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by

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What Happens to Wage Elasticities When We Strip Playometrics? Revisiting Married Women Labour Supply Model

Duo Qin, Sophie van Huellen, Qing-Chao Wang*

Abstract

This paper sheds new light on the well-known phenomenon of dwindling wage elasticities for married women in the US over the recent decades. Results of a novel model experiment approach via sample data ordering unveil considerable heterogeneity across different wage groups. Yet surprisingly constant wage elasticity estimates are revealed within certain wage groups over time as well as across two widely used US data sources, the Current Population Survey (CPS) and the Panel Study of Income Dynamics (PSID). These findings refute the assumed presence of a single-valued aggregate wage elasticity for working wives. Although women's responsiveness to wages remains largely unchanged over time, we find that the composition of working women into different wage groups has changed considerably, resulting in decreasing wage elasticity estimates at the aggregate level. All these findings were methodologically impossible to acquire had we not dismantled and discarded the stereotyped endogeneity-backed instrumental variable route, which hitherto blocked the way towards sample data ordering.

Keywords: instrumental variable, labour supply wage elasticity, parameter stability, selection bias.

JEL classification: J22, C18, C52, C55

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1. Introduction

The relative responsiveness of female workers to changes in wages and income is at the core of labour economics. Historically women's wage elasticity is found to be considerably higher relative to their male counterparts (Killingsworth 1983, Heckman 1993). The theoretical premise for this is that the income effect for women is small while the substitution effect dominates. This is usually explained by the traditional division of labour within families where wives are assumed to substitute between household tasks, market work, and leisure while men only substitute between the latter two. Since household tasks and market work are close substitutes, the wage substitution effect is arguably large for women which results in a positive uncompensated wage effect (income and substitution effect) and relative elastic female labour supply with respect to wage rate, e.g. see Mincer (1962). More recent empirical studies challenge this gap between male and female wage elasticities and observe shrinking elasticities for married women in the US. For instance, Blau and Kahn (2007) find a steady and dramatic reduction in women's wage elasticity by about 50 to 56 per cent during the 1980-2000 period, with respect to both labour force participation and hours of work. Likewise, Heim (2007) observes a 60 to 95 per cent reduction in intensive and extensive margins from 1979 to 2003. The dwindling elasticity has become almost a stylised fact, e.g. see McClelland and Mok (2012). Theoretically, these developments are linked to disbanding traditional gender roles (Goldin 1990) and increasing wage opportunities for women (Juhn and Murphy 1997).

Empirical studies on the wage elasticity gap between males and females are predominantly executed at a micro level. However, microeconomic estimations are everything but uncontroversial and elasticity estimates vary substantially across studies (Killingsworth and Heckman 1986, Blundell and MaCurdy 1999). Furthermore, microeconomic estimates of labour supply elasticities based on hours of work tend to be smaller than elasticities implied by macroeconomic models of fluctuations in aggregated hours of work over the business cycle (Keane and Rogerson 2012). Although studies suggest taking the microeconomic estimate for calibrating aggregated macroeconomic models (Cetty, et al. 2011), such process has been heavily criticised (Peterman 2014, Fiorito and Zanella 2012) and no consensus has been found yet. This unresolved anomaly between macro and micro results as well as the variety of estimates presented by micro models alone put into questions the general reliability or credibility of wage elasticity estimates.

The purpose of this study is twofold: Firstly, the conventional methods for modelling wage elasticity of labour supply are challenged. Secondly, against the background of this critique, a potential way forward is proposed. In particular, the paper targets the instrumental variable (IV) approach to endogeneity, which is further compounded by Heckman's selection bias correction. The IV treatment arises originally from a concern over circular causality between the wage-rate and hours worked. Such an approach is questionable in the present case of married women's labour supply on both economic and econometric grounds. From an economic perspective, it is seriously doubtful whether the majority of working women have the bargaining power to influence their wage rate and it might indeed be reasonable to assume that the great majority are wage takers, which renders the concern for endogeneity substantively superfluous. From an econometric perspective, the IV approach is based on rejecting the wage rate as a valid conditional variable for hours of work and replace it by non-optimal and hence non-unique predictors of this variable. These predictors are generated from instruments which are chosen on the basis of statistical correlation alone rather than causal reasoning, e.g. see Qin (2014a). Such treatment, as will be shown in the following, results in frequent violation of over identification restrictions and obstruction of systematic data learning to locate statistically robust wage elasticity estimates.

In the same vain it is argued that the Heckman selection bias correction procedure is redundant since it targets at the possible omitted variable bias (OVB) of the individual parameter estimates in the instrumented wage equation rather than the hours of work equation. The procedure amounts to adding an additional instrument to the already over-identified and poorly fitted-wage equation which is relatively insensitive to the addition of the correction. This correction is motivated by the fact that the offering wage is unobserved for non-working individuals. While selection bias is a potential concern, depending on the target group, the conventional approach is shown to not enter the parameter of interest significantly for the present case.

We maintain that the IV approach and its selection-bias correction variations are not simply a technical issue of estimator choice for applied modellers, but pose a methodological block to empirical data discovery. By breaking with the textbook paradigm, we are able to suggest a constructive way towards more credible wage elasticity estimates by sample data ordering. This approach is not only close to the economic interpretation of wage elasticities, but also yields additional insights into the nature of wage elasticities within various samples of married working women. In particular, it is shown that wage elasticity parameters vary substantially across different wage groups and even turn negative for high wage earners; an effect which is hidden under the textbook approach. By sample ordering we are, however, able to locate a wage range within which wage elasticity parameters are constant, positive and highly significant. We show that this wage range and parameter estimates are surprisingly invariant across different waves, while the share of women falling within this wage range varies.

These findings shed new light on the two almost established economic phenomena of shrinking elasticities for married women in the US and the gap between micro and macro elasticities. We argue that the finding of shrinking elasticities is actually a result not of changes in disaggregate elasticities per se but a shifting composition of working women in different wage segments over the last decades. Further, the discovery of significant heterogeneity among working women puts into question the assumption of single valued micro elasticities and calls for a theoretical reorientation for those aiming to align micro with macro estimates.

The microeconomic female labour supply model is commonly estimated taking married women at their prime working age with working husbands as the target group. We will follow this approach taking two widely used US based cross-section data sources into consideration – the Current Population Survey (CPS) and the Panel Study of Income Dynamics (PSID). The parallel use of the CPS and PSID sources provide us with a powerful means of cross-checking the degrees of inferability between samples. For estimation the years 1980, 1990, 1999, 2003, 2007, and 2011 are chosen. These firstly coincide with the time periods investigated by two core papers, Blau and Kahn (2007) and Heim (2007) which are based on CPS data, and hence make a good comparative case[1] and secondly go beyond the time frame previously analysed. A detailed description of the datasets and processing of the data can be found in Appendix 1.

The remainder of the paper proceeds as follow. Section 2 dismantles the textbook approach to wage elasticity estimation by revealing fundamental flaws in the endogeneity-backed IV approach and selection bias correction treatment of the wage variable. Section 3 picks up the pieces and suggest alternatives towards a more credible wage elasticity estimate. Section 4 concludes and provides an outlook for future research.

2. How Superfluous Are Endogeneity and Selection Bias Correction Treatments?

The most commonly used empirical model of labour supply for married women with respect to cross-section data is:

(1) $$H_i = \alpha_0 + \alpha_1 ln(w_i) + \alpha_2 ln(I_i) + \sum_j \beta_{ij} X_{ij} + \varepsilon_i$$

[1] Blau and Kahn (2007) pool 1979-81, 1989-91 and 1999-2001 into three samples. We simply choose one mid wave for each of the three. However, we choose 1999 for the third wave because the PSID source does not provide 2000 data.

where H_i denotes wife's total hours of work in household i, w_i her wage rate, I_i her husband wage rate or income, and $\{X_{ij}\}$ a set of explanatory variables of demographic characteristics, such as wife's age, education, work experience and the number of children in the household. α_1 and α_2 are the parameters of interest for the purpose of measuring the hours wage elasticity and hours income elasticity respectively. Here, it suffices our methodological exposition to be focused on the measurement issues around α_1 alone.

It is almost standard practice[2] to estimate model (1) via an IV treatment to w_i out of two major concerns – endogeneity and selection bias.[3] Specifically, the static relationship between H_i and w_i, in (1) associates easily to the classical case of a simultaneous equation model (SEM) between quantity and price, which is widely taught in textbooks. Meanwhile, the observed w_i is believed to suffer from 'selection bias' due to lack of information on what the offering wages might be for those non-working housewives in cross-section data. The IV treatment demands re-specifying (1) into a two-equation model:

$$(2) \qquad \begin{aligned} &H_i = \alpha_0 + \alpha_1 \widehat{ln(w_i)}_{IV} + \alpha_2 ln(I_i) + \sum_j \beta_{ij} X_{ij} + \varepsilon_i \\ &ln(w_i) = \lambda_0 + \sum_k \lambda_{ik} Z_{ik} + u_i \qquad \Rightarrow \quad \widehat{ln(w_i)}_{IV} \end{aligned}$$

which underlies the two stage least square (2SLS) estimation procedure of IV models. In equation (2), $\{Z_{ij}\}$ is a set of IVs such that $Z \supsetneq \{ln(I), X\}$. When selection bias is of concern, an inverse Mills ratio, ρ, is commonly included in Z. The ratio is derived from the residual density function of the following binary response model of labour force participation:

$$(3) \qquad \begin{aligned} &P_i = \theta_0 + \theta_2 ln(I_i) + \sum_m \kappa_{im} Y_{im} + \epsilon_i \qquad P_i = \begin{cases} 1 & if \;\; w_i > 0 \\ 0 & if \;\; w_i = 0 \end{cases} \\ &\rho = \frac{\phi(\epsilon_i)}{\Phi(\epsilon_i)} \end{aligned}$$

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[2] This can be seen from both the wide adoption of Mroz's (1987) study in econometrics textbooks, e.g. Berndt (1991), and the extensive use of IV and 2SLS methods in labour economics research, e.g. see Moffitt (1999).

[3] Another issue of concern is omitted variable bias (OVB). This issue is left aside here mainly for two reasons. First and obviously, it helps us to be more focused on the other two issues. Secondly, OVB should not be a serious problem for the wage parameter estimation in our model because its log specification and value-continuous property within the working population deems its correlations with potentially omitted variables, such as geographic location, tax rate, quite low and unlikely invariant in large samples.

where $\{ln(I), Y\} \supsetneq Z$. Probit is normally used to estimate (3) according to the Heckman two-step procedure (1979).

The underlying reasoning for hours of work being causal for wage-rates lies in the assumption that the harder (more hours) one works, the higher the reward (wage rate). However, there lacks economic ground to assume that married women in general should have the wage bargaining power through their choice of working hour supply. Even if assuming a certain bargaining power this probably arises from seniority and status at the workplace and union representation rather than hours worked (Gersuny 1982). Hence, the endogeneity specification in (2) is substantively superfluous.

However, model (2) is a pseudo SEM in that $ln(w_i)$ is not simultaneously determined by H_i. In fact, the corresponding IV treatment amounts to rejecting $ln(w_i)$ as a valid conditional variable for H_i and accepting, instead, $\widehat{ln(w_i)}_{IV}$, a non-optimal predictor of $ln(w_i)$, as the valid conditional variable (see Qin (2014a) for a detailed exposition). The non-optimality of $\widehat{ln(w_i)}_{IV}$ is easy to see in the context of large cross-section survey samples, because it is virtually impossible to get $\widehat{ln(w_i)}_{IV}$ close to $ln(w_i)$ enough to yield a statistically identical $\hat{\alpha}_1^{IV}$, the IV estimate from equation (2), to $\hat{\alpha}_1^{OLS}$ from equation (1). Consequently, confirmation of the Durbin-Wu-Hausman endogeneity test, a test on $\hat{\alpha}_1^{IV} \neq \hat{\alpha}_1^{OLS}$, is usually achievable. Moreover, the chance of obtaining statistically significant estimates of α_1 becomes higher under the IV treatment compared to OLS, thanks to the non-uniqueness of $\widehat{ln(w_i)}_{IV}$ which results from the very nature of non-optimality.

The above discussion tells us that it is empirically crucial to determine whether we can reject $ln(w_i)$ as a valid conditional variable in (1) in favour of a non-optimal predictor of it as specified in the second equation in (2). Here, we examine this issue from three respects. (i) We examine the validity of IVs by over-identification restriction tests; (ii) we examine the degree of simultaneity between $ln(w_i)$ and H_i by running a genuine SEM; and (iii) we examine the invariance property of $\hat{\alpha}_1^{IV}$ across difference samples.

Textbooks tell us that valid IVs have to be correlated with the suspected 'endogenous' explanatory variables and uncorrelated with other explanatory variables, and that this condition is not testable unless the model is over-identified, i.e. chosen IVs outnumber the suspected 'endogenous' explanatory variables. Fortunately, the just-identification case, i.e. $k = 1$, does not apply to (2) almost surely because it is virtually impossible to get reasonably good fits of $ln(w_i)$ from multiple regression models using large cross-section data, a problem known as the weak IV problem (see Bound, *et al*. (1995)). Hence, the validity of $\{Z_{ij}\}$ is largely testable. What poses as a problem is the non-uniqueness in choosing the IVs. To circumvent this problem, we start our experiment by trying to produce $\hat{\alpha}_1^{IV}$ in line with some existing estimates reported in the literature. The two cases that we choose are Blau and Kahn (2007) and Heim (2007). Since both papers have reported results for three waves of the CPS data 1980, 1990, 2000, we aim to get our $\hat{\alpha}_1^{IV}$ as close as possible to what is reported in those two papers, even our models do not cover all the explanatory variables used by them.[4] Specifically, two groups of experiments are produced. The first group is carried out aiming for a set of IVs which would get us close to the above two cases using the CPS data, and apply the same set of instruments to the PSID data. The second group is carried out seeking a set of IVs for the same purpose using the PSID data alone. Table 1 provides the key results of these experiments.

Several common features are discernible from Table 1. It is not difficult to find IV estimates using the CPS samples which corroborate our targeted values even though our model does not have the same variable coverage as the papers presenting the results we seek to replicate (see the two CPS columns). However, the corroboration is not reproducible when we

[4] As explained in footnote 1, we take 1999 wave here as a proxy for 2000, due to the fact that the PSID source does not have 2000 survey.

apply the same IV set to the PSID data of the same waves (see columns 2 and 5), indicating low degrees of statistical inferability. This goes against the expectation that CPS surveys should be adequately representative with respect to the PSID surveys. Nevertheless, corroboration of the targeted values is still achievable through alteration of the IV set (see columns 3 and 6). These experiments clearly demonstrate the non-uniqueness of the IV route. As expected, $\widehat{ln(w_i)}_{IV}$ obtained from the various sets of the first-stage of the IV procedure are substantially different from $ln(w_i)$, as easily seen from those small adjusted R^2 statistics reported in Table 1, in spite of that equation being 'over-identified'. Consequently, the Durbin-Wu-Hausman endogeneity test statistics endorse the IV estimates for the majority of cases for being different from the OLS estimates. However, the Sargan over-identification restriction test is rejected dominantly, invalidating all of the four IV sets. The rejection comes unsurprisingly since $Z \cap \{ln(I), X\} \neq 0$ for all our IV sets, though violation of the correlation condition is somewhat eased by taking quadratic or cubit forms of the overlapping variables.

