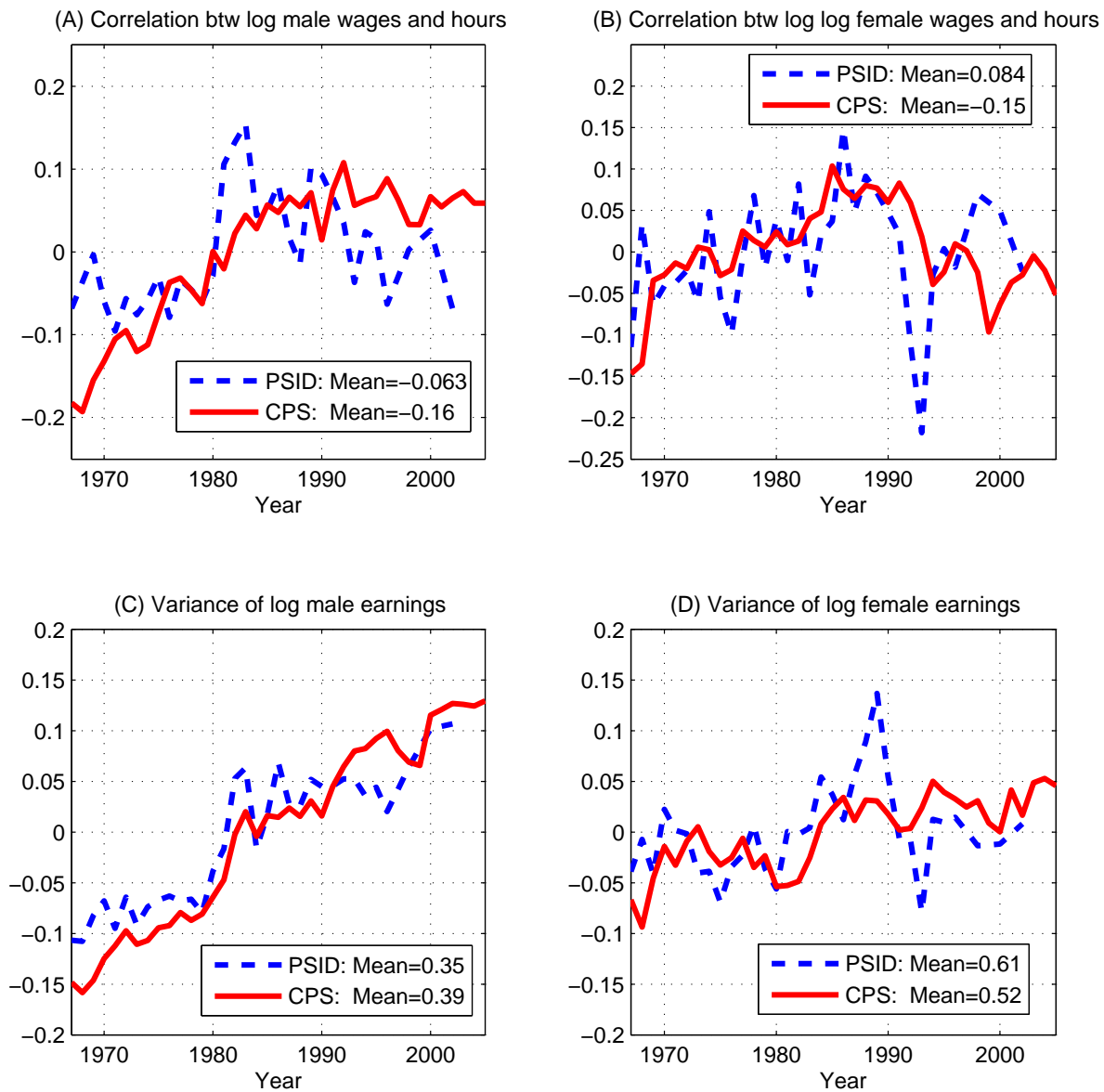


Figure A-3: Comparison between CPS and PSID Sample of Married Households