It is noticeable from Table 1 that those IV estimates with selection-bias corrections do not show much statistically significant difference as compared with the general varied ranges of IV estimates (compare the two CPS columns, or columns 2 and 5 in the PSID case). This finding corroborates many previous findings including Blau and Kahn (2007) and Newey, *et al.* (1990). It demonstrates how superfluous the conventional selection-bias correction is for the present case. The superfluousness is actually implied in the IV-based model (2), where the correction amounts to adding one more instrument, ρ, in the already over-identified IV set, *Z*. Furthermore, this additional instrument, ρ, is derived from instruments, *Y*, which carry notably overlapping information with *Z*. Conceptually, substantive concerns over selection bias is with respect to the 'missing' offering wage rate, not with hours of work. Here, it is epistemologically vital to see that Heckman's method is not designed to resolve the possible misrepresentation problem in making statistical inference, which is based merely on observable wage information, beyond the working population. Rather, the method targets, on the assumption that selection bias exists, narrowly at the possible OLS bias in modelling the wage variable and treats the bias as a special type of omitted variable bias (OVB) (see Heckman (1976)). In our present case, the Heckman method is focused on correcting the possible OVB in λ_{ik} estimated by the OLS in the IV equation of (2). Obviously, the correction is beside the point in view of estimating our parameter interest, α_1. Numerous empirical model results tell us that the estimates of α_1 are sensitive to the choice of $\widehat{ln(w_i)}_{IV}$, as illustrated in Table 1. In contrast, $\widehat{ln(w_i)}_{IV}$ is usually not sensitive, as measured either by the adjusted R^2 or any information criteria, to whether the estimated λ_{ik} suffer from OVB due to missing ρ, especially when ρ is based on heavily overlapping Z and $\{ln(I), Y\}$.[5]

Here, what is probably more relevant than 'selection bias' is the truncation effect in H_i.[6] In order to assess this effect via nonlinear estimation such as tobit, we need to impute the 'missing' offering wage rates. Considering the unsatisfactorily low fit of various regression models or likelihood based methods previously used in the literature, we decide to use the hot deck imputation method here to impute the missing offering wage rates. This method has been widely used by statisticians for handling missing data, e.g. see Andridge and Little (2010), and can be seen as a systematic extension to the method used by Blau and Kahn (2007). The details of our imputation are described in Appendix 2.

Once those 'missing' offering wage rates are imputed, we re-estimate (2) with the IV tobit method using extended data samples including those wives having zero work hours. The main results are summarised in Table 2. It is remarkable how substantially different the IV

[5] This is multicollinear issue and formally demonstrated by Puhani (2000), whereas the similarity of the Heckman correction to the simple OLS correction is shown by Olsen (1980).

[6] It is debatable whether we should use model (1) to characterise the labour supply behaviour of both the working group and non-working group. The truncation effect would not matter here if we assume that wage effect on hours of work differ from that on the labour force participation. This assumption finds support from our subsequent experiment reported in Section 3. Nevertheless, we have tried the tobit route following the practice of Blau and Kahn (2007).

estimates are as compared to those reported in Table 1. The only feature which remains unchanged is the wide acceptance of the 'endogeneity' test jointly with sweeping rejection of the over-identification restrictions. Since the truncation effect on the OLS bias has been shown to be approximately a rescale effect by the shares of the truncated observations in a truncated sample, (see Greene (1981) and Cheung and Goldberger (1984)) we re-run the extended samples simply by the tobit and the OLS, and then calculate the scaled OLS estimates. As seen from Table 3, the scaled OLS estimates are indeed very similar to the tobit estimates. The extra amount of variations in IV tobit estimates in Table 2 as compared to those in Table 1 cannot be possibly accounted for as the truncation effect. The non-optimality of this IV route is too apparent to deserve further comments.

Next, we extend model (1) into a genuine SEM:

$$\begin{aligned} H_i &= \alpha_0 + \alpha_1 ln(w_i) + \alpha_2 ln(I_i) + \sum_j \beta_{ij} X_{ij} + \varepsilon_i \\ ln(w_i) &= \gamma_0 + \gamma_1 H_i + \sum_{j=1}^{l} \delta_{ij} Z_{ij} + \upsilon_i \end{aligned} \tag{4}$$

and estimate it by the FIML (full-information maximum likelihood) method. Notice, (4) augments (2) by adding H_i in its second equation. Hence, over-identification restriction tests still apply here. Table 5 reports the main results of this experiment. Again, the over-identification restriction test is rejected in all of the cases. Notice that more than half of the cases fail to demonstrate the presence of significant simultaneity between α_1 and γ_1 estimates. Worse still, the majority of the wage parameter estimates are now negative, making them far less credible than those IV estimates given in Table 1. In fact, the incredibility of these SEM results have been exposed repeatedly before in macro-econometrics, e.g. see Qin (1993, 2013). In particular, the insurmountable gap between reality and those over-identification restrictions used to circumvent endogeneity created by simple model formulation has also been forcefully criticised (e.g. Sims (1980)).

It is also easily noticeable from tables 1, 2 and 5 how different the IV and FIML estimates can be between the CPS and PSID samples of the same waves. Since parameter invariance plays such a fundamental role in statistical inference, our next experiment turns to the degrees of within-sample invariance.[7] This is carried out via recursive estimations and parameter stability tests. However, both the recursive estimation technique and parameter stability tests are predicated on a unique data ordering assumption (see Zeileis and Hornik (2007)) while there is no natural data ordering scheme in the cross-section context (see Pagan and Vella (1989)). Here, we choose the ordering scheme on the basis of two conditions: (a) the ordering scheme complies with the fixed regressor principle, i.e. it is consistent with the model specification; (b) the ordering scheme is substantively meaningful and relevant (see Qin and Liu (2013) for an exploring experiment with data ordering). Our initial trial is to order data by wife's age, since it is acceptable to treat this age variable as a fixed regressor for both models (1) and (2). Moreover, this ordering scheme can be economically interesting as can be seen from Blau and Kahn (2007, B3 in Section V) and Rupert and Zanella (2014).

The within-sample invariance of the IV estimates is examined by means of two types of parameter stability tests – the commonly used Hansen test and the M-fluctuation test for individual parameter stability developed by Merkle *et al.* (2013). The latter is used because the Hansen test is not directly applicable to IV estimators. Specifically, we use the Hansen test to examine how invariant the IV generating process of $\widehat{ln(w_\iota)}_{IV}$ is, that is, how stable the parameters of the second equation, i.e. the IV equation, of model (2) are. Here, only the joint parameter test statistics are reported in Table 4 to save space. It is clearly shown in the table that most of the IV generating processes are not within-sample invariant. Next, we apply the M-fluctuation test to all the $\hat{\alpha}_1^{IV}$ reported in Table 1 and also to the corresponding $\hat{\alpha}_1^{OLS}$ based on model (1). The test results in Table 4 show that null hypothesis of stability is rejected more often for $\hat{\alpha}_1^{IV}$ than for $\hat{\alpha}_1^{OLS}$ whereas $\hat{\alpha}_1^{IV}$ tends to pass the M-fluctuation test when the test on

[7] It should be noted that this condition was central in the original definition of structural relations by Frisch over 80 years ago. It underlies the concept of super-exogeneity in time-series econometrics, and is deemed a strong condition for causal linear stochastic dependence in psychometrics, e.g. see Qin (2014b).

$\hat{\alpha}_1^{OLS}$ shows strong rejection, e.g. see the 2003 and 2007 CPS results. The latter observation corroborates directly with Perron and Yamamoto's (2013) finding, namely that the IV-based methods have lower power in detecting parameter instability than the OLS-based methods due to the fact that the IV-generated regressors are too smooth to retain enough variations to match those of the modelled variable. The same fact can help explain our former observation as well. Since $\widehat{ln(w_i)}_{IV}$ carry less variations than $ln(w_i)$, variations which are needed to explain those in H_i, the recursive $\hat{\alpha}_1^{IV}$ have to vary more than $\hat{\alpha}_1^{OLS}$ in compensation. Consequently, $\hat{\alpha}_1^{IV}$ suffers from having much larger standard error bands than $\hat{\alpha}_1^{OLS}$ at the same significance level or the same size of the test. To illustrate this situation, we plot in Figure 1 the recursive estimation of $\hat{\alpha}_1^{IV}$ with its 95% confidence interval of the 1999 IV sets reported in Table 1, together with their counterparts of the OLS estimates (the bottom two graphs). The varied and inaccurate as well as prolific properties of the IV estimates are strikingly obvious, especially in comparison to the OLS plots.

The above investigation provides us with abundant evidence to refute the IVs estimates as valid and credible substitutes for the OLS estimates.[8] The evidence strongly points to maintaining $ln(w_i)$ as a valid conditional variable in favour of other non-optimal predictor of it. In other words, we have failed to find adequate and convincing evidence to support the superiority of models (2) and (4) over (1).

3. How Can We Find Credible Wage Elasticity Estimates?

The above results are hopefully compelling enough to show how superfluous both the endogenous assumption and the selection bias correction are for the purpose of measuring the wage elasticity in micro labour supply models. Our findings are apparently devastating, as they throw us back to the 'first generation studies' of labour supply over four decades ago, as

[8] This finding coincides with the views by several other authors, who came to call for caution using IVs (e.g. see Angrist and Krueger (1999)).

described in Berndt (1991, Chapter 11), and pose serious doubts about the micro-econometrics textbook approach. Methodological issues aside, how should we proceed based on the above destructive results?

The preceding within sample parameter stability experiment indicates a possible way forward – sample data ordering. Considering that our focus on α_1 is driven by the need of finding the best possible estimates for the own wage elasticity:

(5) $$\eta_w = \frac{\partial H_i}{\partial w_i}\frac{w_i}{H_i} \approx \hat{\alpha}_1 \frac{1}{\overline{H_i}},$$

the closest measurement to (5) should be based on the data ordering scheme by w_i. In other words, η_w, defined as the percentage change in H_i in response to a one percent change in w_i is best reflected when data is order by w_i so that the incremental change of w_i is revealed. This ordering scheme clearly satisfies condition (b) stated in the previous section. Condition (a) requires w_i not to be simultaneously determined by H_i. Data evidence has failed to show any systematic simultaneity so far (cf. Table 4).

With respect to equation (5), it is obviously better to work with the following log-linear model instead of (1):

(1') $$ln(H_i) = a + \eta_w ln(w_i) + \eta_I ln(I_i) + \sum_j b_{ij}X_{ij} + e_i.$$

The use of semi-log specification in (1) is mainly due to the truncated data feature of H_i. But since we know that the truncation effect can be reasonably well approximated by scaling the OLS estimates, as shown from Table 3, we should be able to leave aside the truncation issue for the time being and focus our experiment on data ordering using the working wife sample only.

Two versions of (1') are estimated with different specifications of I_i. For one specification the husband's wage rate and for the other the family income net of the wife's earning is used. This is because $ln(w_i)$ is usually the most susceptible to the collinear effect by $ln(I_i)$ among all the explanatory variables in (1').[9] The resulting $\hat{\eta}_w^{OLS}$ and their related statistics are reported in Tables 6A and 6B. It is clear from Table 6A that different choice of $ln(I_i)$ do not significantly affect $\hat{\eta}_w^{OLS}$. We thus keep the following modelling experiments on using the family income as I_i.

The probably most noticeable changes in Table 6B are the Hansen parameter stability test statistics under different data ordering schemes. The data ordering scheme by w_i has surely ruined the relative within sample stability of $\hat{\eta}_w^{OLS}$ when data are ordered by wife's age. It should be noted that although full-sample parameter estimates are invariant to different data ordering schemes, their within-sample recursive processes are not unless there is no hidden dependence between randomly collected cross-section sample observations (see Hendry (2009)). Such hidden dependence can be revealed by appropriate data ordering choice, as shown by Qin and Liu (2013). Their choice is based on the observation that many economic variables are scale related and that it is frequently too simple to assume a linear/static model between such scale-dependent variables. This linearity assumption amounts to assuming local interdependence or no hidden dependence between observations from the viewpoint of joint probability distribution. Ordering data by the conditional scale-dependent variable of concern serves as an easy way to test this assumption. When the assumption is rejected, the revealed nonlinear effect can be captured by augmenting a static model into a difference-equation model, which captures the gradient of the nonlinear effect much more effectively than the use of conditional scale-dependent variables in a quadratic or cubic form as usually found in microeconomic labour supply models. In the present case, the ordering scheme by wife's age or by family income largely conceals the hidden nonlinear scale effect by wage rates. This type of ordering schemes is described to as 'regime mixing' by Zeileis and Hornik (2007).

[9] An economic rationale is offered by Eika, *et al.* (2014): assertive mating often results in correlation between non wife family income/husband's wage and wife's income.

The data ordering effect is best illustrated by comparison of the 1999 OLS recursive estimates, under the ordering scheme by women's age, presented in Figure 1 with those of the same wave in Figure 2. A striking pattern emerges when we examine and compare the OLS recursive processes of different waves under the ordering scheme by w_i in Figure 2. The recursive elasticity estimates follow a somewhat smooth convex curve. Considering the recursive nature of increasing sample sizes, the curves tell us that elasticity of low wage rate earners differs significantly from that of high wage rate earners. This leads us to try and partition the sample into two parts. The partition wage values are chosen by two considerations. Statistically, they adequately represent the turning points of the convex curves;[10] economically, they are comparable when converted into real-value terms by the US inflation rates. The key results of the partitioned regressions are reported in Table 7.

Four features are immediately noticeable from this table when comparing it to the previous estimation results summarised in Tables 6A and B. First, there is little statistical difference between the elasticity estimates of the two data sources for most of the waves. Secondly, the elasticity estimates of the lower part are significantly positive whereas those of the upper part are significantly negative. Thirdly, there are signs of reducing severity of the diagnostic test rejections, mainly from the PSID source. Fourthly, parameter instability is still largely present, especially for estimates using the CPS source, as shown by the Hansen test statistics. Inspection of recursive estimation results tells us that the instability mostly occurs at the tail ends of the wage distribution. Therefore, we further partition the two subsamples to cut out the tail ends, aiming to search for the comparable wage rate ranges within which the elasticity estimates remain statistically constant. The search yields a comparable wage range of $4-$10 from the lower end and $10-$22 from the upper end at the 1999 price level. We refer to these two partition ranges as the lower mid group and the upper mid group in Table 8, where

[10] The location of the turning point has been identified with the help of recursive break point Chow test.

the main results of this search are summarised. Two key changes are discernible from Table 7 to Table 8. The elasticity estimates of the upper mid group are statistically insignificant from zero, and all the estimates in the lower mid group have passed the Hansen stability test whereas only two have failed the test in the upper mid group. Figure 3 plots all the OLS recursive graphs of the lower mid group. The degree of parameter stability is quite impressive, especially considering the large sample sizes of the CPS source. However, what is more impressive is the closeness of these estimates not only between the two data sources of the same wave but also across different waves, especially the last four waves.

Since the lower mid group stands out as having the most stable and significantly positive wage elasticity estimates, we try to further investigate the robustness of this finding from two aspects. First, we run the reverse regression model of the upper equation in (4) with data ordered by H_i and try the same sample partition search to see if it is possible to find ranges of work hours in which relatively invariant parameter estimates of γ_1 exist. This experiment can be seen as a crosscheck of whether w_i satisfies data ordering condition (a). The search yields no positive results, as shown in Table 9. The universal lack of parameter stability and the statistical similarity between the two data sources across different waves serve as strong evidence against postulating H_i as a conditional variable for w_i.

The second aspect is to tackle the residual autocorrelation problem, which is widely observed from the diagnostic tests shown in Table 8. The autocorrelation actually indicates the presence of hidden dependence or nonlinear scale effect, as discussed above. Here, we re-estimate the model using the Cochrane-Orcutt autoregressive least-squares method for those instances where the OLS regression fails the residual AR test. Interestingly, the resulting elasticity estimates do not differ statistically from the OLS estimates, as shown in Table 8. This finding indicates that the nonlinear effect by data ordering satisfies the common factor restriction, e.g. see Hendry (1995, Chapter 7). In other words, the ‘short-run’ wage effect is identical to the 'long-run' wage effect. This is not that surprising considering that the 'short-run' of the present case is wage rate incremental (see Qin and Liu (2013) for more discussion on this point).

The discovery of statistically constant elasticity estimates in two sub-groups of working wives not only reconfirms our rejection of models (2) and (4), but also carries a great deal of practical significance, at least from the following five aspects.

The first and obvious implication of our findings is that wage elasticity for the working wives is not a single-valued parameter. The evidence from Table 8 that statistically constant elasticities exist only with respect to certain wage groups undermines the logic foundation of regarding the labour supply wage effect as a single parameter at the micro, i.e. individual agent level. Consequently, a theoretical re-orientation is probably needed for those investigations which are aimed at establishing links between macro and micro labour supply elasticities on the basis of single-valued micro elasticities. These findings also support more heterodox theories of labour market segmentation (e.g. Dickens and Lang (1992), Leontaridi (1998)) and show potential avenues for future empirical research in this field.

Secondly, there is little evidence of dwindling wage elasticities from 1980 to 2011 as far as those statistically constant elasticities are concerned. On the contrary, these estimates have remained remarkably invariant, as shown in Table 8. Although some sign of decreasing elasticities is discernible from the CPS-based estimates of the three waves of 1980, 1990 and 1999, the decrease is statistically too weak to support the claim of dwindling wage elasticities. If we look at the aggregate estimates from tables 1-6, differences in the wage estimates are somewhat more noticeable from these three waves. In order to find explanations to this phenomenon, we look into the share compositions of working wives by our sample partitions.

What we find is a significant decline in the shares in the lower mid group combined with significant increase in the shares of the upper mid group as well as the upper part from 1980 to

1999, whereas the shares have largely stabilised since 1999, as shown from Figure 4. Since the lower mid group is the only one where stable and significantly positive elasticities are found to hold whereas the upper part of the sample contributes to negate the presence of a positive elasticity, it is no wonder that a dwindling elasticity phenomenon has been observed from aggregate sample estimations of the 1980-2000 period. This finding tells us that what has changed over time is not micro elasticities with respect to the lower and upper mid groups, but the distribution of working wives in relatively lower paid jobs. This is in line with Juhn and Murphy's (1997) observation of increasing wage opportunities for women as well as findings by Welch (2000) on a weakening segregation between male and female labour markets by wage rate. This development is further revealed by the shifting distributions of wife's wage rates from 1980 to 2011 as compared to the distributions of husband's wage, see Figure 5. The distributions of wage rates by gender have clearly been converging over the last three decades.

Thirdly, the finding of the two groups within which statistically constant elasticities are present provides us with a new angle to tackle the sample selection bias concern with respect to sample representativeness and statistical inferability. Our recursive partition search locates the tail ends of the female wage rates in the full-working wife samples as being largely at odd with the rest of the sample. From the practical viewpoint of finding sample evidence which would be representative of the population concerned and thus endorses statistical inference, we should partition out the tail end non-representative observations as judged by the *a priori* conditional theory of interest, so as to tighten the conditional range upon which statistical inferences are made. It should be noted also that this research strategy carries special implication to models using panel data. Since most of panel-data based models assume single valued parameters of interest, it is vital to exclude individual elements in the panel which are far from representative of the population of interest. Failure of such exclusion would result in sample selection bias.

Fourthly, the finding that there is no single-valued wage elasticity across the wage earners suggests that it could be over-simplistic to treat the non-working wives as a homogenous group and carry out empirical investigation on aggregate extensive margins by means of binary regression models. From the viewpoint of measuring wage elasticity for labour participation, disaggregate studies may be better off partitioning data by wage rate ranges rather than occupation types. Since our wage imputation method is based on the idea of counterfactual matching of comparable groups, we can exploit the constant elasticity based sample partitions to examine how the imputed wage rates are distributed. It is seen from Table 10 that around 70 per cent of non-working wives in the PSID datasets are potentially similar to the lower-mid group. Results for the CPI samples are somewhat different. While around 60 per cent of the imputed wage data fall within the lower mid group for the 1980, 1990 and 1999 dataset, this share drops to 30 per cent for the later waves. Clearly, more experiments are needed to evaluate the robustness of those imputed wages, but our experiment illustrates how useful the disaggregate information can be to help better design unemployment policies with respect to targeting the right groups.

Fifthly, the constant elasticity based sample partitions also provide us with an easy way to check the necessity or feasibility of grouping data by certain characteristics. For example, our earlier data ordering scheme by age results in relatively stable elasticity estimates, indicating it unnecessary to disaggregate data by age groups. In other words, there lacks strong evidence supporting the hypothesis that different age cohorts have different elasticities. This check is especially useful for the application of the quantile estimation method. This method has gained increasing popularity as an intuitively appealing way to tackle heteroscedasticity and low fit in large micro data sample modelling. The method is based on a conditional quantile function of interest, a function generally without much *a priori* theoretical support. In our case, the method amounts to postulating $Q_\tau(ln(H_i)|ln(w_i), \eta_{w\tau}, \cdot)$ as against $E(ln(H_i)|ln(w_i), \eta_w, \cdot)$, which underlies model (1'). Since statistically constant elasticities are found with our two groups, we can calculate the shares of work hours within these two groups classified by the four quantiles of H_i of the working wife sample. The quantile method would be considered suitable if the shares in one group are dominantly from one quantile. It is clearly seen from Table 11 that there are no dominant quantiles in either of the two groups to warrant the use of quantile regressions.

Finally, we try to seek answers to the following question by exploiting the non-unique ways of data ordering with cross-section data. Do the wives from the two groups have statistically stable income elasticity? We follow the same strategy as before to try and locate income ranges within which the recursive estimates of η_I are statistically constant, when the full-working women sample estimates turn out to be unstable under the data ordering scheme by I_i. The key results of the search are reported in Table 12. We then calculate, for the two wage groups respectively, the shares of the income partitioned by the income ranges reported in Table 12. We find that the two mid wage groups overlap dominantly with the two mid groups of the income ranges where constant estimates of η_I lie, as shown from Table 13. Hence, the answer to the above question is positive. Moreover, the finding that sizeable shares of income in both groups fall into the income range where estimates of η_I are stable but insignificant from zero helps explain why the estimated income elasticities of these two wage groups are not highly significant (the details of those estimates are not reported here to keep the paper short).

The above experiment illustrates how versatile the method is to combine data ordering schemes with recursive partition search for statistically stable estimates of the parameters of interest. It can help us identify various joint ranges of subgroups from data samples to address practical questions relating to various compositional issues in compound with the parameters of interest, in a much more focused and refined manner than aggregate estimation methods.

4. Concluding Remarks

This project re-examines the commonly used married women's labour supply model using six waves of cross-section data from two sources, PSID and CPS, with the intention to reveal the superfluous the endogeneity-backed IV method and the conventional selection bias correction for the purpose of estimating wage elasticity with respect to hours of work. Results of this extensive modelling experiment have not only fulfilled our intension but also revealed that the superfluousness is not harmless. It actually blocks, by denying the conditional status of those *a priori* postulated explanatory variables of interest, the route of systematic data search to identify the locality where statistically invariant estimates of the parameters of interest hold.

Once the route is unblocked, we are able to make two key discoveries, via extensive use of recursive techniques combined with various data ordering schemes. Firstly, comparatively stable and invariant wage elasticity estimates exist only within certain wage ranges over the last three decades, while secondly, the relative shares of working wives in these ranges have changed. This change is especially pronounced during the two decades after 1980, whereby these wage ranges remain remarkably constant in terms of constant-prices. These discoveries with their locality present to policy makers more reliable and accurate wage elasticity estimates than what has been available from previous studies. From the viewpoint of academic research, the power of these discoveries is manifold, as extensively discussed in the previous section. In short, they help explain the previous finding of dwindling wage elasticity estimates using full samples of working wives of the CPS source; they invalidate the use of single-valued micro wage elasticity estimates and also the premise of a single female labour supply market in which all the housewives are treated as one homogenous group; they provide an easy method to evaluate the applicability of quantile techniques and also a broader perspective to deal with sample selection bias than the conventional estimator-based selection bias correction approach.

There is no need to reiterate the contrasting features between the wage elasticity estimates presented in Section 3 versus those in Section 2. The wide range of wage parameter estimates we have produced in Section 2 by following the textbook approach is adequate to show how arbitrary but fertile the endogeneity-backed IV approach is, thanks to it producing non-optimal predictors of the explanatory variables of interest which are *a priori* deemed endogenous. Widespread paranoia over endogeneity bred by textbook econometrics helps entrap mainstream micro-econometric research in continuous production of non-unique IV-based estimates as empirical support for whatever theoretical postulates. The option whether and to what extent, and/or under what circumstances those postulates could be falsified has been largely left unexplored. We therefore challenge this IV-based route as 'playometrics' (Frisch 1970) because it is far from optimal for scientific discovery.

To a large extent, playometric tools are similar to IVs in that they are apparently correlated with but not necessarily causally related to the economic issues of concern. The argument for endogeneity correction on the basis of correlated error terms is a good example, as discussed in details by Qin (2014a). The use of the Heckman selection bias correction in the present case is another, as discussed in Section 2. Both cases fall into 'type III errors' described by Kennedy (2002) as far as the empirical question of how to best estimate and verify labour supply wage elasticity using cross-section survey data is concerned. In other words, both cases are substantively irrelevant to the empirical question of concern even though they are correct within the abstract settings where they are presented in textbooks. Sadly, the cost of such conceptual errors in applied micro-econometric research is substantial in view of the rapid expansion of data information in contrast to our meagre and sketchy understanding of the data.

It is a widely known fact that model fits usually remain low with large cross-section survey data samples whatever estimation methods are used. The fact reflects the highly partial nature of the theories underlying economic models relative to the sample data information. The situation thus provides little substantive ground to resort to full-blown SEMs which invoke the general equilibrium notion. Moreover, large model residuals with rarely fulfilled white-noise properties call for further criteria to assist model evaluation. For this reason, the invariance condition of individual parameters of interest is regarded indispensable in the present project. As shown from our investigation, within sample parameter invariance is predicated on the choice of data ordering schemes. The non-uniqueness of data ordering schemes provides us with a fertile laboratory to seek and identify the locality of statistically stable parameter estimates and also search for hidden dependence in cross-section data. In view of the extensive theoretical interest in partial derivative based elasticity parameters, data ordering by the explanatory variable of interest serves as a natural and powerful tool in bridging theory and data. Obviously, such data ordering assumes the explanatory variable of interest under concern to be a 'fixed' regressor, i.e. a valid conditional or exogenous variable. Once we step out of the textbook straitjacket of 'endogeneity bias' we can better appreciate the role of *a priori* theories. They are seldom proved wrong in postulating key conditional variables but are frequently inadequate or incomplete in specifying either the functional form or other auxiliary explanatory variables necessary due to various special circumstances of the data samples under consideration. It is a strategic mistake to tamper with the incompleteness by modifying the conditional status of those key variables.

It should be noted that our discovery is essentially based on the OLS, a method rigorously banished for limited dependent models in textbook micro-econometrics. The history of macro-econometrics shows us that it takes over two decades for the profession to shake off the endogeneity paranoia from around 1960, when adequate empirical evidence was first presented to resurrect OLS. It is clearly a huge challenge to initiate a similar resurrection in micro-econometrics. Hopefully, applied micro modellers can overcome the endogeneity paranoia sooner than twenty years, with the help of the rapidly growing data availability and data processing technology (see Angrist and Pischke (2010)) as well as the lessons learned from the history of macro-econometrics.

Clearly, much refinement is desired of our current results and also methods of investigation. An obvious next step is the analysis of husband's wage elasticity using the same set of data to compare whether the heterogeneity found for the wife's samples also holds for the husbands' samples. Further, more experiments with the wage imputation methods are desired and ways should be explored as how to utilise disaggregate wage range groups to conduct disaggregate studies of the wage elasticities of labour force participation in a comparable manner with those of the hours of work. Last but not least, adaption of more systematic data mining techniques is desired, especially from recent developments in statistics into micro-econometrics, such as the method of model-based recursive partition (see Kopf *et al* (2013)). Hopefully, such adaptions would lead to new avenues in microeconomic research.

Appendix 1. Data processing

Two USA based cross-sectional data sources have been taken into consideration, which are the March Annual Demographic Survey of the Current Population Survey (CPS) published by the Bureau of Labor Statistics, United States Department of Labor and the Panel Study of Income Dynamics (PSID) conducted by the Survey Research Centre at the University of Michigan. For the CPS data the Center for Economic and Policy Research (CEPR) Uniform Extracts are used.

From both datasets the following variables have been extracted: wife's annual hours of work, wife's hourly wage rate, family income net of wife's income, wife's education, wife's age, husband's annual hours of work, husband's hourly wage rate, husband's education, husband's age, a dummy which takes on 1 if children under 6 are in the household and 0 otherwise, and the number of children in the household. For the CPS data and additional dummy variable for the wife's ethnical background is included; for the PSID data a variable for wife's experience is used, which is not available in the CPS data source.

Following Heim (2007) and Blau and Kahn (2007) the annual hours worked variable in CPS is created by multiplying the usual hours worked per week times the number of weeks worked in the past calendar year. Regarding the hourly wage rate, we follow Heim (2007) in using the hourly wage rate as reported if available and if the wage per week is reported, this is divided by the usual hours worked per week. For the education variable the coding suggested by the CPS March Codebook for item 18h is used. For family income net wife's income, the wife's personal income from wages and salaries (hourly wage rate times annual hours) is subtracted from total family income.

Both CPS and PSID data sets are processed by the following selection criteria.

- Exclude if woman is non-married, divorced, widowed or separated.
- Include only women with age range 25 to 60.
- Exclude if husband is not working (0 wage).
- Exclude if missing data on wife's education.
- Exclude if missing data on husband's education.
- Exclude if wife's annual working hours exceed 4000.
- Exclude if husband's annual working hours exceed 4000.
- Exclude if wife's wage rate exceeds $300 USD or is below $1 USD at 1999 price level per hour.
- Exclude if husband's wage rate exceeds $300 USD or is below $1 USD at 1999 price level per hour.
- Exclude if total family income net of wife's income is smaller than 0.
- Exclude if wife has reported positive working hours but no wage and vice versa.

Table A1 provides detailed summary statistics of the different waves for the two datasets.

Appendix 2. Imputation Method

The missing wage rates are imputed by the hot deck method, e.g. see Little and Vartivarian (2005), Andridge and Little (2010). The method derives each missing value, referred to as a recipient, from a few donors who are found to share similar characteristics with the recipient. The method consists of the following two steps.