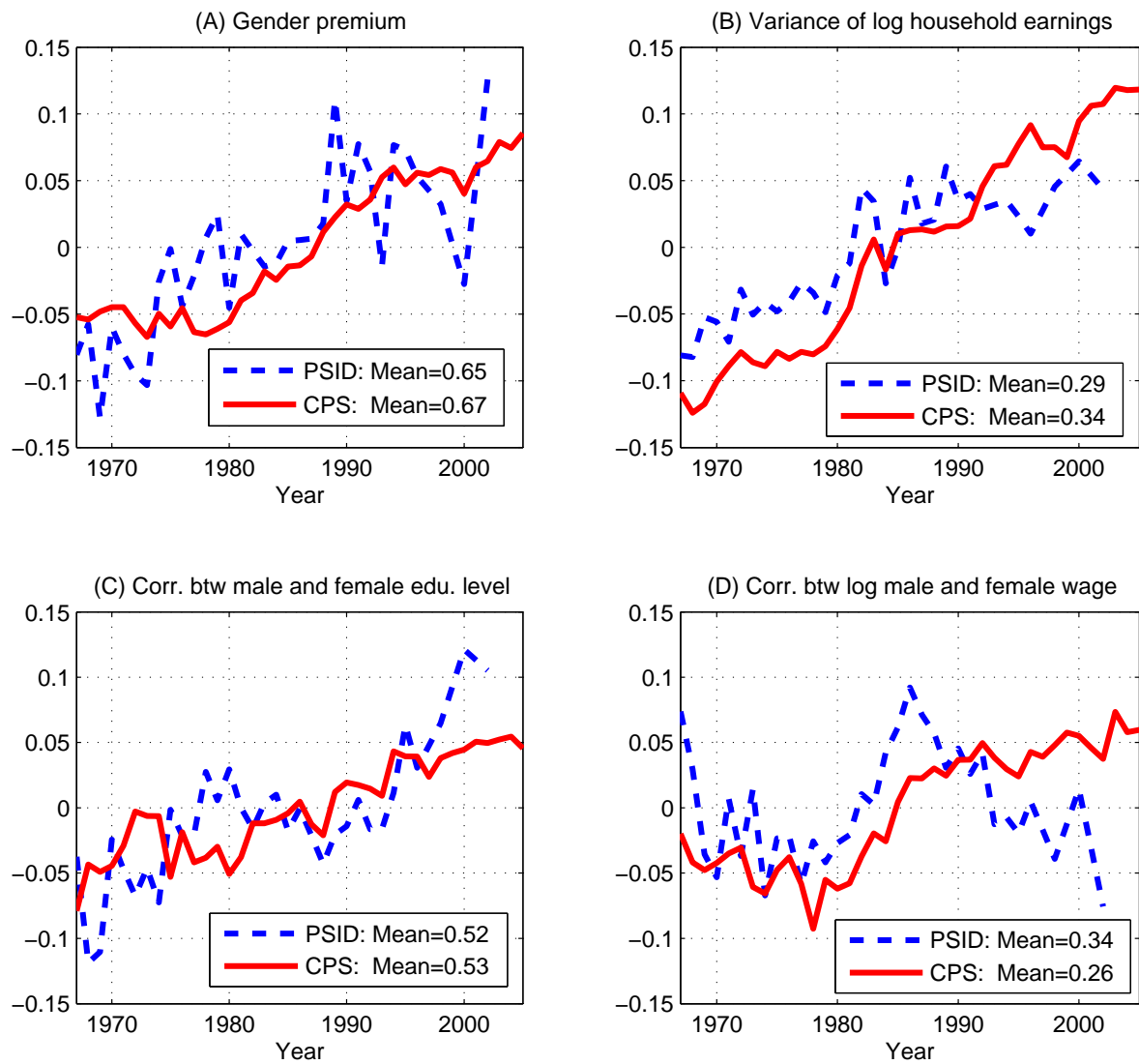


Figure A-4: Comparison between CPS and PSID Sample of Married Households