Step 1: Establish a metric for matching donors to recipients. The purpose of the metric is to produce one summary measure comparable between the recipients and the donors. The metric used here is a multiple regression of the upper equation of (2) using the working wife sample only. Several regressions have been experimented with various choices of regressors and the selected model must have all the regressors with statistically stable parameters. The fitted wages are then calculated as representing the summary measures of the donors. The fitted model is used to 'predict' a series of the summary measures of all the recipients. We have also tried the alternative of running a binary model, i.e. a labour force participation model, using the full sample including the non-working wives, with the aim to use the fitted probability scores for the 2nd step matching. However, it is difficult to assess how invariant the estimated coefficients and thus how credible the 'predicted' probability scores are. The trial matched results tend to be smoother than those by the OLS regression metric, making the imputed missing wage rates appear less similar to the observed wage rates, as compared to those imputed by the OLS regression metric. We have therefore abandoned this binary regression metric.

Step 2: Match recipients with their closest neighbours by their summary measures from step 1. This is done by a combination of the nearest-neighbour matching method and the radius matching method. Specifically, we set a starting radius to search for a set number of donors from the lower end of the wage scale (the number is set at five here, in line with what is commonly used in the programme evaluation matching literature). For those recipients which have not yet got enough donors, we gradually enlarge the radius until the required number of donors are found. The missing wage value of a recipient is taken as the average of the observed wage rates of the donors.

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Table 1. IV estimates of α_1 in model (2) and related statistics, working wife samples

Calibration case		Blau and Kahn (2007, Model 4, Table 6)			Heim (2007, Table 1)		
		CPS	**PSID**	**PSID**	**CPS**	**PSID**	**PSID**
IVs		Set 1		Set 2	Set 3		Set 4
1980	Target	$\hat{\alpha}_1^{IV} \approx 366.4 = 0.252 * 1454$			$\hat{\alpha}_1^{IV} = 533.7$, 95% C.I.(-128.7, 1196.1)		
	$\hat{\alpha}_1^{IV}$	314.294**	-166.399	222.999**	332.244**	-166.98*	295.2**
	95% C.I.	(232.9, 395.7)	(-333.3, 0.47)	(62.4, 383.6)	(251.1, 413.4)	(-333, -1.2)	(130.4, 460)
	Hausman	17.6683**	16.8924**	1.4593	21.9117**	17.0288**	4.692*
	1st adj.R^2	0.1164	0.1929	0.1809	0.1181	0.1933	0.1740
	Over-id.	118.26**	17.8094**	75.4455**	139.099**	17.8187**	65.307**
	Elasticity	0.2095	-0.1109	0.1487	0.2215	-0.1113	0.1968
1990	Target	$\hat{\alpha}_1^{IV} \approx 352.7 = 0.216 * 163$			$\hat{\alpha}_1^{IV} = 534$, 95% C.I.(124.8, 943.2)		
	$\hat{\alpha}_1^{IV}$	317.371**	79.63	328.29**	318.2681**	68.339	385.93**
	95% C.I.	(265.2, 369.5)	(-15.1, 174.3)	(223.6, 423)	(266.2, 370.3)	(-26.1, 162.8)	(286.9, 484.9)
	Hausman	15.331**	5.8480*	13.125**	15.664**	7.3365**	23.437**
	1st adj.R^2	0.1987	0.2618	0.2415	0.1983	0.2648	0.2286
	Over-id.	78.558**	19.8407**	68.957**	86.5651**	23.6909**	63.578**
	Elasticity	0.2116	0.0531	0.219	0.2122	0.0456	0.2573
1999	Target	$\hat{\alpha}_1^{IV} \approx 213.3 = 0.122 * 1748$			$\hat{\alpha}_1^{IV} = 303.7$, 95% C.I.(-161.3, 768.7)		
	$\hat{\alpha}_1^{IV}$	259.362**	82.727	221.75**	262.9916**	81.3817	267.82**
	95% C.I.	(209.2, 309.6)	(-30.6, 196.1)	(111, 332.5)	(212.9, 313.1)	(-31.99, 194.8)	(149.1, 386.5)
	Hausman	22.2944**	0.4613	4.4123*	23.8535**	0.4989	7.364**
	1st adj.R^2	0.2078	0.2320	0.2194	0.2080	0.2317	0.2177
	Over-id.	84.886**	31.3218**	30.717**	91.9335**	32.548**	14.137**
	Elasticity	0.1729	0.0552	0.1478	0.1753	0.0543	0.1785
2003	$\hat{\alpha}_1^{IV}$	207.1**	172.87**	314.07**	207.741**	177.3855**	344.115**
	95% C.I.	(169.3, 245)	(35.2, 310.5)	(178.2, 449.9)	(170.0, 245.5)	(42.6, 312.2)	(200.3, 488)
	Hausman	22.567**	3.6356	19.1**	22.935**	4.0707*	23.138**
	1st adj.R^2	0.2164	0.2001	0.1823	0.2038	0.1998	0.1806
	Over-id.	168.77**	19.609**	19.753**	170.089**	19.7775**	13.0213**
	Elasticity	0.1381	0.1152	0.2094	0.1395	0.1183	0.2294
2007	$\hat{\alpha}_1^{IV}$	178.55**	92.669	217.796**	178.267**	86.893	296.759**
	95% C.I.	(142, 215.1)	(-20.7, 206)	(96.88, 338.7)	(141.8, 214.8)	(-25.9, 199.7)	(162.9, 430.7)
	Hausman	9.5622**	0.018	5.923*	9.4702**	0.0005	13.32**
	1st adj.R^2	0.2203	0.2289	0.1862	0.2122	0.2288	0.1754
	Over-id.	155.41**	26.182**	47.478**	155.672**	26.432**	32.734**
	Elasticity	0.119	0.0618	0.1452	0.1188	0.0579	0.1978
2011	$\hat{\alpha}_1^{IV}$	292.8**	331.814**	423.402**	292.306**	335.46**	437.553
	95% C.I.	(255.8, 330)	(202.4, 461)	(288.9, 557.9)	(255.3, 329.3)	(206, 464.9)	(300.1, 575)
	Hausman	68.682**	11.234**	23.28**	68.682**	11.7021**	25.19**
	1st adj.R^2	0.2451	0.1849	0.1618	0.2282	0.1848	0.1681
	Over-id.	111.62**	7.9784	29.226**	113.109**	9.1695	26.2**
	Elasticity	0.1952	0.2212	0.2823	0.1949	0.2236	0.2917

Note: C.I. stands for confidence interval; Hausman is the Wu-Hausman test of endogeneity; Over-id. stands for Sargan over-identification tests; ** and * indicate significance at 1% and 5% respectively. 1st adj.R^2 stands for adjusted R^2 of the first stage regression from the 2SLS/IV procedure; IV set 1: Husband's education, husband's wage rate in log, wife's education, wife's education in quadratic and cubic forms. IV set 2: Wife's education, its quadratic and cubic forms, wife's previous years of work, wife's age in cubic form. IV set 3: Same IVs as in Set 1 plus inverse Mill's ratio conditional on family non-wife income in log, wife's education, wife's age in cubic, number of children, presence of children under 6. IV set 4: Wife's education, wife's previous years of work, wife's age in cubic form and the same inverse Mill's ratio as in Set 3. Elasticity is evaluated at 1500 hours.

Table 2. IV tobit estimates of α_1 in model (2) and related statistics using the same IV sets as in Table 1, full samples including non-working wives

		CPS	PSID	PSID	CPS	PSID	PSID
IVs		Set 1		Set 2	Set 3		Set 4
1980	$\hat{\alpha}_1^{IV}$	1103.22	722.38	1260.62	1162.553	734.9121	1408.975
	95% C.I.	(1038,1169)	(529.2,915.6)	(1070,1451)	(1099,1226)	(541.7,928.1)	(1204,1614)
	Wald	18.99**	3.14	80.16**	6.21*	3.83	103.36**
	Over-id.	297.854**	34.789**	152.895**	353.823**	48.346**	121.252**
1990	$\hat{\alpha}_1^{IV}$	768.3579	596.1497	1090.07	777.22	600.07	1246.528
	95% C.I.	(730.0,806.7)	(481.8,710.6)	(980.8,1199)	(739.2,815.2)	(486.1,714.1)	(1128,1365)
	Wald	91.83**	0.54	112.53**	83.67**	0.43	172.53**
	Over-id.	225.775**	77.268**	266.414**	237.921**	77.815**	165.987**
1999	$\hat{\alpha}_1^{IV}$	674.6063	508.9325	784.589	680.8055	515.2407	930.1164
	95% C.I.	(637.4,711.9)	(371.6,646.3)	(647.7,921.5)	(643.7,717.9)	(378,652.5)	(782.4,1078)
	Wald	89.34**	0.02	23.91**	83.08**	0.07	46.72**
	Over-id.	175.907**	66.341**	115.620**	187.119**	68.125**	64.593**
2003	$\hat{\alpha}_1^{IV}$	626.9265	492.3992	763.7196	627.5508	517.1577	864.2152
	95% C.I.	(598.1,655.7)	(338,646.8)	(614.1,913.4)	(598.7,656.4)	(364.7,669.7)	(705.5,1023)
	Wald	169.57**	0.00	16.64**	167.73**	0.11	27.80**
	Over-id.	384.788**	28.452**	71.022**	386.904**	32.104**	48.613**
2007	$\hat{\alpha}_1^{IV}$	624.1504	485.6784	677.1806	623.2197	485.0906	851.3809
	95% C.I.	(597.0,651.3)	(348.3,623.0)	(534.1,820.3)	(596,650.5)	(349.6,620.6)	(691.9,1011)
	Wald	159.96**	0.01	9.45**	161.11**	0.01	26.88**
	Over-id.	448.117**	54.741**	99.299**	447.535**	54.743**	59.157**
2011	$\hat{\alpha}_1^{IV}$	645.2837	850.8864	1004.48	644.3989	860.8814	1047.094
	95% C.I.	(619.6,671.0)	(701.9,999.9)	(852.5,1157)	(618.7,670.1)	(711.8,1010)	(890,1204.2)
	Wald	143.01**	11.13**	31.44**	144.24**	12.36**	36.83**
	Over-id.	238.034**	31.499**	48.468**	238.488**	36.007**	39.539**

Note: C.I. stands for confidence interval; Wald is the Wald test of exogeneity; Over-id. stands for Sargan over-identification tests; ** and * indicate significance at 1% and 5% respectively. IV sets are identical to those in Table 1. Elasticity is evaluated at 1500 hours.

Table 3. Tobit estimates of α_1 in model (1), the corresponding OLS and scaled OLS estimates

		Tobit		OLS		Scaled OLS	
		PSID	**CPS**	**PSID**	**CPS**	**PSID**	**CPS**
1980	$\hat{\alpha}_1$	380.931	-370.906	283.254	-169.7745	405.808	-265.796
	95% C.I.	(295.1, 466.8)	(-407.3, -334.5)	(221.2, 345.3)	(-191.7, -147.9)		
1990	$\hat{\alpha}_1$	437.991	338.016	351.125	284.513	452.714	382.385
	95% C.I.	(374.0, 502.0)	(307.0, 369.1)	(298.0, 404.3)	(259.0, 310.0)		
1999	$\hat{\alpha}_1$	393.458	106.9957	312.449	109.0798	390.561	142.368
	95% C.I.	(326.0, 460.9)	(74.2, 139.8)	(245.7, 379.2)	(83.4, 134.8)		
2003	$\hat{\alpha}_1$	430.031	-183.6984	327.306	-104.1236	397.699	-137.519
	95% C.I.	(353.5, 506.5)	(-208.5, -158.9)	(262.0, 392.6)	(-123.4, -84.8)		
2007	$\hat{\alpha}_1$	421.387	38.39097	330.237	53.65889	400.287	71.353
	95% C.I.	(347.1, 495.6)	(13.1, 63.7)	(266.5, 394.0)	(34.2, 73.1)		
2011	$\hat{\alpha}_1$	560.137	-64.5882	434.183	-15.6025	538.689	-21.054
	95% C.I.	(484.8, 635.5)	(-92.6, -36.6)	(371.8, 496.6)	(-37.0, 5.8)		

Note: C.I. stands for confidence interval.

Table 4. Parameter stability tests: (i) the 1st stage regression to generate $\widehat{ln(w_i)}_{IV}$; (ii) $\hat{\alpha}_1^{IV}$ of model (2) using the same IV sets as in Table 1; (iii) $\hat{\alpha}_1^{OLS}$ of model (1), full working wife samples

		CPS	**PSID**	**PSID**	**CPS**	**PSID**	**PSID**	**CPS**	**PSID**
IVs		Set 1		Set 2	Set 3		Set 4	OLS	
1980	Joint Hansen	7.714**	0.89675	1.2766	11.856**	1.1871	1.3837	N/A	
	M-fluctuation	2.2881**	1.2364	0.7142	2.3939**	1.2453	0.8677	1.2632	0.7003
	(*p*-value)	(0.0000)	(0.094)	(0.6875)	(0.0000)	(0.0899)	(0.4389)	(0.0822)	(0.7108)
1990	Joint Hansen	11.50**	2.7602**	3.0590**	14.79**	3.7128**	3.1808**	N/A	
	M-fluctuation	1.0649	1.629**	1.3849*	1.0951	1.5676*	1.1185	0.9612	0.9392
	(*p*-value)	(0.2068)	(0.0099)	(0.0432)	(0.1816)	(0.0147)	(0.1637)	(0.3139)	(0.3409)
1999	Joint Hansen	10.56**	5.4582**	1.8842	11.471**	5.9742**	1.8770*	N/A	
	M-fluctuation	1.9557**	1.5463*	1.6401**	1.9663**	1.554*	1.5426*	0.6965	0.755
	(*p*-value)	(0.001)	(0.0168)	(0.0092)	(0.0009)	(0.016)	(0.0171)	(0.7171)	(0.6188)
2003	Joint Hansen	8.507**	3.5908**	1.9347*	9.438**	3.9149**	1.8215*	N/A	
	M-fluctuation	2.183**	0.7086	0.9672	2.1802**	0.7596	0.9239	1.6381**	1.43*
	(*p*-value)	(0.0001)	(0.6969)	(0.3069)	(0.0001)	(0.611)	(0.3606)	(0.0093)	(0.0334)
2007	Joint Hansen	6.293**	2.6137**	3.3213**	6.903**	3.2933**	3.2798**	N/A	
	M-fluctuation	1.2126	0.9086	0.668	1.2081	0.89	0.7072	1.7704**	0.4358
	(*p*-value)	(0.1056)	(0.381)	(0.7637)	(0.108)	(0.4066)	(0.6991)	(0.0038)	(0.9913)
2011	Joint Hansen	7.339**	4.8357**	2.0595*	7.950**	4.8868**	1.8507*	N/A	
	M-fluctuation	1.3061	0.5972	0.6583	1.3134	0.5838	0.6501	1.1847	1.6098*
	(*p*-value)	(0.066)	(0.8679)	(0.779)	(0.0635)	(0.885)	(0.7919)	(0.1208)	(0.0112)

Note: Joint Hansen stands for the joint Hansen parameter stability test for all the λs and σ_{u_i} in the lower equation of model (2) which generates $\widehat{ln(w_i)}_{IV}$; M-fluctuation stands for the double maximum statistics (DM) M-fluctuation test for parameter stability by Merkle *et al* (2013); * and ** indicate significance level at 5% and 1% respectively.

Table 5. FIML estimates of α_1 for $\ln(w_i)$ and γ_1 for h_i in model (4) and related statistics

		Working women sample without selection bias		Full sample with non-workers without selection bias	
		PSID	CPS	PSID	CPS
1980	α_1	-663.988	-390.794	-266.489	-825.867
	t-stat^	-3.27**	-4.81**	-1.62	-9.02**
	γ_1	0.00022	0.000295985	0.00011	0.000112739
	t-stat^	2.78**	11.40**	2.88**	6.64**
	Over-id.	28.647 [0.0001]**	73.122 [0.0000]**	31.943 [0.0000]**	124.60 [0.0000]**
1990	α_1	-287.037	-74.0089	-181.509	-182.757
	t-stat^	-2.82**	-1.42	-1.92	-3.01**
	γ_1	0.00027	0.000258521	0.00022	0.000155719
	t-stat^	4.33**	9.90**	6.19**	9.06**
	Over-id.	31.396 [0.0000]**	110.23 [0.0000]**	31.549 [0.0000]**	138.42 [0.0000]**
1999	α_1	-609.557	-211.142	-377.825	-402.726
	t-stat^	-3.8**	-3.31**	-2.72**	-5.22**
	γ_1	0.000000153	0.000206674	0.0001	0.000115700
	t-stat^	0.00169	5.42**	2.08*	5.12**
	Over-id.	16.550 [0.0111]*	108.89 [0.0000]**	26.913 [0.0002]**	122.70 [0.0000]**
2003	α_1	-164.8	-351.48	-63.0877	-588.229
	t-stat^	-0.842	-6.86**	-0.36	-9.25**
	γ_1	0.00004	0.000180449	0.0001	0.0000508823
	t-stat^	0.6354	6.03**	1.99	2.90**
	Over-id.	38.832 [0.0000]**	122.37 [0.0000]**	43.802 [0.0000]**	170.52 [0.0000]**
2007	α_1	-214.64	-266.109	-162.506	-548.217
	t-stat^	-1.79	-5.95**	-1.33	-8.84**
	γ_1	0.000067	0.000173201	0.000098	0.0000996420
	t-stat^	0.523	4.93**	1.69	5.12**
	Over-id.	39.725 [0.0000]**	80.461 [0.0000]**	35.591 [0.0000]**	85.537 [0.0000]**
2011	α_1	219.577	-78.3481	170.565	-56.3384
	t-stat^	1.09	-1.64	0.996	-0.894
	γ_1	-0.00036	0.000116232	0.00004	0.0000202683
	t-stat^	-2.39*	3.15**	0.571	1.21
	Over-id.	45.133 [0.0000]**	78.302 [0.0000]**	40.639 [0.0000]**	157.62 [0.0000]**

Note: C.I. stands for confidence interval; t-stat^ stands for *t*-test based on HCSE robust standard errors; Over-id. stands for Sargan over-identification tests; ** and * indicate significance at 1% and 5% respectively.

Table 6A. Estimates of $\hat{\eta}_w^{OLS}$ in model (1') and related statistics, working wife samples ordered by w_i

		$ln(I_i)$ using husband wage rate		$ln(I_i)$ using non-wife family income	
		PSID	**CPS**	**PSID**	**CPS**
1980	η_w	0.1054	0.0643**	0.0915	0.0604**
	95% C.I.^	(-0.0315,0.2423)	(0.0105,0.1182)	(-0.0439,0.2268)	(0.0070,0.1139)
	AR 1-2 test:	23.360 [0.0000]**	804.89 [0.0000]**	105.97 [0.0000]**	795.77 [0.0000]**
	Normal. test:	1823.1 [0.0000]**	21396. [0.0000]**	1810.0 [0.0000]**	21253. [0.0000]**
	RESET test:	8.8543 [0.0001]**	16.824 [0.0000]**	6.3416 [0.0018]**	25.769 [0.0000]**
1990	η_w	0.1615**	0.2235**	0.1458**	0.2218**
	95% C.I.^	(0.0989,0.2240)	(0.1843,0.2627)	(0.0846,0.2071)	(0.1825,0.2610)
	AR 1-2 test:	43.640 [0.0000]**	678.45 [0.0000]**	43.999 [0.0000]**	676.23 [0.0000]**
	Normal. test:	3174.6 [0.0000]**	27681. [0.0000]**	3155.4 [0.0000]**	27353. [0.0000]**
	RESET test:	9.5577 [0.0001]**	146.46 [0.0000]**	10.635 [0.0000]**	114.92 [0.0000]**
1999	η_w	0.1305**	0.0947**	0.1219**	0.0926**
	95% C.I.^	(0.0546,0.2064)	(0.0589,0.1304)	(0.0459,0.1978)	(0.0571,0.1280)
	AR 1-2 test:	7.2759 [0.0007]**	439.84 [0.0000]**	7.5549 [0.0005]**	441.26 [0.0000]**
	Normal. test:	2872.1 [0.0000]**	29232. [0.0000]**	2796.9 [0.0000]**	29061. [0.0000]**
	RESET test:	12.484 [0.0000]**	58.163 [0.0000]**	10.310 [0.0000]**	38.031 [0.0000]**
2003	η_w	-0.0193	0.0652**	-0.0233	0.0635**
	95% C.I.^	(-0.0992,0.0606)	(0.0383,0.0921)	(-0.1015,0.0549)	(0.0366,0.0904)
	AR 1-2 test:	26.462 [0.0000]**	958.81 [0.0000]**	27.154 [0.0000]**	952.95 [0.0000]**
	Normal. test:	3806.7 [0.0000]**	51467. [0.0000]**	3771.7 [0.0000]**	51051. [0.0000]**
	RESET test:	4.7041 [0.0092]**	102.35 [0.0000]**	2.0922 [0.1237]	52.963 [0.0000]**
2007	η_w	0.0811*	0.0832**	0.0722*	0.0773**
	95% C.I.^	(0.0135,0.1487)	(0.0566,0.1097)	(0.0066,0.1378)	(0.0512,0.1035)
	AR 1-2 test:	39.750 [0.0000]**	773.51 [0.0000]**	41.538 [0.0000]**	780.35 [0.0000]**
	Normal. test:	4043.5 [0.0000]**	48555. [0.0000]**	4000.9 [0.0000]**	48375. [0.0000]**
	RESET test:	10.934 [0.0000]**	132.26 [0.0000]**	7.4330 [0.0006]**	74.285 [0.0000]**
2011	η_w	0.1440**	0.0786**	0.1460**	0.0775**
	95% C.I.^	(0.0657,0.2222)	(0.0501,0.1071)	(0.0658,0.2262)	(0.0493,0.1056)
	AR 1-2 test:	11.143 [0.0000]**	882.49 [0.0000]**	11.196 [0.0000]**	874.96 [0.0000]**
	Normal. test:	4465.0 [0.0000]**	44067. [0.0000]**	4348.3 [0.0000]**	43288. [0.0000]**
	RESET test:	20.646 [0.0000]**	56.446 [0.0000]**	18.563 [0.0000]**	59.066 [0.0000]**

Note: C.I. stands for confidence interval; ^ stands for HCSE robust standard errors used; ** and * indicate significance at 1% and 5% respectively. AR 1-2 test stands for 2nd-order residual autocorrelation test; Normal. test stands for residual normality test; RESET test stands for Ramsey regression specification test.

Table 6B. Hansen parameter instability test statistics under different data ordering schemes for $\hat{\eta}_w^{OLS}$ in the right two columns of Table 6A

	Ordered by	**1980**	**1990**	**1999**	**2003**	**2007**	**2011**
CPS	**Age**	1.4209**	2.0299**	1.5980**	2.0369**	1.8514**	1.7945**
	Income	0.35413	1.5616**	1.0103**	1.7882**	1.1242**	2.1583**
	Wage	14.442**	11.990**	10.172**	13.754**	10.596**	10.872**
PSID	**Age**	0.051762	0.089821	0.093238	0.15852	0.16041	0.46426
	Income	0.22696	0.4553	0.26751	0.17328	0.35785	0.39903
	Wage	1.0210**	1.5180**	1.1481**	1.4238**	2.1837**	1.8662**

Note: ** and * indicate significance at 1% and 5% respectively.

Table 7. Estimates of $\hat{\eta}_w^{OLS}$ in model (1') and related statistics, working wife samples partitioned into two, data ordered by w_i

	PSID	CPS	PSID	CPS
1980	**< $5**		**> $5**	
η_w	0.4008**	0.7523**	-0.7344**	-0.8744**
95% C.I.^	(0.2354,0.5662)	(0.6793,0.8254)	(-1.1540,-0.3148)	(-0.9706,-0.7784)
Hansen test	0.097470	1.2795**	0.79390**	5.4997**
AR 1-2 test:	44.488 [0.0000]**	259.18 [0.0000]**	42.455 [0.0000]**	232.38 [0.0000]**
Normal. test:	598.05 [0.0000]**	9105.4 [0.0000]**	1260.2 [0.0000]**	7108.9 [0.0000]**
RESET test:	4.0836 [0.0171]*	18.388 [0.0000]**	22.236 [0.0000]**	112.47 [0.0000]**
1990	**< $8**		**> $8**	
η_w	0.2780**	0.6017**	-0.3489**	-0.4034**
95% C.I.^	(0.0912,0.2005)	(0.5341,0.6693)	(-0.4933,-0.2044)	(-0.4818,-0.3251)
Hansen test	0.24888	1.1302**	0.43981	3.6915**
AR 1-2 test:	28.174 [0.0000]**	203.75 [0.0000]**	4.0878 [0.0170]*	304.19 [0.0000]**
Normal. test:	1160.6 [0.0000]**	8186.1 [0.0000]**	1908.7 [0.0000]**	16933. [0.0000]**
RESET test:	4.6074 [0.0101]*	24.824 [0.0000]**	25.942 [0.0000]**	92.994 [0.0000]**
1999	**< $10**		**> $10**	
η_w	0.3601**	0.3489**	-0.1304*	-0.3361**
95% C.I.^	(0.1836,0.5366)	(0.2824,0.4153)	(-0.2557,-0.0050)	(-0.4020,-0.2702)
Hansen test	0.083408	0.39901	0.25306	2.1439**
AR 1-2 test:	3.2069 [0.0410]*	114.53 [0.0000]**	1.6441 [0.1936]	214.87 [0.0000]**
Normal. test:	581.82 [0.0000]**	7568.7 [0.0000]**	2086.3 [0.0000]**	15967. [0.0000]**
RESET test:	1.0228 [0.3601]	21.939 [0.0000]**	5.4624 [0.0044]**	89.717 [0.0000]**
2003	**< $11**		**> $11**	
η_w	0.1976**	0.3225**	-0.4171**	-0.2890**
95% C.I.^	(0.0544,0.3408)	(0.2687,0.3762)	(-0.5696,-0.2646)	(-0.3360,-0.2420)
Hansen test	0.066383	1.1583**	0.45268	3.4500**
AR 1-2 test:	4.2232 [0.0150]*	257.47 [0.0000]**	12.054 [0.0000]**	492.32 [0.0000]**
Normal. test:	409.73 [0.0000]**	9296.9 [0.0000]**	3580.2 [0.0000]**	36000. [0.0000]**
RESET test:	0.6505 [0.5221]	20.417 [0.0000]**	28.754 [0.0000]**	160.74 [0.0000]**
2007	**< $13**		**> $13**	
η_w	0.3395**	0.3299**	-0.2396**	-0.2367**
95% C.I.^	(0.1855 0.4934)	(0.2783,0.3814)	(-0.3424,-0.1368)	(-0.2841,-0.1894)
Hansen test	0.45521	0.47376*	0.093207	1.2606**
AR 1-2 test:	15.908 [0.0000]**	238.84 [0.0000]**	9.4808 [0.0001]**	372.39 [0.0000]**
Normal. test:	891.89 [0.0000]**	9769.9 [0.0000]**	2507.1 [0.0000]**	34758. [0.0000]**
RESET test:	2.1334 [0.1191]	22.140 [0.0000]**	7.1945 [0.0008]**	77.495 [0.0000]**
2011	**< $13.50**		**> $13.50**	
η_w	0.3278**	0.3330**	-0.2057**	-0.2517**
95% C.I.^	(0.1452,0.5105)	(0.2756,0.3904)	(-0.3452,-0.0663)	(-0.3015,-0.2019)
Hansen test	0.16577	1.1026**	0.35168	-10.1**
AR 1-2 test:	6.4511 [0.0017]**	241.38 [0.0000]**	0.2538 [0.7759]	445.02 [0.0000]**
Normal. test:	803.83 [0.0000]**	7703.4 [0.0000]**	3244.4 [0.0000]**	31573. [0.0000]**
RESET test:	0.6919 [0.5009]	22.142 [0.0000]**	32.758 [0.0000]**	120.92 [0.0000]**

Note: C.I. stands for confidence interval; ^ stands for HCSE robust standard errors used; * and ** indicate significant at 5% and 1% respectively. Wage partition values are real-value comparable after deflation by the US inflation rates. AR 1-2 test stands for 2nd-order residual autocorrelation test; Normal. test stands for residual normality test; RESET test stands for Ramsey regression specification test.

Table 8. Estimates of $\hat{\eta}_w^{OLS}$ in model (1') and related statistics, working wife samples partitioned into lower mid and upper mid groups, plus RAL estimates for autocorrelated residual correction of the lower mid group, data ordered by w_i

	Lower Mid Group				Upper Mid Group	
	PSID		CPS		PSID	CPS
	OLS	RAL	OLS	RAL	OLS	OLS
1980	**$2.00-$5.00**				**$5.00-$10.50**	
η_w	0.3297*	0.2924	0.9236**	0.9312**	0.2681	-0.1175
95% C.I.^	(0.032,0.628)	(-0.065,0.650)	(0.829,1.018)	(0.816,1.046)	(-0.094,0.630)	(-0.262,0.027)
Hansen test	0.066046		0.25999		0.38964	1.1773**
AR 1-2 test:	35.470[0.000]**		237.79[0.000]**		44.640[0.000]**	200.80[0.000]**
Normal. test:	661.40[0.000]**	748.76[0.000]**	9666.6[0.000]**	8366 [0.000]**	1073.9[0.000]**	10157.[0.000]**
RESET test:	3.7315[0.024]*		10.588[0.000]**		3.8483[0.022]*	7.1779[0.001]**
1990	**$3.00-$8.00**				**$8.00-$17.00**	
η_w	0.4124**	0.4075**	0.7719**	0.7718**	-0.0755	0.0375
95% C.I.^	(0.247,0.577)	(0.208,0.607)	(0.687,0.857)	(0.668,0.875)	(-0.248,0.097)	(-0.055,0.129)
Hansen test	0.063294		0.36629		0.024241	0.15996
AR 1-2 test:	37.539[0.000]**		170.11[0.000]**		9.3500[0.000]**	224.43[0.000]**
Normal. test:	1206.8[0.000]**	1291.8[0.000]**	8698.4[0.000]**	7629 [0.000]**	1674.6[0.000]**	17938.[0.000]**
RESET test:	5.5774[0.004]**		17.764[0.000]**		5.6574[0.004]**	15.072[0.000]**
1999	**$4.00-$10.00**				**$10.00-$22.00**	
η_w	0.5095**	0.5098**	0.3916**	0.3936**	0.1129	0.0668
95% C.I.^	(0.257,0.762)	(0.254,0.766)	(0.292,0.491)	(0.276,0.512)	(-0.052,0.278)	(-0.017,0.150)
Hansen test	0.069269		0.30388		0.067335	0.66744*
AR 1-2 test:	3.1499[0.044]*		95.103[0.000]**		1.1189[0.327]	174.29[0.000]**
Normal. test:	692.82[0.000]**	674.62[0.000]**	8096.8[0.000]**	7523 [0.000]**	1769.5[0.000]**	16403.[0.000]**
RESET test:	2.3625[0.095]		20.585[0.000]**		12.551[0.000]**	13.450[0.000]**
2003	**$4.50-$11.00**				**$11.00-$24.00**	
η_w	0.2071		0.4530**	0.4542**	-0.0142	0.0248
95% C.I.^	(-0.024,0.439)		(0.369,0.537)	(0.350,0.558)	(-0.170,0.142)	(-0.038,0.088)
Hansen test	0.051773		0.29838		0.095798	0.33216
AR 1-2 test:	2.7872[0.062]		255.25[0.000]**		6.5423[0.002]**	297.37[0.000]**
Normal. test:	328.04[0.000]**		10014.[0.000]**	8559 [0.000]**	2418.1[0.000]**	31624.[0.000]**
RESET test:	2.0790[0.126]		22.154[0.000]**		1.3935[0.249]	32.201[0.000]**
2007	**$5.00-$13.00**				**$13.00-$27.00**	
η_w	0.6299**	0.6347**	0.4295**	0.424609**	-0.1118	-0.0239
95% C.I.^	(0.360,0.900)	(0.313,0.956)	(0.359,0.500)	(0.337,0.512)	(-0.275,0.051)	(-0.091,0.043)
Hansen test	0.046116		0.26206		0.063481	0.28024
AR 1-2 test:	18.531[0.000]**		229.09[0.000]**		19.088[0.000]**	311.17[0.000]**
Normal. test:	889.41[0.000]**	899.67[0.000]**	10816.[0.000]**	9526 [0.000]**	2012.6[0.000]**	28177.[0.000]**
RESET test:	1.5972[0.203]		34.515[0.000]**		10.836[0.000]**	7.1955[0.001]**
2011	**$5.50-$13.50**				**$13.50-$29.50**	
η_w	0.4793**	0.4859**	0.4349**	0.4323**	0.0901398	0.0053
95% C.I.^	(0.175,0.784)	(0.175,0.796)	(0.345,0.525)	(0.319,0.545)	(-0.067,0.247)	(-0.057,0.067)
Hansen test	0.13927		0.30747		0.020069	0.36278
AR 1-2 test:	6.4968[0.002]**		224.95[0.000]**		0.97459[0.378]	234.79[0.000]**
Normal. test:	920.93[0.000]**	806.70[0.000]**	8782.1[0.000]**	7364 [0.000]**	2407.3[0.000]**	22546.[0.000]**
RESET test:	1.1799[0.308]		18.097[0.000]**		1.5094[0.222]	24.795[0.000]**

Note: RAL is the r^{th}-order autoregressive least-squares method; C.I. stands for confidence interval; ^ stands for HCSE robust standard errors used; * and ** indicate significant at 5% level and 1% respectively. Wage partition values are real-value comparable after deflation by the US inflation rates. AR 1-2 test stands for 2^{nd}-order residual autocorrelation test; Normal. test stands for residual normality test; RESET test stands for Ramsey regression specification test.

Table 9. OLS estimates of γ_1 in the lower equation of (4) and related statistics, full working wife samples and subsamples in various partitions, data ordered by H_i

		1980	1990	1999	2003	2007	2011
Full sample							
PSID	γ_1	0.000082**	0.000083**	0.000064*	-0.000008	0.000035	0.000065**
	p-value of t-test^	0.0003	0.0000	0.0122	0.6356	0.1174	0.0054
	Hansen test	0.5524*	1.5082**	1.1711**	0.5951*	0.5064*	1.6662**
CPS	γ_1	0.000058**	0.000122**	0.000081**	0.000064**	0.000072**	0.000077**
	p-value of t-test^	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Hansen test	59.27**	55.4**	61.4**	98.3**	103.1**	94.53**
Part-timers							
1-1680 hours per year							
PSID	γ_1	0.000095*	0.00011**	0.00016**	0.000001	0.000098	0.00019**
	p-value of t-test^	0.0284	0.0029	0.0077	0.9788	0.0617	0.0005
	Hansen test	0.0947	0.2481	0.0262	0.9170*	0.1231	0.0837
CPS	γ_1	-0.000046**	0.000076**	-0.000032	-0.000006	0.000018	-0.000004
	p-value of t-test^	0.0020	0.0000	0.1704	0.7252	0.3949	0.8688
	Hansen test	2.36**	1.01**	1.82**	4.33**	4.23**	3.29**
1-1000 hours per year							
PSID	γ_1	0.000006	-0.000016	0.00027	-0.00045**	0.000097	0.00015
	p-value of t-test^	0.9573	0.8694	0.1122	0.0018	0.4870	0.3376
	Hansen test	0.3851	0.1088	0.0807	0.1591	0.0893	0.1349
CPS	γ_1	-0.000145**	0.000021	-0.000188**	-0.000212**	-0.000186**	-0.000266
	p-value of t-test^	0.0000	0.6316	0.0028	0.0000	0.0007	0.0000
	Hansen test	0.91**	0.27	0.62*	2.28**	1.19**	1.58**
1000-1680 hours per year							
PSID	γ_1	-0.00007	0.00028*	0.000126	0.00046**	0.000368**	0.00024
	p-value of t-test^	0.5874	0.0178	0.3496	0.0039	0.0081	0.0699
	Hansen test	0.0319	0.0931	0.0263	0.0824	0.1016	0.0721
CPS	γ_1	0.000052	0.000038	0.000205**	-0.000004	0.000088	-0.000025
	p-value of t-test^	0.1747	0.4114	0.0001	0.9199	0.0575	0.5846
	Hansen test	1.80**	2.26**	2.03**	4.80**	3.76**	3.16**
Full-timers							
>1680 hours per year (35 hours per week)							
PSID	γ_1	-0.0002**	-0.00019**	-0.000137**	-0.00017**	-0.00007	-0.00022**
	p-value of t-test^	0.0045	0.0000	0.0070	0.0000	0.1505	0.0000
	Hansen test	0.1520	0.2044	0.1392	0.3486	0.0923	0.2045
CPS	γ_1	-0.000041	-0.000032	-0.000020	-0.000070**	-0.000054**	-0.000062**
	p-value of t-test^	0.1400	0.2088	0.4203	0.0004	0.0076	0.0041
	Hansen test	124.1**	132.2**	107.0**	185.5**	190.0**	174.4**
1680-2400 hours per year (35-50 hours per week)							
PSID	γ_1	-0.00006	-0.0001	-0.000326**	-0.00032	-0.000054	-0.00021
	p-value of t-test^	0.5663	0.2303	0.0016	0.7047	0.5250	0.0512
	Hansen test	0.2151	0.2549	0.1329	0.2457	0.1830	0.2289
CPS	γ_1	0.000260**	0.000310**	0.000352**	0.000214**	0.000346**	0.000284**
	p-value of t-test^	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Hansen test	132.1**	151.7**	144.4**	261.1**	264.0**	248.5**

Note: p-value is the probability of the test statistics; ^ stands for HCSE robust standard errors used; * and ** indicate significant at 5% and 1% respectively.

Table 10. Wage distribution of the imputed offering wage rates for nonworking women, percentage shares calculated by the partitions given in Tables 7 and 8

	PSID				CPS			
	Lower part	Upper part	Lower mid group	Upper mid group	Lower part	Upper part	Lower mid group	Upper mid group
1980	84.77%	15.23%	78.52%	13.80%	47.90%	52.10%	47.80%	44.21%
1990	89.83%	10.17%	70.10%	8.47%	67.31%	32.69%	66.37%	30.19%
1999	75.71%	24.29%	69.37%	19.26%	51.02%	48.98%	49.99%	40.15%
2003	76.67%	23.33%	71.49%	19.01%	26.54%	73.46%	26.40%	52.85%
2007	76.09%	23.91%	71.10%	17.88%	39.35%	60.65%	38.25%	46.98%
2011	83.60%	16.40%	71.08%	14.46%	31.69%	68.31%	30.77%	51.46%

Note: group partitions are the same as those given in Table 6 and Table 7.

Table 11. Shares of working wives with wage rates in the lower and upper mid groups in Table 8, by four quantile ranges of hours of work, H_i (in %)

		Lower Mid Group				Upper Mid Group			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
1980	PSID	25.9	26.2	21.6	26.3	16.6	22.3	33.6	27.5
	CPS	25.6	27.2	27.2	19.5	18.6	20.2	33.5	27.4
1990	PSID	30.2	23.2	22.7	23.9	14.9	24.5	33.0	27.6
	CPS	30.3	28.2	18.7	22.8	16.4	23.2	24.9	35.6
1999	PSID	31.8	23.8	20.3	24.1	16.7	25.2	31.9	26.1
	CPS	30.8	27.4	22.7	19.2	17.1	24.4	24.5	34.0
2003	PSID	32.5	22.2	25.1	20.2	17.2	25.2	29.4	28.2
	CPS	30.4	28.3	21.9	19.4	17.9	24.8	29.0	28.3
2007	PSID	31.2	21.1	25.7	22.0	17.3	26.6	30.9	25.2
	CPS	30.1	27.3	22.9	19.7	18.4	24.2	28.8	28.6
2011	PSID	32.1	25.1	20.5	22.3	18.0	22.5	38.2	21.3
	CPS	32.2	27.2	22.0	18.6	19.0	24.1	20.9	27.9

Table 12. OLS estimates of η_I in (1') and related statistics, working wife samples and partitioned subsamples, data ordered by w_i (income in $1,000 USD)

	Samples:	**Full**	**Lower end**	**Upper end**	**Lower mid**	**Upper mid**	**Joint mid**
1980		**Full**	**<$17**	**>$17**	**$6.5-17**	**$17-45**	**$6.5-45**
PSID	η_I	-0.158	0.047	-0.308	-0.052	-0.194	-0.205
	95% C.I.^	(-0.25,-0.07)	(-0.09,0.18)	(-0.52,-0.09)	(-0.32,0.22)	(-0.45,0.06)	(-0.32,-0.09)
	Hansen	0.246	0.109	0.066	0.071	0.046	0.065
CPI	η_I	-0.143**	-0.019	-0.217**	-0.034	-0.218**	-0.177**
	95% C.I.^	(-0.17,-0.11)	(-0.08,0.04)	(-0.29,-0.15)	(-0.13,0.07)	(-0.31,-0.13)	(-0.22,-0.13)
	Hansen	0.685*	0.052	0.052	0.042	0.051	0.164
1990		**Full**	**< $27**	**> $27**	**$10.4-27**	**$27-71**	**$10.4-71**
PSID	η_I	-0.127	-0.057	-0.225	-0.117	-0.354	-0.191
	95% C.I.^	(-0.17,-0.08)	(-0.12,0.00)	(-0.33,-0.12)	(-0.28,0.04)	(-0.51,-0.19)	(-0.26,-0.12)
	Hansen test	0.427	0.170	0.091	0.151	0.026	0.177
CPI	η_I	-0.135**	-0.024	-0.267**	-0.043	-0.264**	-0.161**
	95% C.I.^	(-0.16,-0.12)	(-0.08,0.02)	(-0.32,-0.22)	(-0.13,0.05)	(-0.34,-0.18)	(-0.20,-0.13)
	Hansen test	1.364**	0.146	0.048	0.150	0.049	0.323
1999		**Full**	**< $34.5**	**> $34.5**	**$13.2-34.5**	**$34.5-91**	**$13.2-91**
PSID	η_I	-0.103	0.029	-0.157	0.096	-0.198	-0.091
	95% C.I.^	(-0.15,-0.06)	(-0.07,0.13)	(-0.24,-0.07)	(-0.08,0.28)	(-0.33,-0.06)	(-0.16,-0.02)
	Hansen test	0.366	0.068	0.061	0.050	0.058	0.251
CPI	η_I	-0.086**	0.059*	-0.143	0.045	-0.180**	-0.117**
	95% C.I.^	(-0.11,-0.07)	(0.01,0.11)	(-0.18,-0.10)	(-0.05,0.15)	(-0.25,-0.11)	(-0.15,-0.08)
	Hansen test	1.398**	0.031	0.114	0.029	0.052	0.305
2003		**Full**	**< $38.1**	**> $38.1**	**$14.6-38.1**	**$38.1-100.5**	**$14.6-100.5**
PSID	η_I	-0.121	-0.060	-0.204	-0.258	-0.267	-0.156
	95% C.I.^	(-0.23,-0.01)	(-0.17,0.05)	(-0.31,-0.10)	(-0.44,-0.08)	(-0.46,-0.08)	(-0.23,-0.08)
	Hansen test	0.0911	0.189	0.105	0.052	0.157	0.199
CPI	η_I	-0.106**	0.004	-0.169**	-0.012	-0.218**	-0.127**
	95% C.I.^	(-0.13,-0.09)	(-0.03,0.04)	(-0.20,-0.14)	(-0.08,0.06)	(-0.28,-0.16)	(-0.15,-0.10)
	Hansen test	2.008**	0.034	0.243	0.025	0.131	0.717*
2007		**Full**	**< $42.9**	**> $42.9**	**$16.4-42.9**	**$42.9-113.3**	**$16.4-113.3**
PSID	η_I	-0.103	-0.021	-0.197	0.061	-0.197	-0.086
	95% C.I.^	(-0.15,-0.06)	(-0.09,0.05)	(-0.29,-0.11)	(-0.12,0.24)	(-0.35,-0.04)	(-0.16,-0.01)
	Hansen test	0.382	0.138	0.017	0.065	0.028	0.194
CPI	η_I	-0.104**	0.028	-0.158**	-0.037	-0.202**	-0.141**
	95% C.I.^	(-0.13,-0.09)	(-0.02,0.07)	(-0.19,-0.13)	(-0.11,0.02)	(-0.25,-0.15)	(-0.17,-0.12)
	Hansen test	1.517**	0.203	0.179	0.055	0.113	0.346
2011		**Full**	**< $46.5**	**> $46.5**	**$17.8-46.5**	**$46.5-122.8**	**$17.8-122.8**
PSID	η_I	-0.094	0.002	-0.222	0.044	-0.283	-0.099
	95% C.I.^	(-0.15,-0.04)	(-0.12,0.13)	(-0.31,-0.13)	(-0.16,0.25)	(-0.45,-0.12)	(-0.18,-0.02)
	Hansen test	0.463	0.079	0.063	0.066	0.035	0.240
CPI	η_I	-0.101**	0.025	-0.211**	0.092*	-0.209**	-0.099**
	95% C.I.^	(-0.12,-0.08)	(-0.01,0.06)	(-0.25,-0.18)	(0.02,0.16)	(-0.26,-0.16)	(-0.13,-0.07)
	Hansen test	2.877**	0.267	0.056	0.065	0.019	1.059**

Note: C.I. stands for confidence interval; ^ stands for HCSE robust standard errors used; * and ** indicate significant at 5% and 1% respectively. Income partition values are real-value comparable after deflation by the US inflation rates.

Table 13. Income compositions of the two wage groups in Table 8, by the income partitions given in Table 12

	Lower mid wage group					Upper mid wage group				
Income:	**lower tail**	**lower mid**	**upper mid**	**upper tail**	**Mid two**	**lower tail**	**lower mid**	**upper mid**	**upper tail**	**Mid two**
1980										
PSID	5.3%	45.2%	46.7%	2.86%	91.9%	3.8%	29.3%	62.6%	4.26%	91.9%
CPS	4.4%	39.2%	53.5%	3.0%	92.7%	2.2%	30.9%	61.7%	5.2%	92.6%
1990										
PSID	9.6%	45.9%	41.1%	3.4%	87.0%	6.96%	46.24%	43.18%	3.62%	89.4%
CPS	6.9%	40.9%	47.4%	4.9%	88.3%	2.9%	28.2%	60.6%	8.4%	88.8%
1999										
PSID	4.9%	39.8%	48.6%	6.71%	88.4%	2.29%	27.72%	57.16%	12.83%	84.9%
CPS	6.6%	39.8%	46.6%	7.0%	86.4%	3.0%	25.6%	60.0%	11.4%	85.6%
2003										
PSID	6.4%	44.2%	41.9%	7.52%	86.1%	3.98%	29.22%	57.86%	8.93%	87.1%
CPS	5.5%	39.8%	47.8%	6.9%	87.6%	2.9%	28.4%	58.2%	10.5%	86.6%
2007										
PSID	6.7%	47.6%	40.3%	5.44%	87.9%	2.95%	21.85%	61.71%	13.48%	83.6%
CPS	5.4%	40.6%	46.3%	7.7%	87.0%	2.7%	28.1%	58.0%	11.2%	86.2%
2011										
PSID	12.0%	43.1%	38.1%	6.74%	81.2%	4.65%	32.82%	54.88%	7.66%	87.7%
CPS	7.8%	42.6%	42.8%	6.8%	85.5%	3.5%	29.5%	57.6%	9.5%	87.0%

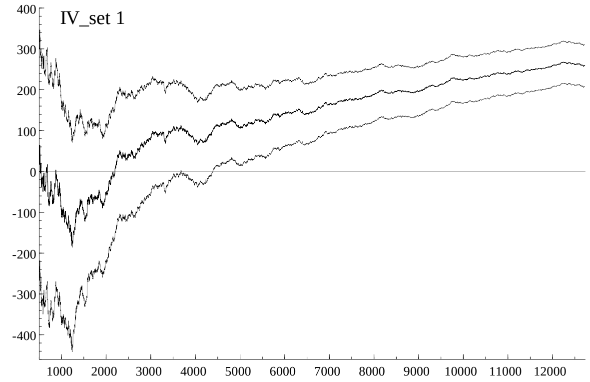
Table A1. Summary Statistics for the PSID and CPS samples

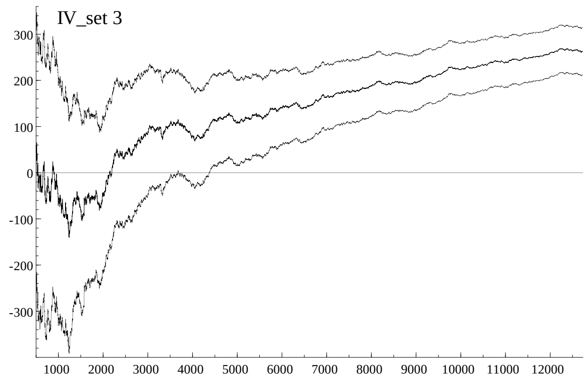
		1980	1990	1999	2003	2007	2011
PSID	Total Sample	2,517	3,712	2,399	2,638	2,729	2,912
	Working wife sample	1,760	2,895	1,943	2,163	2,265	2,359
	Rate of labour force participation	70%	78%	81%	82%	83%	81%
	Average annual working hours*	1,397	1,585	1,691	1,728	1,712	1,699
	Average hourly wage rate*	5.46	9.30	14.64	17.06	19.87	21.57
CPS	Total Sample	22,117	19,914	16,607	27,738	26,050	23,886
	Working wife sample	14,127	14,817	12,724	21,002	19,590	17,701
	Rate of labour force participation	64%	74%	77%	76%	75%	74%
	Average annual working hours*	1,471	1,623	1,738	1,733	1,773	1,765
	Average hourly wage rate*	5.27	9.68	14.37	17.22	19.98	21.91

Note: *conditional on working.

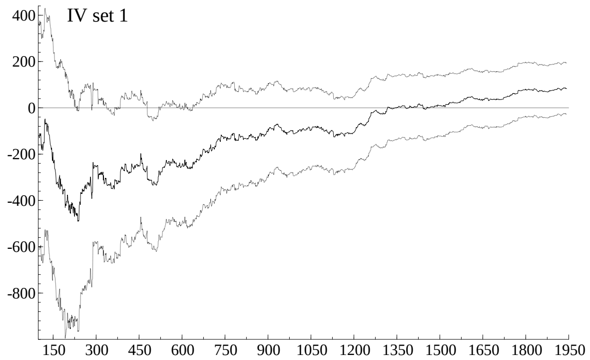
Figure 1. Recursive estimation of α_1 with 1999 data; data ordered by women's age variable

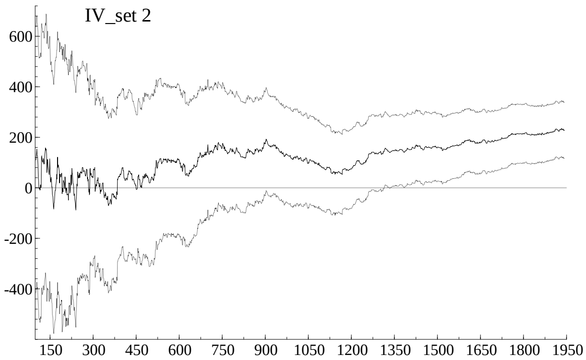
IV estimation using CPS data

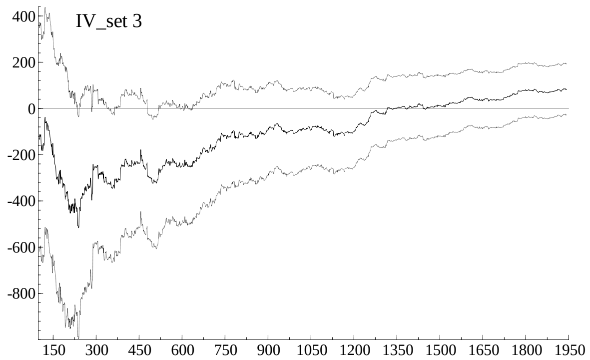


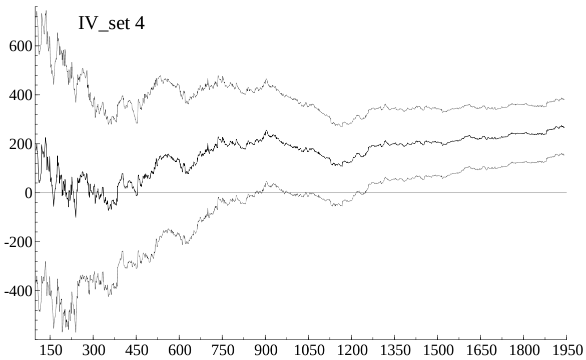


IV estimation using PSID data



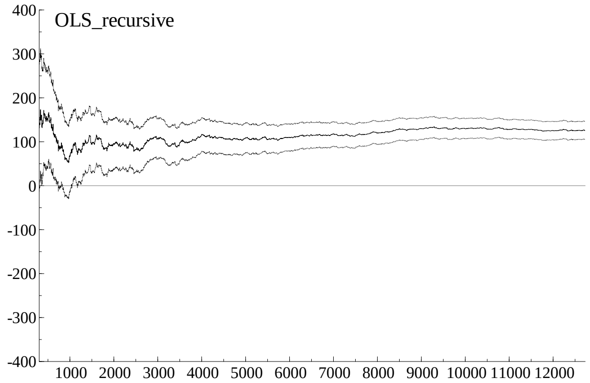






OLS estimation

CPS	PSID



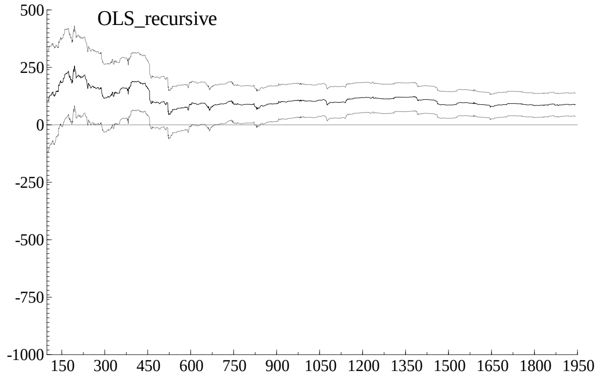


Figure 2. OLS recursive estimation of η_w in Model (1') when data are ordered by wage

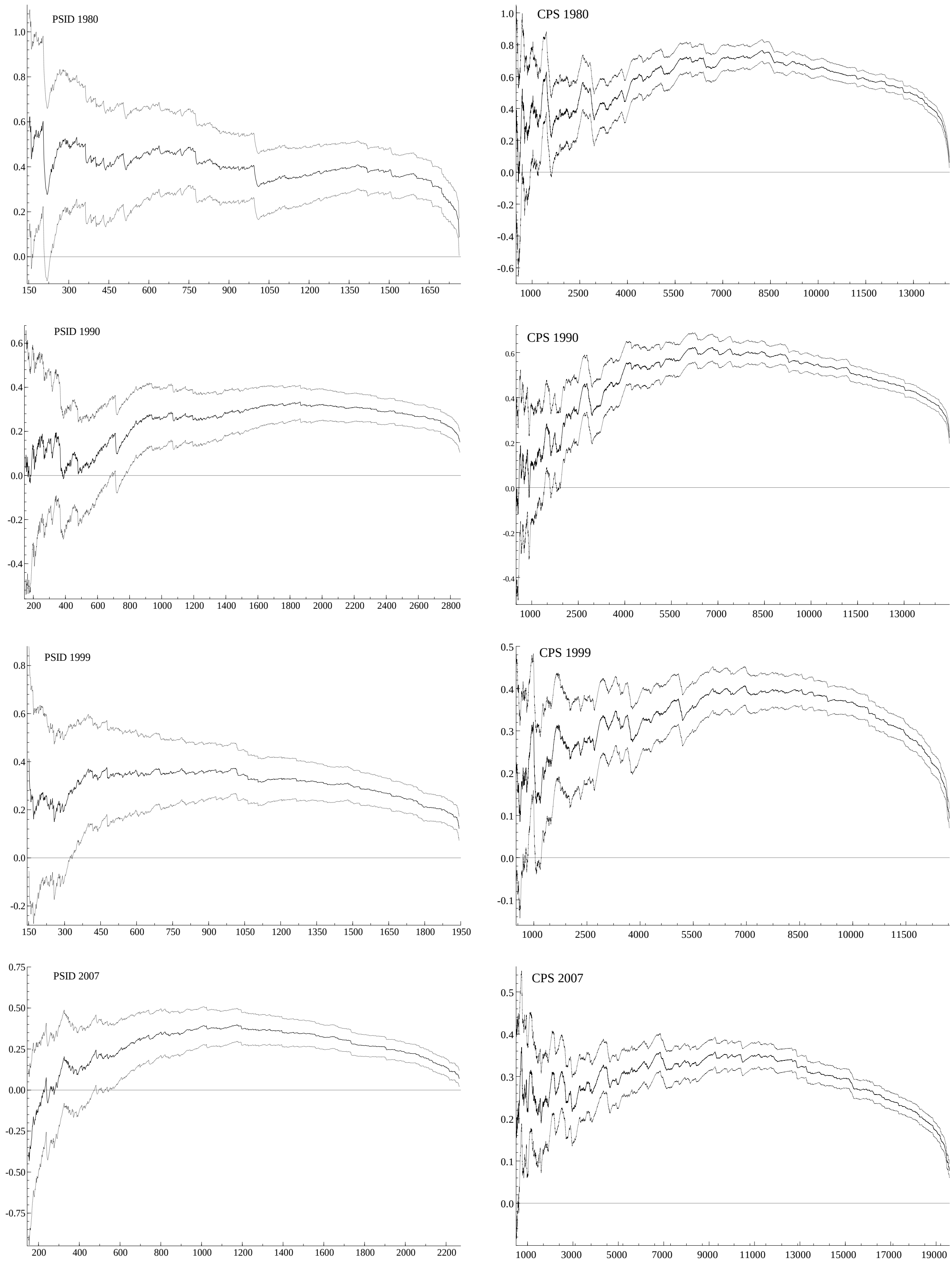


Figure 3. Recursive estimation of η_w for the lower mid group, data ordered by wage

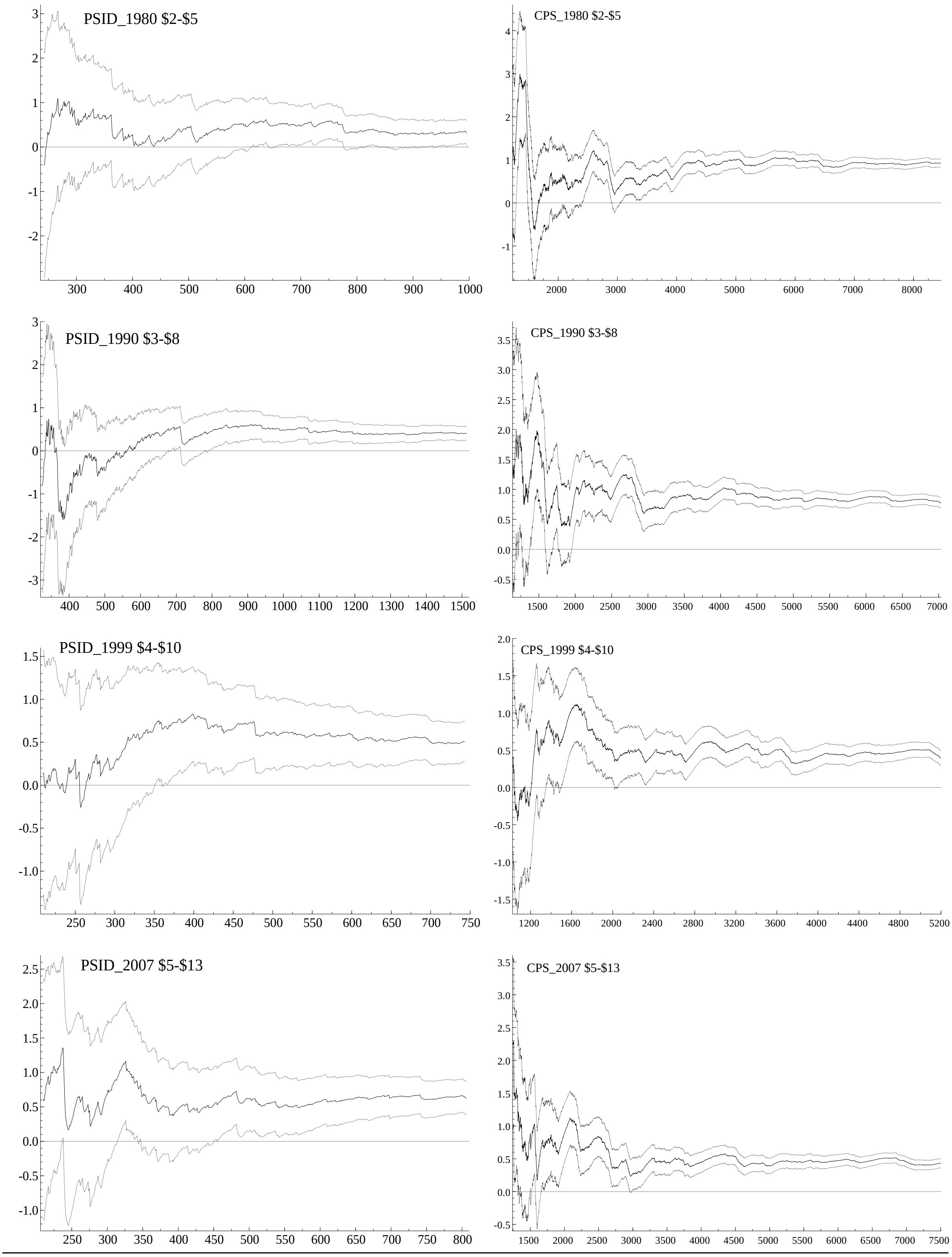
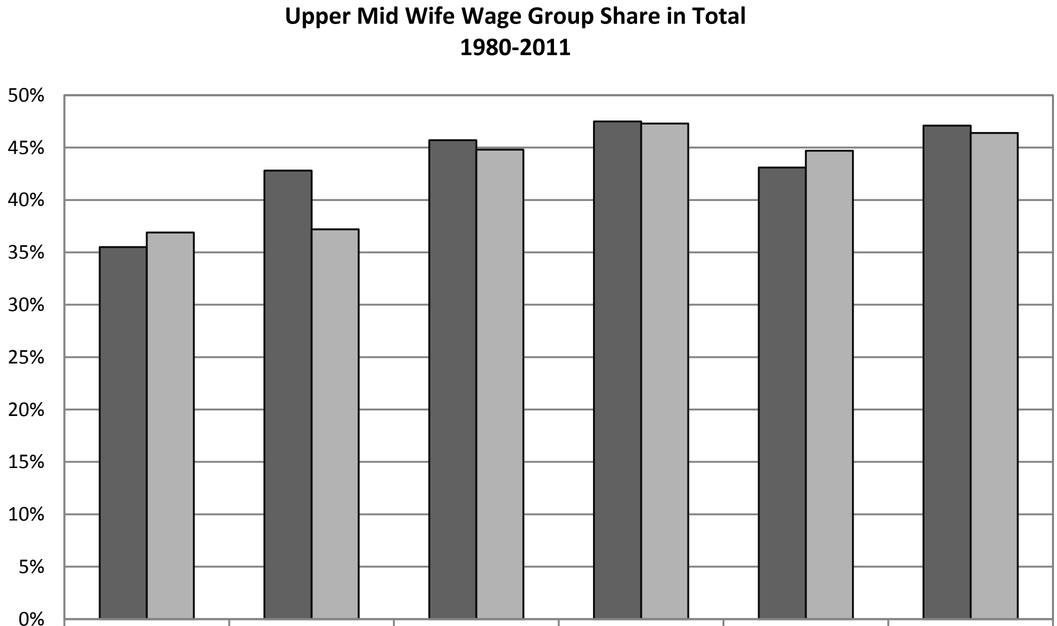


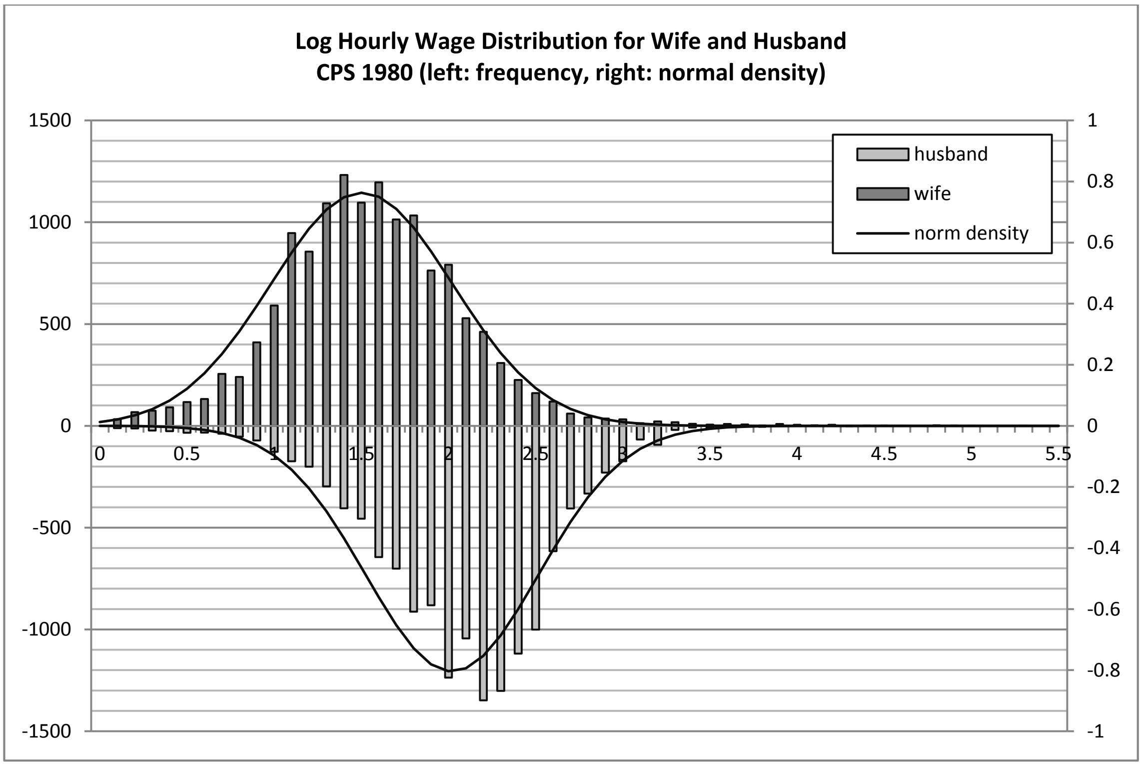
Figure 4. Lower and upper mid wife wage group share in total

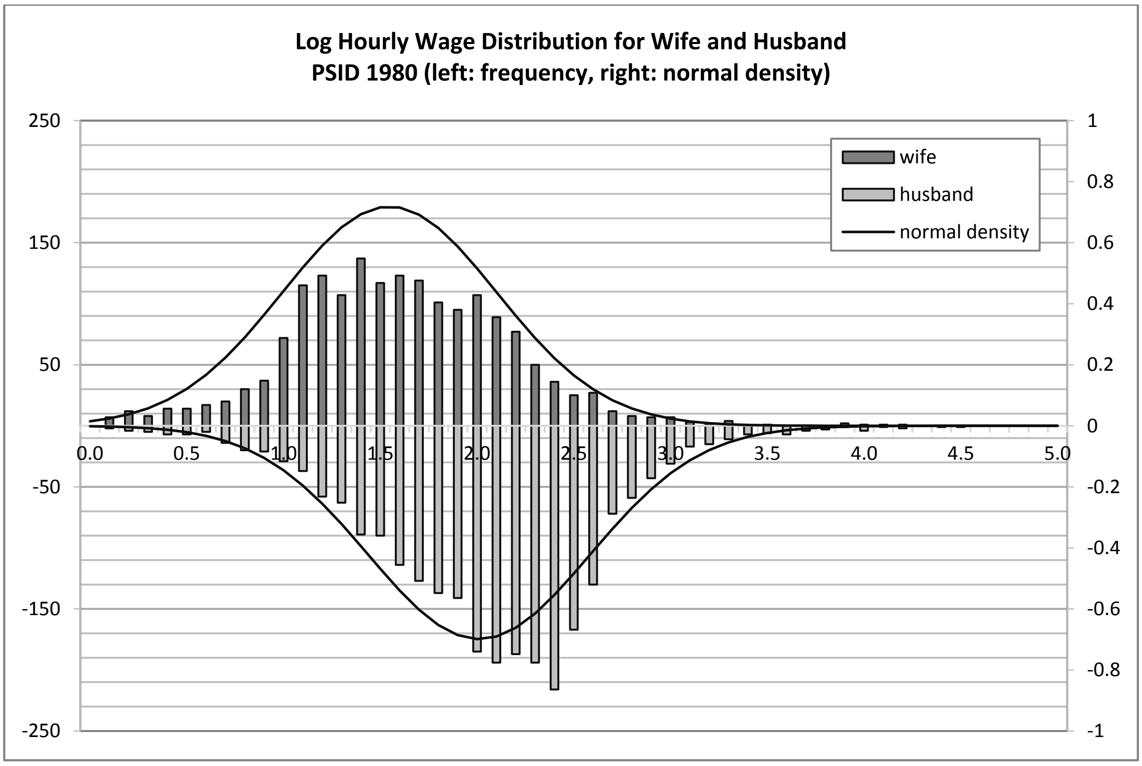
	1980	1990	1999	2003	2007	2011
CPS	54.7%	44.2%	36.7%	30.9%	34.5%	29.8%
PSID	49.1%	45.8%	33.7%	29.0%	31.6%	28.8%

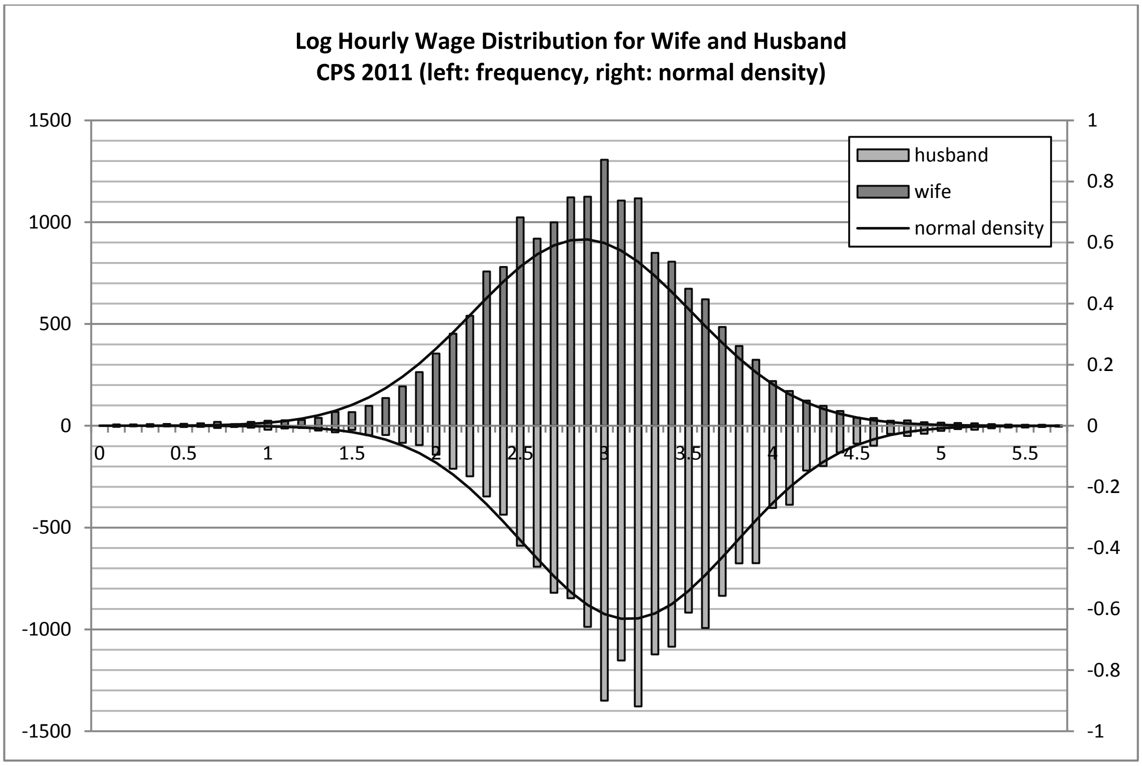


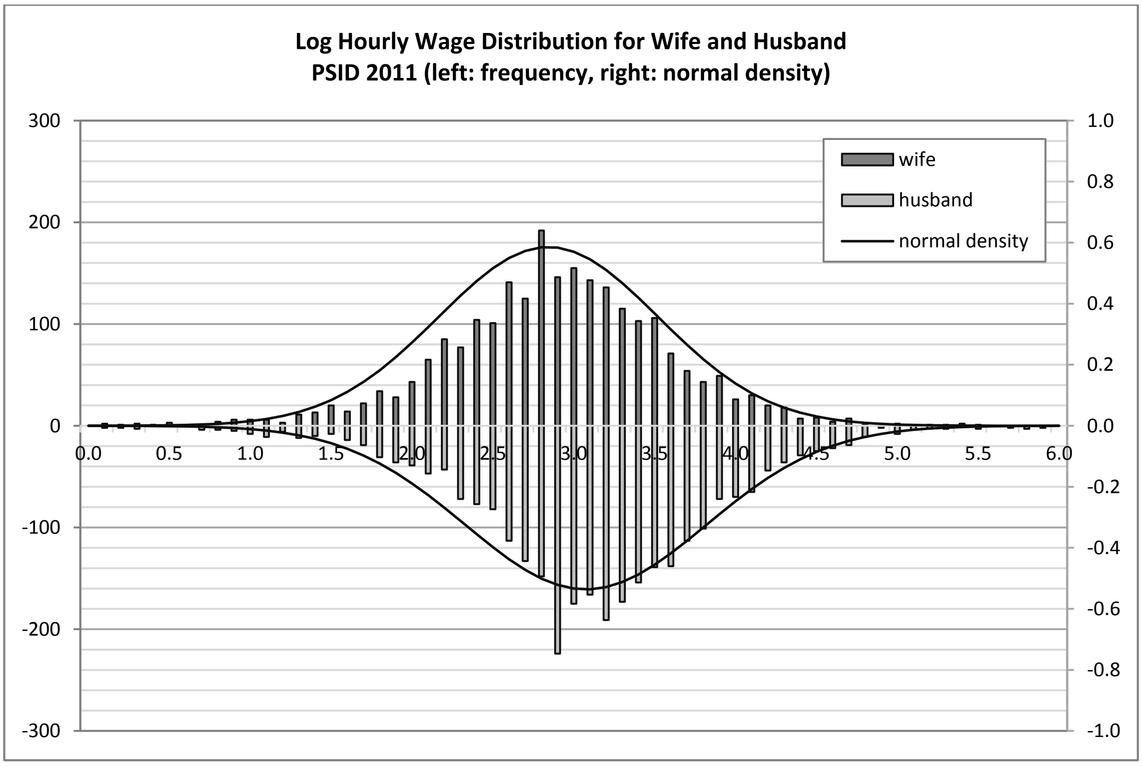
	1980	1990	1999	2003	2007	2011
CPS	35.5%	42.8%	45.7%	47.5%	43.1%	47.1%
PSID	36.9%	37.2%	44.8%	47.3%	44.7%	46.4%

Figure 5. Distribution of wife's and husbands' wage rates in 1980 and 2011






Log Hourly Wage Distribution for Wife and Husband
CPS 2011 (left: frequency, right: normal density)
husband
wife
normal density
1500
1000
500
0
-500
-1000
-1500
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5


Log Hourly Wage Distribution for Wife and Husband
PSID 2011 (left: frequency, right: normal density)
wife
husband
normal density
300
200
100
0
-100
-200
-300
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
6.0